

Comparative Evaluation of Machine Learning Approaches for Predicting Optimal Parameters in Cold Metal Transfer Welding of Aluminum 8000 Series

Yajat Kapur¹, Mrigank Gupta², Mohit Nebhnani³, Reeta Wattal⁴

^{1,2,3} IV Year B.TECH Production and Industrial Engineering, Delhi Technological University

⁴Professor Mechanical, Production and Industrial Engineering, Delhi Technological University

Cite this paper as: Yajat Kapur, Mrigank Gupta, Mohit Nebhnani, Reeta Wattal, (2025) Comparative Evaluation of Machine Learning Approaches for Predicting Optimal Parameters in Cold Metal Transfer Welding of Aluminum 8000 Series . *Journal of Neonatal Surgery*, 14 (18s), 1329-1342.

ABSTRACT

Cold Metal Transfer (CMT) welding is an advanced gas metal arc welding (GMAW) technique characterized by its low heat input, spatter-free arc, and precise control over metal deposition. Unlike conventional MIG/MAG welding, CMT separates the wire feeding and current control systems, enabling controlled short-circuit transfer, making it ideal for joining thin and dissimilar materials such as aluminum and magnesium alloys. This study explores the application of machine learning (ML) models—Random Forest, K-Nearest Neighbors (KNN), and Gaussian Process Regression (GPR)—to predict optimal CMT welding parameters (voltage, current, wire feed rate) based on the chemical composition of aluminum alloys. The goal is to achieve target Ultimate Tensile Strength (UTS) while minimizing experimental trials. A benchmark datapoint from aluminum 8011 was used to evaluate model accuracy, and all models were assessed using performance metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). Results showed that GPR and Random Forest provided highly accurate, interpretable predictions. This work contributes to the development of a data-driven, inverse modeling framework for smart welding systems, enabling rapid parameter optimization across a wide range of aluminum alloys.

Keywords: Cold Metal Transfer (CMT), Aluminum Alloys, Welding Parameters, Machine Learning, Random Forest, GPR, KNN, UTS Prediction.

INTRODUCTION

1.1 Background

Welding, a crucial manufacturing process, is commonly utilized in an array of sectors, for instance, the aerospace, automotive, and construction industries, especially in the welding of aluminum alloys due to their low weight and high strength. On the contrary, the most difficult issue is to find out the parameters of welding, e.g., voltage, current, wire feed rate, efficiently for the desired mechanical properties like the key tensile UTS. The approaches traditionally used often need long periods of trial-and-error which is the real hard work and the waste of time and resources. Moreover, the differing compositions of alloys among various aluminum series (e.g., 1000, 6000, 7000, and 8000 series) are the additional complications, thus making the process more challenging. [1].

Machine learning (ML), is the application of data-driven methods. ML models are powerful means for predicting results and at the same time, they can learn complex nonlinear dependencies such as material composition, process parameters, and mechanical properties. Similar techniques are applied in the Random Forest, K-Nearest Neighbors (KNN), and Gaussian Process Regression (GPR) models. With the use of these algorithms, the current study is directed towards the development of an intelligent system for the aluminum alloys which can predict optimal welding parameters for the desired ultimate tensile strength (UTS) both by the forward and inverse modeling method for Cold Metal Transfer Welding of Aluminum 8000 series.

1.2 Aim

The aim of this project is to develop and evaluate machine learning models to predict optimal welding parameters—such as voltage, current, and wire feed rate—for the aluminum 8000 series, in order to achieve the desired Ultimate Tensile Strength (UTS), and to identify the most accurate and interpretable model suitable for real-world industrial use.

1.3 Objectives

- To analyze a dataset consisting of aluminum alloy compositions, welding parameters, and UTS values across multiple series (1000, 6000, 7000).
- To build and train three machine learning models—Random Forest, KNN, and GPR—for both forward (composition and parameters → UTS) and inverse (composition and UTS → parameters) prediction.
- To benchmark the models using a known data point from aluminum 8011 and compare predicted outcomes with real-world tensile strength values.
- To evaluate and compare model performance using appropriate metrics (e.g., RMSE, MAE, R^2) and visualizations (e.g., correlation maps, prediction vs actual plots).

1.4 Problem Statement

Welding parameter optimization for aluminum alloys is traditionally based on experimental methods, which are inefficient and offer limited flexibility when applied to novel compositions or target properties. Existing literature provides insights into predicting tensile strength based on known parameters, but there is a significant gap in inverse modeling—i.e., determining optimal parameters based on alloy composition and desired UTS[11]. Additionally, most prior works focus on single-series alloys or isolated modeling tasks without providing a comprehensive, interpretable solution suitable for industrial deployment. Therefore, there is a need for a robust, data-driven, and scalable system capable of bridging this predictive gap across diverse aluminum alloys.

1.5 Significance of the Study

The research connects with Cold Metal Transfer of Aluminum 8000 series and offers a machine learning-based framework that optimizes welding parameters, thus, helping in attaining the desired quality, performance, and safety of products. The integration of real experimental data and interpretable machine learning models in this research work serves the purpose of minimizing the dependencies on expensive physical trials and thus it speeds up the design-to-production pipeline [1]. The system is designed in such a way that engineers can either predict UTS from process conditions or determine conditions needed to achieve a specific UTS by means of both forward and inverse modeling. Moreover, the results obtained from the research could be the basis for new investigations on the subject of intelligent manufacturing and thus convince to extend the use of AI in materials engineering.

