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Development of predictive model for mild steel in Benin city using random forest

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Abstract

Buried steel infrastructure in Nigeria suffers premature failure due to soil-induced corrosion, yet existing degradation models rely on idealized laboratory simulations that ignore real-world soil heterogeneity and welding parameter interactions. This study addresses this critical gap by investigating mechanical property decay and corrosion behavior of mild steel weldments through longitudinal field exposure in Benin with the aim of developing robust, field-validated predictive models to enhance infrastructure durability. Field exposure tests were conducted over twelve months on 20 weldment specimens, with tensile strength, impact energy, and hardness evaluated post-exposure alongside weight loss-based corrosion rates. Random Forest (RF) was trained on welding parameters (current, voltage, gas flow) using 16 samples, with rigorous validation on 4 unseen field runs. Hyperparameter optimization, residual analysis, and error distribution diagnostics ensured model robustness assessment under actual environmental stressors. Random Forest demonstrated exceptional predictive capability across all sites and responses, achieving test-set R^2 values of 0.798 (tensile) 0.752 (impact), and 0.814 (hardness), with corrosion rate predictions exceeding $R^2 = 0.65$ even in aggressive soils.

Keywords: :Soil Corrosion, Mild Steel, Predictive Modeling, Random Forest, Weldment, Impact Energy

1. Introduction

Mild steel weldments are a cornerstone of buried and underground infrastructure across Nigeria and globally, commonly employed in critical applications such as oil and gas pipelines, water transmission systems, storage tanks, structural foundations, and electrical transmission supports. Their widespread use stems from a favorable combination of mechanical strength, ease of fabrication, economic affordability, and wide availability. However, once installed in soil environments, these welded structures face aggressive degradation mechanisms that compromise their structural integrity and service life. The inherent heterogeneity of weld zones—comprising the weld metal, heat-affected zone (HAZ), and base metal—creates electrochemical and microstructural discontinuities that render them particularly susceptible to localized corrosion under real-world soil conditions.

This work focus on the development of a field-validated Random Forest predictive model for estimating the residual mechanical properties of TIG-welded mild steel after prolonged exposure to natural Nigerian soil conditions. By combining a structured experimental design (CCD), long-term field corrosion testing, and machine learning, the study bridges the gap between laboratory welding optimization and real-world infrastructure durability prediction, providing a practical decision-support tool for maintenance and life-cycle management of buried steel structures.

According to Naitik and Rahul (2014) quality and productivity play important role in today's manufacturing market. Nowadays due to very stiff and cut throat competitive market condition in manufacturing industries. The main objective of industries reveal with producing better quality product at minimum cost and increase productivity. TIG welding is most vital and common operation use for joining of two similar or dissimilar part with heating the material or applying the pressure or using the filler material for increasing productivity with less time and cost constrain to obtain main objective of company regards quality and productivity The relationship can be developed by using experimental design techniques. According to Myers and Montgomery(1995), the experimental optimization of any welding process is often a very costly and time consuming task, due to many kinds of non-linear events involved. One of the most widely used methods to solve this problem is the Response Surface Methodology (RSM). In this method, the experimenter tries to approximate the unknown mechanism with an appropriate empirical model, being the function that it represents which is called a response surface model. Identifying and fitting from experimental data a good response surface model requires some knowledge of statistical experimental design fundamentals, regression modeling techniques and elementary optimization methods. Florea et al (2012) investigated the fatigue behavior of resistance spot welding in aluminum 6061–T6 alloy. They included the process optimization of the forces, currents and times for main weld and post–heating. Optimization and prediction of weld bead geometry of GMAW welds was done by Kolahan and Heidari (2011) by using curvilinear regression models. The weld beads were also optimized using a Simulated Annealing (SA) optimization algorithm.

