Machine Learning-Based Weldability Assessment and Optimization of Resistance Spot Welding Joints: A Data-Driven Framework

Vinayak Gurav , Divya Shrivastava
Department of Mechanical Engineering,
Shiv Nadar Institution of Eminence Deemed to be
University NCR-Delhi, India
vg697@snu.edu.in, divya.shrivastava@snu.edu.in

Abstract

Resistance spot welding (RSW) is a crucial metal joining process across diverse industries, with a prominent role in the automotive industry. This paper proposes a conceptual framework of data-driven welding analytics by building a machine learning (ML) model and parameter-less optimization algorithm to assess the weldability of spot welded joints. It leverages experimental and simulation data to train the ML model, enabling it to predict weld quality accurately. Various regression-based Machine learning algorithms are implemented to predict weld nugget size. The performance of these algorithms is evaluated by three performance measures: Root Mean Square Error (RMSE), Mean Square Error (MSE), and R-squared. The result shows that Gaussian process regression outperforms other ML algorithms in predicting weld quality. Furthermore, in addition to welding analytics, the proposed framework incorporates a Teaching learning-based optimization (TLBO) algorithm to optimize expected weld quality. The robustness of this optimization algorithm is confirmed through 10 independent runs, maintaining consistent population size and termination criteria.

Keywords
Resistance spot welding (RSW); Machine learning (ML); Optimization; Teaching learning-based optimization (TLBO); Regression learning.

1. Introduction
Resistance spot welding (RSW) finds extensive application in sheet metal fabrication within automotive, aerospace, rail vehicles, and home appliances owing to its simplicity, high production rate, and ease of adoption of automation Hamidinejad et al. (2012). The several car brands and models contain an average of 3000-6000 numbers of the spot to assembly the body in white (BIW). It works on the principle of Joules heating. In RSW, the essential heat required for coalescence is generated by passing an electric current through a stack of sheets sandwiched between electrodes (see Figure 1). The amount of heat generated can be expressed by the equations.

$$H = I^2RT \tag{1}$$

Where H is heat energy in joules, I is current in amperes, R is resistance in ohms, and t is the time for the current to pass through the sheet in seconds. RSW represents a complex thermos-mechanical process involving thermal, electrical, mechanical, and metallurgical phenomena Zhang (2006). This complex phenomenon substantially impacts the overall quality and integrity of the welded joints. The quality of the weld joint is assessed by nugget size, weld strength (Tensile shear strength, Cross tensile strength, peel strength, fatigue strength), modes of failures, micro-hardness, and metallographic evaluation(Jagadeesha 2017; Kishore et al. 2021; Rao et al. 2017). Several methods are available to estimate the quality of welds classified as destructive and non-destructive. In the destructive method, the weld joint is physically separated by applying an external force, allowing for the assessment of quality characteristics. However, it is time-consuming and cumbersome and cannot be applied for inline testing. However, in non-destructive methods, weld quality is estimated using sensor and ultrasonic testing without separating the weld joint Triyono et al. (2011).