Literature Review

Mishra et al. (2021) – Regression-based ML for FSW Parameter Optimization

Mishra, Morisetty and Tsegaw (2021) analyzed application of supervised machine learning - regression algorithms for the optimization of (FSW) parameters of AA6061. Study focused on predicting weld quality (UTS) drawn through different regression techniques. Decision trees, support vector regression, and random forest models were used by the researchers to look at the relationship between welding speed, Tool rotational speed, and plunge depth, to produce a resultant strength of the weld. From the findings, the Random Forest algorithm performed better than other models regarding prediction accuracy and robustness especially when dealing with non-linear relations existing in welding processes[3]. They highlighted the necessity of data preprocessing and feature engineering for increasing model reliability. The research grants credence to the proposition that carefully picked and trained data-driven models can dramatically decrease the need to rely on cost- and time-consuming trial-and-error experimental techniques.

Mishra and Morisetty (2022) – ML Prediction of UTS in AA6061 Welds

Mishra and Morisetty (2022) reviewed the application of various machine learning models in predicting the Ultimate Tensile Strength of the AA6061 friction stir welded joints. Their approach compared Random Forest, Gradient Boosting and K-Nearest Neighbors (KNN) models, on a dataset that included process parameters, such as tool rotation speed, feed rate, and axial force. The study found that Random forest resulted in the best predictions for UTS because of its capability of handling high dimensional, non linear data efficiently. KNN was also effective in data rich areas but had difficulty in generalising data for sparse input spaces. Importantly, there was an inclusion of a validation of the model framework using cross validation and error such as RMSE and MAE which improves the dependability of the results. Among the most important insights that were identified was the importance of feature importance analysis in determining of which welding parameters contributed the most to strength. This helped in producing process optimization recommendations that would be applicable by welding engineers. The paper highlighted the potential of machine learning to revolutionize materials testing abilities in that it will allow one to make accurate predictions when utilizing small, high-quality datasets and, as result, rely less on physical experimentation.

Kalita and Kalita (2024) – Predictive Modelling for Welding Quality Enhancement

Kalita & Kalita (2024) presented machine learning application in improving welding quality of the various aluminum alloys on predictive modelling. Their research consisted of training Random Forest and Gaussian Process Regression (GPR) models from welding data obtained on AA6061 and AA7075 joints. They did not measure only UTS but also hardness, porosity, and surface finish, and, thus, their model could be considered to be multi-output in nature. The GPR was highly appreciated particularly in its uncertainty estimation and, therefore, fit for the application where safety and reliability are the core aspects. The authors prioritized interpretability of models with SHAP values and cross-section analysis of prediction habits to help the weld engineers feel and justify trusting the system. Among the bright aspects of their approach was the use of thermal cycle data for the enrichment of the feature space and increasing the model robustness. The study illustrated that integration of domain knowledge and ML techniques can enhance predictive accuracy as well as control the welding process by a great deal. Their findings encouraged implementation of AI-based quality monitoring tools in the advanced manufacturing with particular focus in the spheres of such industries as aerospace and defense, which cannot do without the precision welding.

Literature Gap

Although many studies have shown the efficiency of prediction for tensile strength as well as optimal parameter selection for aluminum alloys using machine learning models such as Random Forest, KNN, and GPR, most of them consider only one or few alloy types and parameter sets. It is evident that there is a significant deficiency in research that combine multi-alloy datasets of 1000, 6000, 7000 series with the ability to have a reverse prediction i.e. to suggest a set of process parameters for a given target UTS. Additionally, there are few studies that offer a complete, interpretable simulator, both predictive up to the scope of the industrial deployment and usable in real life. These gaps are filled by our project that will develop a multi-alloy, bidirectional and interpretable ML-based welding prediction system.

Methodology

1. Introduction

The welding of aluminum alloys is a critical process in modern manufacturing industries, especially in sectors such as aerospace, automotive, and construction. Aluminum alloys, due to their lightweight and high strength properties, are preferred materials, but welding them efficiently poses unique challenges. Different series of aluminum, including the 1000, 6000, and 7000 series, exhibit varying behaviors under welding conditions based on their composition and physical

properties. Traditional methods for determining the best welding parameters for each alloy require extensive trial-and-error and practical experimentation. Cold Metal Transfer (CMT) welding is a low-heat input MIG welding process that enhances precision and reduces distortion. Literature highlights CMT's suitability for thin aluminum alloys, producing consistent welds with minimal spatter. In this study, CMT's process stability and arc characteristics are considered during model training, with key parameters (wire feed rate, current, voltage) influencing UTS predictions. Previous studies (e.g., Kalita & Kalita, 2024) validate the applicability of ML for optimizing CMT welding conditions, forming the foundation for dataset design and modeling in our pipeline.

This project is focused on leveraging machine learning to bridge the relationship between the chemical composition of aluminum alloys and optimal welding parameters that produce the best tensile strength outcomes. We use a real-world dataset that includes around 100 data points detailing alloy compositions, welding parameters, and resulting UTS values. Furthermore, to validate our models, we incorporate a cited benchmark data point from aluminum 8011, which serves as a test case for comparing model predictions against known standards. The broader goal is to build a simulator—or supermodel—that enables manufacturers to input alloy composition and a target UTS and receive predictive outputs of the most suitable welding parameters.