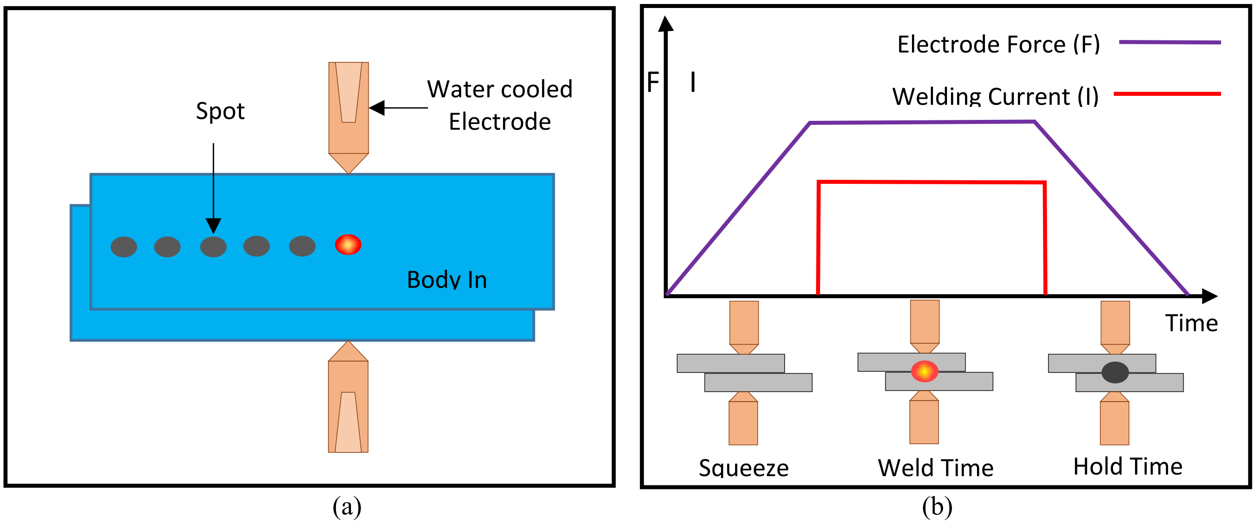


Figure 1. (a) RSW process (b) Weld time cycle in RSW.

Smart manufacturing is currently undergoing a rapid transformation, primarily fueled by the continuous advancements in the fourth industrial revolution technologies, e.g., cloud technology, big data analytics, the industrial internet of things (IIoT), as well as artificial intelligence (AI) and machine learning (ML) applications. In RSW, a large amount of data is generated through advanced sensors and data extraction systems. However, this data cannot be utilized effectively in decision-making. Such data has a great potential to assess and predict the quality of weld joints by developing a data-driven framework. In light of this, the present study proposes an innovative data-driven framework. This framework involves the acquisition of experimental data from a physical RSW machine, which is subsequently integrated with simulation data. These combined datasets are then employed to facilitate the application of a machine-learning algorithm, aimed at predicting the weldability of RSW. Additionally, the predicted values are further optimized by applying a parameterless optimization algorithm, such as the Teaching Learning-based Optimization algorithm (TLBO). As per our study, such a synergistic approach cannot be implemented in the decision-making of the quality of RSW so far. In this paper, a partial framework has been implemented using an experimental dataset available in the literature, which involve building a machine learning algorithm and optimization of process parameter.

2. Literature review

Throughout the literature, research has been conducted to develop analytical, computational, and simulation models and conducted experiments to predict, analyze, and optimize quality characteristics and behavior of RSW. Research has been carried out to leverage the advanced machine learning technique to predict the output of RSW using the available past and real-time data. Over the last three decades, many researchers have developed computational models using the Finite Element Method (FEM), which provides temperature distribution, stress-strain study, and analysis of the RSW process to deal with nonlinear behaviors and complex interactions between thermal, mechanical, electrical, and metallurgical phenomena. Zhigang et al. (2006) introduced a coupled electric-thermal 2D axisymmetric FEM model for analyzing the transient thermal dynamics in RSW. Their research focuses on predicting temperature distribution during the RSW process. Nazari et al. (2020) developed the FE model to investigate the influence of the welding parameter on the residual stresses and weld nugget growth. Their findings highlight a reduction in residual stresses with increased current and weld time. Further study showed that increasing electrode force causes an increase in residual stresses, while increased holding time creates peaks in residual stress levels.

Analytical models play a crucial role in understanding complex processes like RSW. While they may have limitations in capturing all real-world variables, they offer valuable theoretical insights. Cho and Cho (1985) presented analytical models for predicting dynamic contact resistance (DCR) and validated them with experimental results. The analytical result showed a reasonably accurate prediction of DCR. Real-time control of weld nuggets is challenging due to measurement complexities. To address this, Chen and Farson (2006) developed a one-dimensional and two-dimensional axis symmetrical analytical model for heat conduction in RSW. Their work provides temperature insight, profiles, and steady-state results, paving the way for future integration into real-time monitoring and control systems.

RSW presents a challenging scenario due to its complex interaction between inputs and output parameters, making it nonlinear and inconsistent. Many researchers have explored diverse machine-learning algorithms to address this complexity. These ML algorithms gain critical insights from the dataset and enable accurate weld quality prediction. Martín et al. (2009) proposed an artificial neural network (ANN) model, which was trained using supervised learning to predict tensile shear load-bearing capacity.