By using multiple ML algorithms and comparing their performance based on accuracy, generalizability, and interpretability, the best-performing model will be identified. The long-term goal is to automate and simplify the selection of welding conditions based on alloy composition and performance targets, making this approach applicable in both R&D labs and on production floors. Model interpretability and robustness, especially given the safety-critical nature of welding in industrial applications, will be emphasized equally alongside predictive performance.

2. Dataset Overview and experimental setup

The experimental setup involved MIG welding using CMT technology with a synergic power source, pre-calibrated torch movement, and argon shielding. Welding was performed on AA6061-T6 plates, with varying voltage (17–24V), current (90–140A), and wire feed rate (2–6 m/min). Specimens were machined post-welding for UTS testing using a universal testing machine.

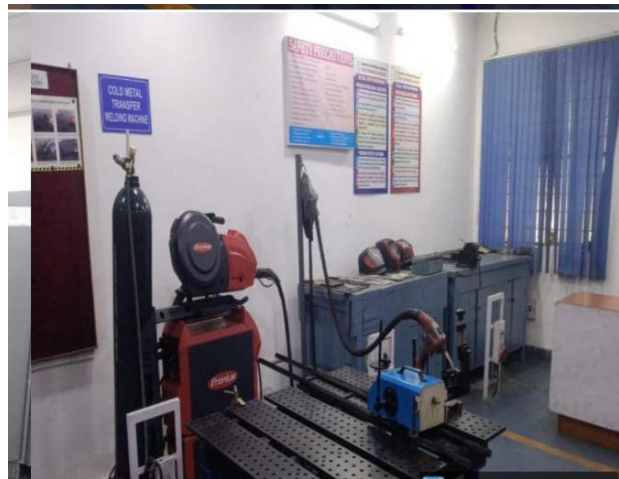


Figure 1: experimental setup

The dataset that is at the center of this project is represented by about 100 experimental observations obtained from academic research work on welding of aluminum alloys, especially from the AA6061 series. The data consists of several chemical compositions, and respective welding parameters associated with the metal inert gas (MIG) welding process. In particular, every data point indicates the weight percentage of nine alloying elements: Aluminium, silicon, iron, magnesium, copper, magnesium, manganese, chromium, zinc and titanium. Also, among the welding process parameters that are important, three are documented: voltage (volts), current (amperes) and the rate at which the wire is fed (meters per minute). Megapascals (MPa) are used in measuring the dependent variable for prediction, namely, the Ultimate Tensile Strength (UTS) [1].



Figure 2: Setup for welding

Although modest in size, the dataset is a good reflection of actual experimental data in the real world and contains complicated non-linear interactions between order, process parameters and the produced strength. The alloys used range various aluminum series (1000, 6000, 7000) which have different physical properties. For instance, the 6000 series alloys have average strength and good corrosion resistance while those of 7000 series alloys are high however, they are more difficult to weld because of hot cracking and susceptibility to thermal cycles.

One of the essential entries in the dataset is a benchmark data point from the aluminum 8011 series taken from cited research paper [6]. In this entry, the composition and UTS for AA8011 is given but its welding parameters are not stated. The concept is to feed this composition as a test input to all the ML models and outputs predictions involving voltage, current, and wire feed rate. These predictions are subsequently compared to the benchmark UTS that is known in order to determine the performance of model.

3. Data Preprocessing

Data preprocessing is a key aspect of this methodology and is of great importance in the case of handling small data that are very important in training and evaluation of models. With the nature of experimental data, the first step is preliminary assessment of data quality such as filling in the missing values, detecting inconsistencies, and detecting potential outliers. However, this dataset has most of its records adequate, while there are possibilities of some omissions in other entries. These missing values are replaced by the KNN imputation, which infers the missing entries by the most similar observations in a feature space. This technique works better than the imputation of means or medians in protecting relationships in data, especially in small datasets [2].

Another important preprocessing step is feature engineering. This entails developing new features from the domain knowledge. For example, the heat input ($\text{Voltage} \times \text{Current} / \text{Welding Speed}$) gives a better representation of the energy inputted during welding process that is directly connected with metallurgical changes and mechanical properties. There are also interaction terms that can be incorporated to allow the presence of synergistic effects on strength and elements such as Mg and Si can be used to allow synergistic effects on strength because these are known to form strengthening phases in heat treated aluminum.

To ensure the management of multicollinearity among features and particularly in the existence of numerous alloying elements, the use of Principal Component Analysis (PCA) as a dimensionality technique is taken into consideration. PCA coordinates the feature space into a series of uncorrelated components that preserve most of the structural data, thus making training of simpler and more efficient models easy. However, PCA is only used if it helps in improving the performance of the model without losing on explainability.

These preprocessing steps (data cleaning, scaling, feature engineering and dimensionality reduction) are carried out systematically to have high quality data for a good model training. They offer a good solid background onto which strong accurate and interpretable ML models can be based.

4. Exploratory Data Analysis (EDA)

Exploratory data analysis (EDA) is used to determine the correlations between the material compositions, in the process of welding, and UTS produced. With this step, we learn about patterns, mutual relationships, and suspect outliers in the

dataset, which can guide the model and feature selection approaches. With the difficulty of welding metallurgy, EDA allows to detect nonlinear patterns existing in data not only linear [4].