The number of neurons in the hidden layers of the ANN was determined to minimize overfitting, and it was found that four neurons in the hidden layers minimize the mean square error (MSE). In other research, they employed ANN to predict the pitting corrosion behavior of RSW joints Martín et al. (2010). Pashazadeh et al. (2016) investigated the impact of welding parameters on nugget diameter and weld penetration through a full factorial experiment. They employed the ANN-Genetic algorithm to predict the number of weld spots before electrode tip dressing. In the RSW process, analysis of the dynamic contact resistance (DCR) signal has been extensively used to develop a non-destructive weldability assessment system to predict the nugget width of the RSW joint. Hence, Zaharuddin et al. (2017) used DCR signal to predict the spot weld strength of CR780 high-strength steel sheet.

They investigated the strength of the spot weld of CR 780 using the Adaptive neuro fuzzy inference system (ANFIS). The findings were then compared with conventional ANN results using performance measure (RMSE) and mean absolute percentage error (MAPE). Zhao et al. (2021) discussed the complicated and uncertain relationship between welding parameters and DCR signals. Principal component analysis was conducted to eliminate redundant information in the DCR signal, and a regression-based ANN model was developed to predict weld nugget diameter. Amiri et al. (2020) employed ultrasonic non-destructive testing to investigate the strength of spot weld joints. Ultrasonic tests were conducted for different sample specimens to create datasets, and a machine learning method was deployed to predict tensile strength and fatigue life. And finally, a genetic algorithm was used to optimize the ML model. Recently machine learning algorithms have been widely utilized in RSW processes. However, the varying performance metrics associated with different algorithms often yield inconsistent results. Therefore, it is very crucial to compare and determine an efficient model. In this regards Gavidel et al. (2019) have conducted an extensive and systematic comparison of prediction models. Their approach used bootstrapping and hypothesis testing methodologies to evaluate an efficient model.

3. Data-driven framework for weldability assessment

In the literature, very few authors have proposed a framework combining experimental data with simulation data to assess the quality of the welding process. Such a framework offers several challenges in terms of data accessibility, data integration, simulation model accuracy, model validation, computational resources etc. In this paper data-driven framework is proposed and considered experimental data collected from the machine layer and data from the simulation model, and are used as a dataset for the machine learning algorithm. Then best predicted ML model is used as an initial population size for a parameter less optimization algorithm. Then optimized data is feedback to the machine layer to effectively control the next welding. This data-driven framework for weldability assessment is shown in Figure 2.

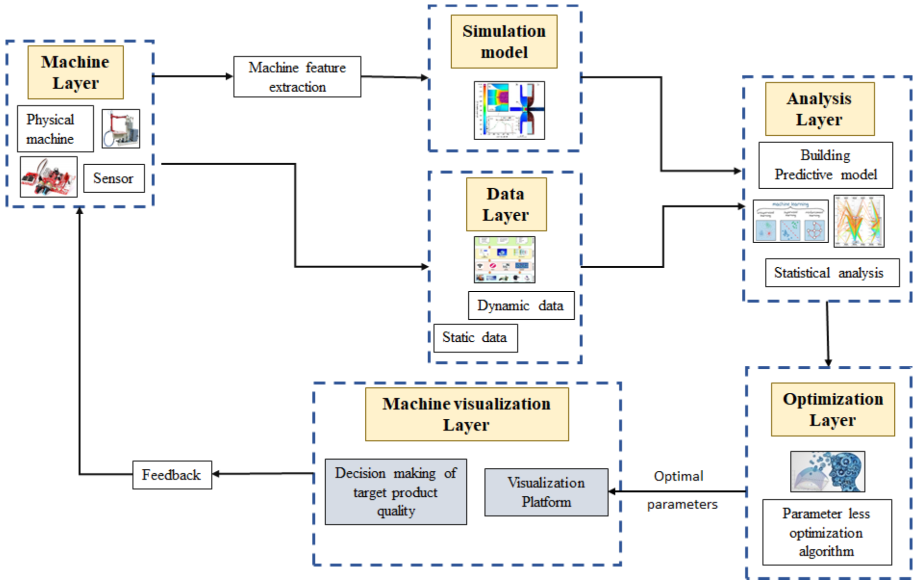


Figure 2. Data-driven framework for weldability assessment

Different layers of this framework are discussed in this section.