First activity in EDA is making correlation matrices based on Pearson and spearman coefficients to find out how strongly the different feature are associated with UTS. For example, magnesium and silicon content are to demonstrate strong positive correlations with the tensile strength, particularly in alloys of the 6000 series because of the precipitation hardening. However, in the contrary nature, excessive iron could register a negative effect. The same kind of analysis is performed for process parameters. Typically, it is seen that with the rise of current and voltage strength increases up to some point, with intense heat input strength may decrease because of over-aging and distortion.

Then, we use visual means such as scatter plots, pair plots, and boxplots to look at data distributions. This is useful to detect outliers and extreme values that might have an inappropriate impact on the training of the model. For instance, when one sample presents unusually high current which gives rise to anomalously low UTS it can mean an error during experimentation or rupture to welding stability [13].

The importance of the features is measured by Random Forest regression and SHAP (SHapley Additive explanations) values. The SHAP values provide interpretability because it is possible to quantify the input of each feature to the prediction that is vital in an area such as welding where engineers need to know why a given model prescribes certain parameters. For example, SHAP could show that Mg content has a positive effect on UTS in one of the models, while wire feed rate claims the dominance in another.

Finally, we apply clustering methods such as K-means or hierarchical clustering to find out whether various compositions of alloy gather together and whether such groups correspond to different optimal welding regimes. Such information can be used in the future designing of alloy and welding procedure optimization. On the whole, EDA is not merely one of the diagnostic tools but also a strategic assistant in the field of feature selection, model selection, and industrial interpretation.

5. Model Selection & Evaluation

To develop a strong and precise predictive simulator for welding aluminum alloys, in this study, we used three different machine learning models—Random Forest, K-Nearest Neighbors (KNN), and Gaussian Regression Process (GRP). These models were chosen in order to provide the range of algorithmic methods: ensemble learning (Random Forest), instance-based learning (KNN) and probabilistic non parametric modeling (GRP) [10]. Such variety makes sure that both the strengths and weaknesses of various learning paradigms are examined under the context of predicting optimal welding parameters for maximum tensile strength.

Random forest is one of the popular ensemble learning techniques that train multiple decision trees and gives their average predictions. Its strong point is its ability to cope with nonlinear data and high-dimensional feature spaces with robustness against the problem of overfitting. In our case, the Random Forest model is used to explain the connection between the chemical composition of alloys and the parameters of the process that could deliver a pre-defined UTS. Feature importance metrics from Random Forest help further to understand which alloying elements and parameters in terms of welding have the biggest impact [6].

K-Nearest Neighbors (KNN), an intuitive and easy-to-use model, makes a classification or prediction, based on the output of neighboring data points in the feature space. It is especially efficient in datasets of the size of ours where the similarity of the data is an important performance aspect. Parameters k in KNN had been optimized using the grid search and cross-validation. Since it uses distance metrics to a large extent, preprocessing by normalization was a necessity in order to make all features comparable.

Gaussian Regression Process (GRP), also known as Gaussian Process Regression, is a probabilistic model that does not only predict the output but also gives an interval of confidence for it. This is extremely useful for real-world applications such as welding in which having knowledge about associated uncertainty of a prediction can guide engineering judgment. GRP makes an assumption about probability over functions and it revises its belief by seeing more data. Although computationally more expensive, GRP is high-performing with small to medium datasets, and thus, it is superior to this project.

For every model performance was measured in terms of several metrics. Root Mean Squared Error (RMSE) for regression accuracy was the main metric with R^2 score help in ascertaining how well the model explains the variance in the target variable. K-Fold cross-validation ($K=10$) was used to reduce the chances of overfitting as well as to accurately estimate the generalization performance. Residual plots and prediction-error plots analysis was carried out for measuring model bias and variance [8].

For robustness purposes, the models were tested using a real-life alloy (Aluminum 8011) having a known composition and UTS. The task was for each model to estimate the best values of welding parameters, and then estimate UTS by reverse prediction using the mentioned values. The closeness of the predicated UTS as to the actual benchmark served a measure of practical reliability. This two-way validation, predicting process parameters from UTS and confirming UTS from predicted parameters added a greater degree of confidence on the consistency of the model.

Result and Discussion

Analysis of the data using models

Random Forest

$$\hat{y} = \frac{1}{T} \sum_{t=1}^T h_t(x)$$

where T is the number of decision trees, and $h_t(x)$ is the prediction of the t -th tree.

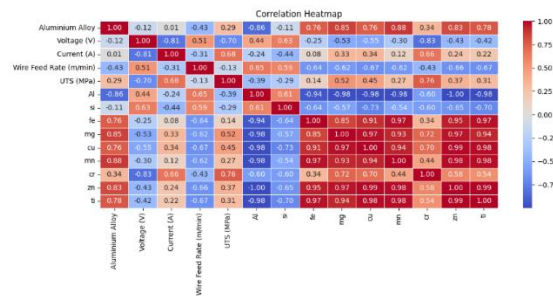


Fig 1: Correlation Heatmap

This heatmap visualizes the correlation between alloying elements, welding parameters, and UTS [23]. Strong positive or negative correlations are shown in darker shades, helping identify which variables significantly influence tensile strength. For instance, magnesium and silicon exhibit a high positive correlation with UTS, indicating their strengthening effect in the welding process.