- Machine layer- This layer consists of the physical machine of RSW, integrated with a sophisticated communication system designed to seamlessly capture real-time input process parameters and material-related information for precise execution of welding joints.
- Data layer- This layer receives two distinct categorical data - static and dynamic. Static data, data corresponding to materials, and data that does not change after the welding process, i.e., such data remain constant throughout all welding processes. Dynamic data corresponds to the process parameters of RSW. Table 1 provides an overview of the data elements essential for weldability assessment.
- Simulation model- the purpose of the simulation model is to create big data, which is very costly and time-consuming while conducting experiments. The initial phase of this model involves validation with experimental results or established research findings. Subsequently, simulations are carried out to create big datasets channeled into ML algorithms for predicting desired quality characteristics. A simulation model can also receive data from the machine layer.
- Analysis layer- In the analysis layer, data received from the data layer and simulation model is further used to build machine learning models capable of predicting the output of RSW. Additionally, statistical analysis techniques are employed to develop a regression-based mathematical model within this layer. The combined model is further used for optimization purposes.
- Optimization layer- In this layer, Response surface methodology (RSM) is used to develop a relationship between process parameters and output variables in mathematical equations. This equation is used as an objective function to optimize the desired output quantity. A well-known parameterless optimization algorithm, Teaching Learning Based Optimization (TLBO), is employed to optimize the process parameter.
- Machine visualization layer- The machine visualization layer is dedicated to visualizing the optimized process parameters. This visualization occurs through a user-friendly graphical interface. Furthermore, feedback to physical machine aiming to improve the performance.

Table 1. Static, Dynamic, and response parameters of RSW

Process parameters		**Response parameter**
Static parameter	**Dynamic parameter**	
• Materials grade • Thickness of sheet • Types of coating (EG, GA, GI, None)	• Welding current • Weld time • Electrode force	• Nugget size • Tensile shear strength • Cross tensile strength

• Coating materials	• Dynamic Contact Resistance (DCR)	• Peel strength
• Carbon equivalence	• Voltage	• Expulsion Occur (Yes / No)
• Machine Type		• Penetration into sheet
• Electrode size and shape		• Indentation
• Surface coating material and thickness		• Microhardness
• Bulk Resistance		• Microstructure Evaluation
		• Defect occur (Yes / No)
		• Absorption energy

4. Result and discussion

In this paper, experimental data were obtained from Zhao et al. (2016) and used to establish the relationship between the input and response variables using the response surface method (RSM). The RSM facilitated the development of a mathematical equation to generate a dataset comprising 125 data points. Subsequently, 80% of this dataset was used to train the machine learning model, while 20% was used for testing purposes. Six regression-based ML algorithms were employed to predict the response variable. In this study, weld nugget size was used as a response variable.

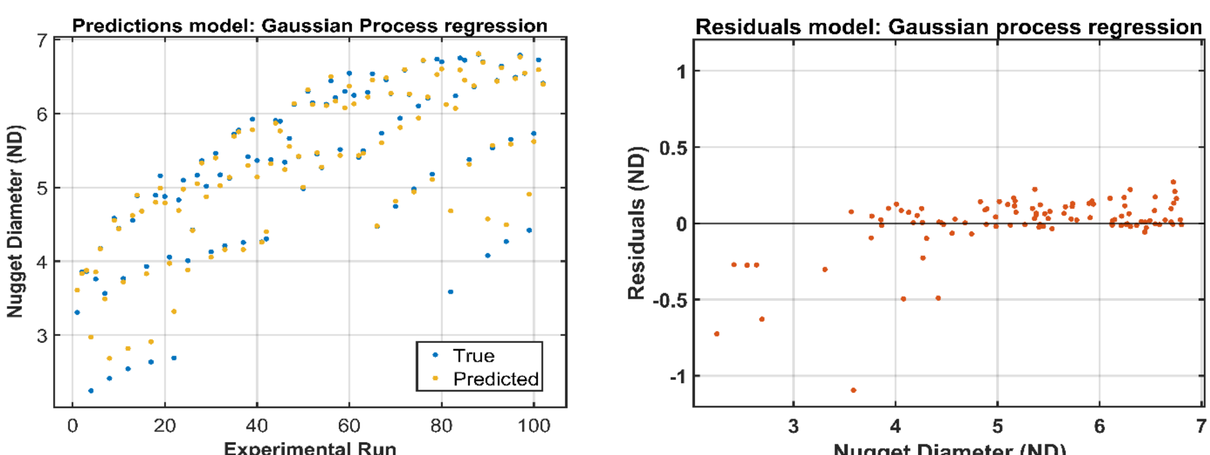
Three performance measures were employed to evaluate these ML algorithms: Root Mean Square Error (RMSE), Mean Square Error (MSE), and R-squared. Equations 2, 3 and 4 show this performance measure's mathematical expression. The performance of the ML algorithms was summarized in Table 2, revealing that Gaussian process regression (GPR) exhibited superior performance compared to the other ML algorithms. Conversely, the prediction accuracy of the linear regression (LR) ML algorithm was notably low. Figures 3 and 4 compare a measured and predicted value for weld nuggets for GPR and LR ML algorithms.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2 \qquad 2$$

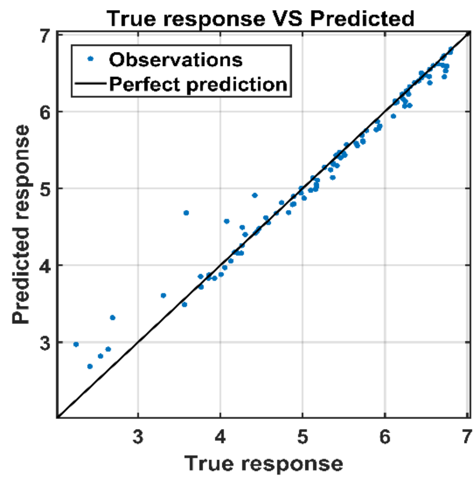
$$RMSE = \sqrt{MSE} \qquad 3$$

$$R - Square\ (R^2) = 1 - \frac{\sum_{i=1}^{n}(x_i - \hat{x}_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \qquad 4$$

Where n= data points, x_i= actual values, $\hat{x}$= predicted values, n= numbers of observations, $\sum_{i=1}^{n}(x_i - \hat{x}_i)^2$= sum of the squared difference between actual and predicted values and $\sum_{i=1}^{n}(x_i - \bar{x})^2$= total sum of squares, which represents the variance of the actual values.



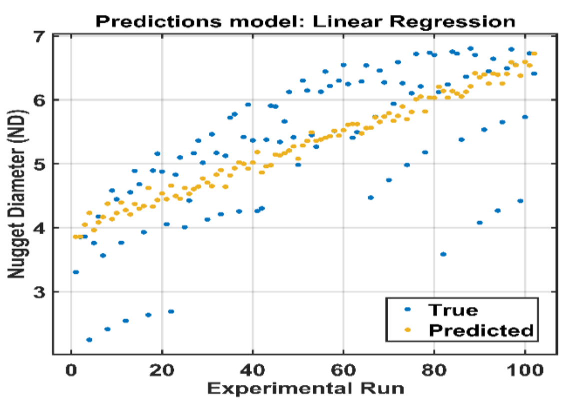
(a) (b)



(c)

Figure 3. Gaussian process regression (GPR) (a) prediction model (b) Residuals model (c) True VS predicted response

Furthermore, Predicted values provided by the GPR algorithm were employed for optimization using the TLBO optimization algorithm.



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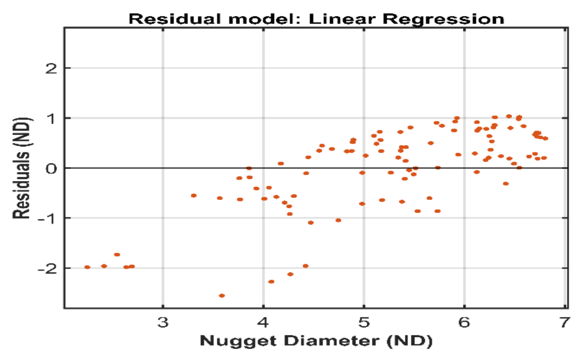