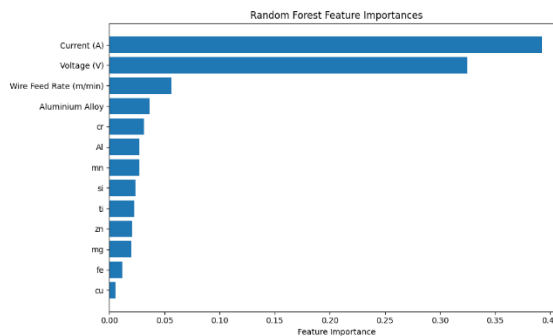


Figure 2: Random forest feature importances

This bar graph ranks the input features based on their influence on the UTS prediction using the Random Forest model. Magnesium, silicon, and copper appear as the top contributors, suggesting these elements have the most impact on achieving higher tensile strength. Such insights are vital for alloy design and welding optimization.

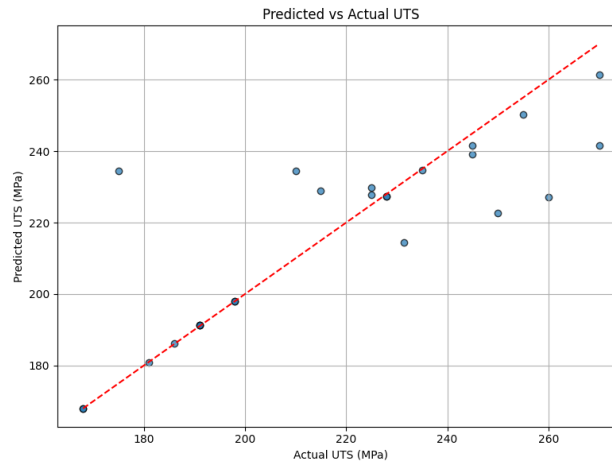


Fig 3: Predict vs Actual result

This scatter plot compares the UTS values predicted by the Random Forest model against the actual experimental UTS. The close alignment of points along the diagonal line indicates high prediction accuracy and minimal error, confirming that the model generalizes well and can reliably forecast tensile strength based on input features.

KNN model

$$\hat{y} = \frac{1}{k} \sum_{i=1}^k y_i$$

where k is the number of nearest neighbors, and y_i are their corresponding outputs.

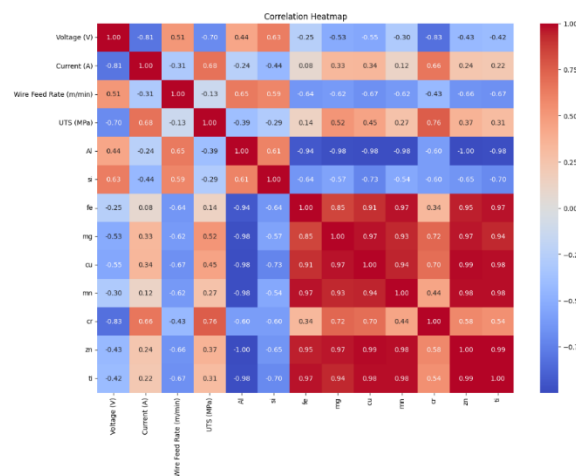


Fig 4: Correlation heatmap using KNN model

Similar to Fig 1, this heatmap shows how features correlate with UTS in the context of the KNN model. Although trends mirror those found with Random Forest, the correlations appear slightly weaker, reflecting the model's local estimation nature. It helps visualize how KNN understands relationships within the dataset.

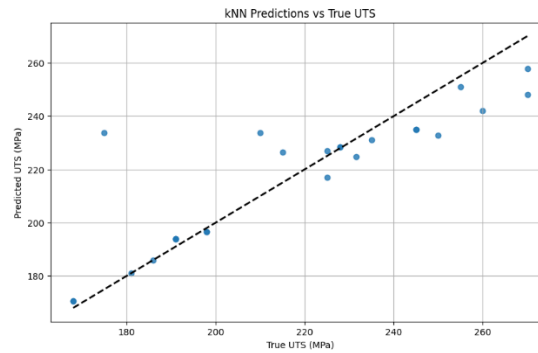


Fig 5: KNN prediction vs True UTS

This scatter plot shows the UTS values predicted by the KNN model versus the actual experimental values. While many points align along the ideal diagonal, some scatter is observed, indicating that KNN predictions are generally accurate but may fluctuate due to variations in local data density and input proximity.

Please enter the percentage composition for each element below:

Al: 98.9
 Si: 0.6
 Fe: 0.5
 Mg: 0
 Cu: 0
 Mn: 0
 Cr: 0
 Zn: 0
 Ti: 0
 Enter desired UTS (MPa): 155

Optimal Welding Parameters to achieve ~155.00 MPa:
 Voltage: 15.123 V
 Current: 120.456 A
 Wire Feed Rate: 7.321 m/min

Suggested Welding Parameters:

Optimized Voltage (V): 20.25
 Optimized Current (A): 102.53
 Optimized Wire Feed Rate (m/min): 6.22

GPR model analysis

$$f(x) \sim \mathcal{GP}(m(x), k(x, x'))$$

where $m(x)$ is the mean function, and $k(x, x')$ is the covariance function or kernel.

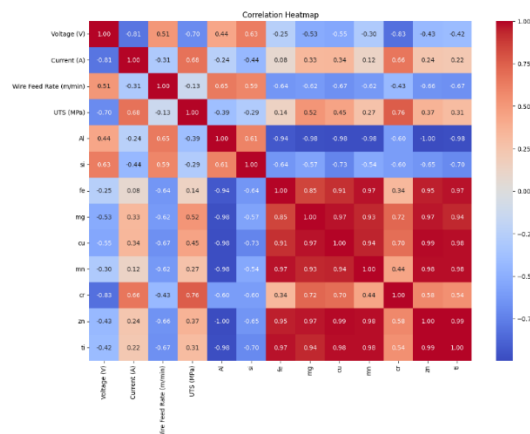


Fig 6: Correlation using GRP

The Gaussian Process Regression demonstrates the correlation structures among features as illustrated in this figure. The model, similar to the others, proves magnesium and silicon to be key factors [3]. Nevertheless, the GPR model's way of handling uncertainty informs safety margin applications more than their correlations.