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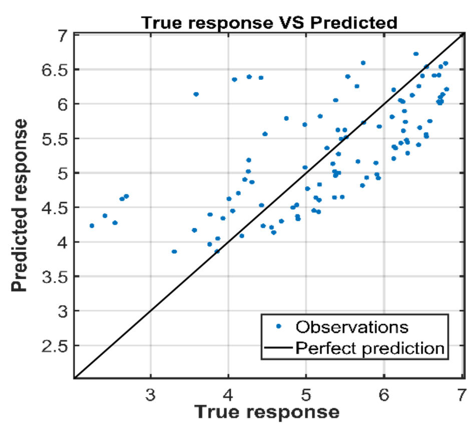

(c)

Figure 4. Linear regression ML algorithm (a) prediction model (b) Residuals model (c) True VS predicted response

Table 2. Performance measure for predicting RSW nugget size using regression ML algorithms.

ML algorithms	**Performance measure**		
	RMSE	**MSE**	**R-square**
Gaussian process regression (GPR)	0.1915	0.0366	0.97
SVM (Medium Gaissian SVM)	0.2394	0.0573	0.96
Neural Network (Medium NN)	0.3659	0.1338	0.9
Kernel (SVM Kernel)	0.6276	0.3938	0.69
Linear Regression	0.6667	0.4449	0.65
SVM (Linear SVM)	0.8567	0.734	0.43

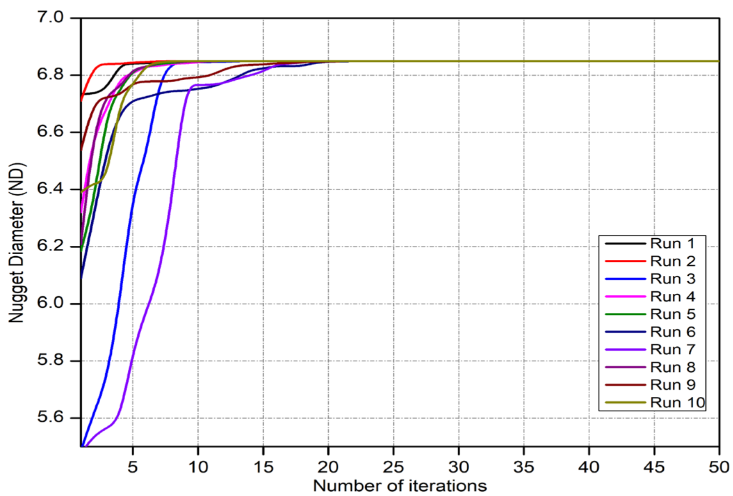

Figure 5. Convergence graph for optimization of weld nugget size using TLBO algorithm

5. Conclusion

The present study proposed a robust framework designed to predict and optimize the weldability of the RSW process. It incorporates all analytics phases, from real-time data collection to prediction of weld quality to optimization of the process parameters. The machine learning algorithm employed in this paper has significant potential to enhance prediction accuracy and add intelligence to the welding process. This approach can reduce the time required for destructive testing, substantially improving production efficiency by reducing lead time and overall operational costs. The novelty of proposed framework is not only to predict the weld quality but also optimize the predicted value. The beauty of this optimization algorithm is that it requires only population size and termination criteria, eliminating the need for algorithm-specific parameters that often require meticulous selection along with population size and termination criteria.

However, this framework is not limited to only RSW. It may also be applied to other joining processes like l arc welding, laser welding, friction stir welding, TIG/MIG welding, etc

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Biographies

Vinayak Gurav is Research Scholar at Shiv Nadar Institution of Eminence Deemed to be University, Dadri, India. He received his M.Tech degree from Indian Institute of Technology, Roorkee (IITR), India. His research interest includes Manufacturing Engineering, metal joining process, Optimization Technique, Production and Operations Management.

Divya Shrivastava is currently working as an associate professor at Shiv Nadar Institution of Eminence Deemed to be University, Dadri, India. She received her Ph.D. in the area of industrial engineering from Indian Institute of Technology Delhi (IITD), India. She is a member of the review committee of several renowned international journals and has many awards and prizes to her credit. Her research interest includes Quality Control, Production and Operations Management, Maintenance Management, Supply Chain Management, integration with operations planning.