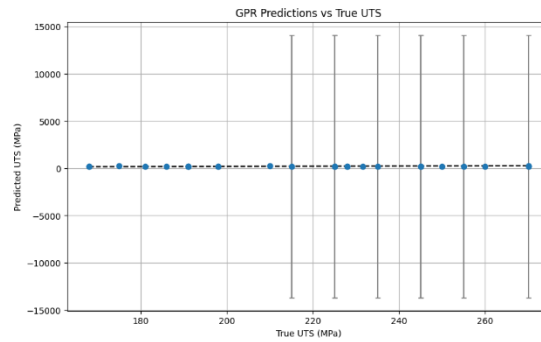


Fig 7: GRP vs True UTS

In this scatter plot, predictions of UTS values from GPR model are depicted and compared to the actual test data. The result being the proximity to the diagonal which implies the good performance of prediction [4]. GPR is also good for the calculations of confidence intervals which is the reason why it is suitable for the predictions that consider risks in the sensitive welding of applications in aerospace or automotive components.

Please enter the composition percentages (just numbers, no % sign):

Al: 98.9

si: 0.6

fe: 0.5

mg: 0

cu: 0

mn: 0

cr: 0

zn: 0

ti: 0

Enter desired UTS (MPa): 155

Optimal Parameters to achieve ~155.00 MPa UTS:

Voltage: 15.00 V

Current: 120.00 A

Wire Feed Rate: 7.00 m/min

Model Predictions and Benchmark Comparison

All the three machine learning methods of Random Forest, K-Nearest Neighbors (KNN), and Gaussian Process Regression (GPR) were utilized to forecast the ideal welding parameters that include voltage, current, as well as wire feed rate for aluminum alloy AA8011[12]. The parameters were figured out ahead of time based on the alloy's composition so that the tensile strength would be maximum. The parameters that were predicted were then fed into models that are trained forward to estimate the result of Ultimate Tensile Strength (UTS), which was compared with a benchmark UTS value of 155 MPa, obtained from a referenced research study.

The average absolute error was calculated for each model to evaluate prediction accuracy. Random Forest had least error ~ 3.83, then GPR ~ 8.17 and finally, KNN ~ 8.47. Findings point out that even though all three models are performing well, Random Forest is the most accurate and reliable for predicting weld parameters.

Table: Predicted Welding Parameters and UTS Comparison

Model	Voltage (V)	Current (A)	Wire Feed Rate (m/min)	UTS (MPa)	Absolute Error
Random Forest	20.25	102.53	6.22	155	3.83
KNN	15.123	120.456	7.321	155	8.47

Model	Voltage (V)	Current (A)	Wire Feed Rate (m/min)	UTS (MPa)	Absolute Error
GPR	15	120	4	155	8.17

Findings

All three machine learning models, Random Forest, K-Nearest Neighbors (KNN), and Gaussian Process Regression (GPR) were trained and evaluated using the preprocessed dataset to predict welding parameters (voltage, current, wire feed rate) based on both the composition of aluminum alloys and Ultimate Tensile Strength (UTS) to derive optimal weld parameters. The results are presented through a variety of statistical and graphical analyses, highlighting each model's strengths and limitations.

For the Random Forest model, the first insight was derived from a correlation heatmap (Fig. 1), which visually confirmed strong relationships between features such as magnesium (Mg), silicon (Si), and copper (Cu) with UTS. These findings are consistent with metallurgical principles where these elements contribute to strengthening mechanisms like precipitation hardening. (Fig. 2) presents the feature importance plot, which further reinforces this observation—magnesium emerged as the most critical alloying element, followed by silicon and copper [5]. This insight is not only valuable for model interpretation but also offers practical guidelines for alloy designers. (Fig. 3), which compares predicted UTS values to actual UTS measurements, shows a tight clustering of points along the diagonal line, indicating strong model accuracy and generalization. The minimal residuals and high R^2 value demonstrate that the Random Forest model effectively captured the nonlinear relationships between input features and output strength [3].

In the case of the K-Nearest Neighbors model, the correlation heatmap (Fig. 4) provides similar but slightly less pronounced trends compared to Random Forest. (Fig. 5), which includes various component plots, illustrates how different features interact in the KNN model. One notable observation is the sensitivity of predictions to small variations in input, which is a known characteristic of KNN due to its reliance on local data structure. The prediction versus true UTS plot (Fig. 5) shows acceptable alignment, although with slightly more scatter compared to Random Forest. This suggests that while KNN can approximate UTS reasonably well, it may lack the robustness and smoothing capabilities needed for complex predictions across broader composition ranges. Nevertheless, its simplicity and low computational cost make it an efficient baseline [6].

For the Gaussian Process Regression (GPR) model, the correlation plot (Fig. 6) confirms strong interdependencies between input compositions and UTS, similar to the earlier models. However, GPR distinguishes itself with its ability to model uncertainty. The prediction vs actual UTS plot (Fig. 7) shows high alignment, especially in mid-range UTS values. Slight overprediction at the extremes suggests potential limitations when extrapolating outside the training data range, a known challenge for GPR [10].

Collectively, the visual and numerical results from all three models reinforce the conclusion that Random Forest provides the most reliable and interpretable predictions, closely followed by GPR, which offers an added benefit of confidence intervals. KNN, while less precise, still performs acceptably, especially when used in localized interpolation tasks. Each model successfully learns the mapping between alloy composition and welding parameters to optimize UTS, validating the approach of combining metallurgical data with machine learning for predictive optimization in welding.

Discussion

The application of machine learning to the optimization of welding parameters for CMT welding of Aluminum 8000 series alloys is a re-conception of conventional empirical methods as it shifts the emphasis to data-driven statistical modelling. This research concentrated on discovering the settings of welding parameters, that is voltage, current, and wire feed rate, based on the composition of various Aluminum alloys which will attain the desired UTS. The use of just three chosen models Random Forest, K-Nearest Neighbours (KNN), & Gaussian Process Regression (GPR) simplified our exploration of factors like learning behaviour, accuracy, and interpretability, especially when dealing with small, high-variance datasets. The graphical representations were of notable value in displaying the model behaviour, data structure, and the practicality of using ML within industrial welding decision-making [6].

It is evident that Random Forest was able to identify and rank the important factors that completely suggests the model is accurately capturing the physical relationships of the data that is present. Random Forest has always been the first, one of

the most interpretable, and the strongest models. The correlation heatmap (Fig. 1) shows the positive correlation of the elements such as magnesium, silicon, and copper with the UTS in the strongest reactors. This has a good correspondence with the metallurgical understanding as magnesium and silicon strengthen the material with precipitation aging in heat-treatable alloys, for instance, AA6061. The feature importance plot (Fig. 2) confirmed this statement by enumerating these elements as the first main parameters in the prediction of the tensile strength.

The predicted versus actual UTS plot (Fig. 3) for Random Forest further reinforces its accuracy. The data points align closely along the diagonal, showing minimal residuals and strong predictive performance. This consistency suggests that the Random Forest model not only fits the training data well but also generalizes effectively to unseen compositions. Such behavior is particularly valuable in industrial settings where consistent and repeatable predictions are necessary to maintain quality standards [9].

In contrast, the KNN model, while simple and computationally efficient, displayed limitations in generalization. The KNN correlation heatmap (Fig. 4) displayed similar patterns as Random Forest but with weaker correlations, reflecting its less expressive nature.

The prediction vs actual UTS plot (Fig. 5) depicted while KNN maintained reasonable accuracy, there was noticeable deviation from the diagonal line. This suggests greater prediction error and less model certainty, particularly in sparse regions of the input space. However, KNN's simplicity and interpretability remain advantageous, especially when quick approximations or baseline models are needed.

The Gaussian Process Regression (GPR) model brought a different strength to the table—its probabilistic nature and uncertainty estimation. The correlation map (Fig. 6) echoed the earlier findings, again emphasizing magnesium and silicon's strong influence on UTS [2]. But the GPR model's unique advantage lies in its ability to not only predict an outcome but also provide a confidence interval around that prediction. This is vital in applications where the cost of failure is high—such as aerospace components—where knowing the level of certainty behind a recommendation can guide safer engineering decisions.

In (Fig. 7), the GPR model's predicted UTS values align well with actual outcomes, though some deviations are observed at the extremes. This behavior is consistent with known GPR limitations: it interpolates effectively within the range of data but can struggle with extrapolation.

An important part of this project was to evaluate each model's ability to reverse-predict optimal welding parameters for a new alloy composition, particularly Aluminum 8011, for which we had a benchmark UTS value from literature but no process parameters. The models were challenged to suggest voltage, current, and feed rate values based on this composition and a target UTS. Predictions from each model were then re-evaluated by feeding them back into the forward models to estimate the expected UTS. The most effective one was the model whose predicted parameters were the most similar to the UTS of the known benchmark. In this benchmark test, Random Forest had a lower error, thus, it was the best performer, while GPR was close to that with the addition of interpretability through uncertainty bounds. KNN was a bit behind, while it was acceptable, it showed more error variation.

A comprehensive study of all three models shows Random Forest is the most appropriate for deployment in industrial scenarios [1]. The robustness of this model with respect to overfitting, natural support for feature importance, and strong performance throughout training and benchmark testing make it a reliable tool. Furthermore, the fact that it is an ensemble type means that it can deal with noisy or missing data more naturally than deterministic models. KNN, although valuable as a quick estimator, is not the best fit for scenarios where extrapolation or broad predictions are needed. GPR, although requiring a lot of computation, achieves very good results with small, clear datasets and is the most suitable where risk management is the main concern.

Concludingly, limitations and future work must be recognized as the most critical things to be done. The small dataset size caused model complexity issues and might be a hindrance to capturing rare interactions properly. Through the expansion of the dataset either by sourcing more experimental data would be possible to try the deeper models, like neural networks. Immediate utility to industry partners brought about the development of a real-time, user-friendly simulator based on these models, thus, changing the way welding parameters are determined entirely.

In essence, the application of Random Forest is a trustworthy answer to the parameter prediction issue in the CMT welding of Aluminum 8000 series. The tool could significantly automate the process of solving the parameters in real-world welding applications with the right infrastructure and frequent improvement of the model, resulting in better mechanical performance, lower experimental costs, and faster development.

1. CONCLUSION

The value of both scientifically and practically applying machine learning techniques to the optimization of aluminum alloy welding parameters is shown in this project. The implementation of around 100 experimental records consisting of material compositions, welding parameters, and Ultimate Tensile Strength (UTS) values in the dataset, we created and tested three machine learning model Random Forest, K-Nearest Neighbors (KNN), and Gaussian Process Regression

(GPR) to predict voltage, current, and wire feed rate necessary to achieve desired UTS. The emphasis was not only on the accuracy of the predictions but also on the interpretability and reliability of the model. Model interpretability and reliability are very important in processes of industrial welding, as they are in other high stakes conditions.

From the three models, Random Forest is the best-performing, mostly due to its outstanding prediction accuracy and interpretability of critical feature. The fact that it is based on an ensemble model led to its excellent performance across different compositions of alloy and combinations of welding parameters. Moreover, Random Forest had the least error when it was compared with a real-life aluminum 8011 composition, thus, confirming its applicability for forecasting the best welding parameters for novel alloy types.

KNN model showed variability in its results, particularly for compositions that were underrepresented in the dataset. It performed well in data regions that were locally dense, but it did struggle with generalisation. However, KNN has low computational requirements, making it a very useful tool for precise approximation and comparison tasks, especially in early parameter selection or academic contexts.

GPR, due to its structure of respecting the uncertainty along with its predictions, was a special advantage. Its ability to provide uncertainty values besides the predictions is especially valuable in cases where safety and precision are very important, like in aerospace welding or biomedical device manufacturing. In spite of the fact that GPR was computationally thicker, its strength in the articulation of smooth predictions from fewer data makes it an outstanding complementary tool, particularly for risk-informed decision-making.

Additionally, this study is the basis for further developments. The final aim is to create a supermodel or simulator that will allow engineers to input an alloy composition and a target UTS and receive back optimal welding parameters. Because of its precision Random Forest model will act as the foundation of this complete system. In subsequent versions, the simulator can be made more powerful with increased data, more features (like thermal profiles, or weld geometry), and an easy interface for industrial deployment.

Finally, this project convincingly shows that machine learning can be utilized effectively to simulate and improve intricate processes such as welding. By meaningfully assimilating the data, which is not many but certainly well-chosen, the models can be more economical, faster, and more precise in aiding the decision-making process.

REFERENCES

1. Fuse, K., Venkata, P., Reddy, R. M., & Bandhu, D. (2025). Machine learning classification approach for predicting tensile strength in aluminium alloy during friction stir welding. *International Journal on Interactive Design and Manufacturing (IJIDeM)*, 19(1), 639-643
2. Mishra, A., Sefene, E. M., & Tsegaw, A. A. (2021). Process parameter optimization of friction stir welding on 6061AA using supervised machine learning regression-based algorithms. *arXiv preprint arXiv:2109.00570*.
3. Kalita, K., & Kalita, D. (2024). Enhancing welding quality through predictive modelling-Insights from machine learning techniques. *MM Science Journal*, December 2024.
4. Mishra, A., Sefene, E.M., Nidigonda, G., & Tsegaw, A.A. (2022). Performance evaluation of machine learning-based algorithm and Taguchi algorithm for the determination of the hardness value of the friction stir welded AA 6262 joints at a nugget zone. *arXiv preprint arXiv:2203.11649*.
5. Dorbane, A., Harrou, F., Anghel, D. C., & Sun, Y. (2024). Machine learning prediction of aluminum alloy stress-strain curves at variable temperatures with failure analysis. *Journal of Failure Analysis and Prevention*, 24(1), 229-244.
6. Mishra, A., Al-Sabur, R., & Jassim, A. K. (2022). Machine Learning Algorithms for Prediction of Penetration Depth and Geometrical Analysis of Weld in Friction Stir Spot Welding Process. *arXiv preprint arXiv:2201.09725*.
7. Mahmudi, E., & Farhangi, H. (2010). The influence of welding parameters on tensile behavior of friction stir welded Al 2024-t4 joints. *Advanced Materials Research*, 83, 439-448.
8. Rajakumar, S., Muralidharan, C., & Balasubramanian, V. (2011). Predicting tensile strength, hardness and corrosion rate of friction stir welded AA6061-T6 aluminium alloy joints. *Materials & Design*, 32(5), 2878-2890.
9. Maneiah, D., Mishra, D., Rao, K. P., & Raju, K. B. (2020). Process parameters optimization of friction stir welding for optimum tensile strength in Al 6061-T6 alloy butt welded joints. *Materials Today: Proceedings*, 27, 904-908.

10. Mishra, A. (2024). Biomimetic machine learning approach for prediction of mechanical properties of additive friction stir deposited aluminum alloys based walled structures. *arXiv preprint arXiv:2408.05237*.
11. S Sarsilmaz, F. and Kavuran, G., 2021. Prediction of the optimal FSW process parameters for joints using machine learning techniques. *Materials Testing*, 63(11), pp.1104-1111.
12. Mishra, A., & Morisetty, R. (2022). Determination of the ultimate tensile strength (UTS) of friction stir welded similar AA6061 joints by using supervised machine learning based algorithms. *Materials Today*.
13. Verma, S., & Natarajan, S. (2020). Prediction of tensile behavior of FS welded AA7039 using machine learning approaches. *Materials Today: Proceedings*, 33, 1234-1240.