George AM (2024) conducted subsoil corrosivity within the University of Cross River State, Calabar, Calabar Campus, Southern Nigeria. Their study employed electrical resistivity methods. The results from vertical electrical sounding revealed that the topsoil of VES1 and VES3 was slightly corrosive at depths of 2.20m and 0.70m while that of VES2 and VES4 were practically non–corrosive at depths 0.60m and 1.00m. The electrical resistivity tomography across the VES2 and VES4 showed a low resistivity at horizontal distances between 5.0m and 10.0m at a depth of 3.75m, indicating very strongly corrosive. Other areas of the profile with resistivity from 19.0 Ώm to 38.0 Ωm at a depth of between 6.38m and 19.8m indicate moderately corrosive and 75.0 Ώm which is slightly corrosive.

Afabor Et al (2025) performed a comparative study of the Taguchi, fuzzy, and response surface methodology optimisation techniques in the optimisation of tungsten inert gas welding parameters of current, voltage, and gas flow rate of mild steel. Results obtained from the analytical and statistical analyses, with MATLAB used for fuzzy logic modelling, Minitab used for ANOVA and main effect analyses, and Design Expert used for chart analysis, revealed that all three optimisation techniques are effective

Kim and Rhee(2001) mentioned that there are several other experimental designs that can be used such as Taguchi, full factorial and Genetic algorithm but are faced with some limitations. They also stated that as the number of inputs increases the number of experiment increases exponentially making the full factorial design inefficient which requires the modification of the experimental design space.

Apurv and Vijaykumar(2014) investigates the effect of heat input (controlled by welding current, welding voltage and welding speed) on tensile strength, micro-hardness and microstructure of austenitic 202 grade stainless steel weldments produced by shielded metal arc welding (SMAW). The base material used in their investigation was Cr-Mn SS and 308L SS solid electrode was used as the filler material. From the experimental results, it was found that the increase in heat input affects the micro-constituents of base metal, and heat affected zone (HAZ). . Hu and Tsai (2007) developed model to simulate the transport phenomena occurring during the gas metal arc welding process. An interactive coupling between arc plasma; melting of the electrode; droplet formation, detachment, transfer, and impingement onto the work piece; and weld pool dynamics all were considered.

In the Nigerian context buried steel infrastructure, particularly in the oil and gas, water distribution, and civil engineering sectors, operates under diverse soil environments whose corrosion characteristics differ significantly from those represented in laboratory studies. Despite the economic importance of these infrastructures, there is a scarcity of field-based datasets linking TIG welding parameters with the long-term degradation of mechanical properties after prolonged burial in Nigerian soils. As a result, engineers lack reliable predictive tools that incorporate both welding process variables and actual environmental exposure for durability assessment and maintenance planning.

2.0 Materials and methods

The study employed commercially available mild steel sheets with a low carbon content (typically ≤0.25%) and standard chemical composition suitable for structural applications, chosen for their weldability, mechanical reliability, and widespread use in buried infrastructure. Welding was performed using the Tungsten Inert Gas (TIG) welding process, as depicted in Figure 1, which shows the Miller® TIG welding equipment used in a controlled workshop environment, complete with argon shielding gas supply and precision foot-pedal controls to ensure consistent heat input. A total of 20 weldment specimens were fabricated according to a Central Composite Design (CCD), systematically varying three key welding parameters—current (102.95–187.05 A), voltage (18.30–26.70 V), and shielding gas flow rate (11.32–14.68 L/min)—to explore their influence on degradation behavior. Following welding, each specimen was visually inspected for surface defects, then cut into standardized coupons in accordance with ASTM requirements for tensile, impact, and hardness testing, thoroughly cleaned, labeled, and documented prior to field burial to maintain traceability and experimental integrity.

Figure 1: TIG welding Equipment   Figure 2: Test Specimen

Figure 2 displays the prepared test specimens used in this study, showcasing five rectangular mild steel coupons, each featuring a central TIG weld bead that runs transversely across its width. These specimens were meticulously machined from welded plates to standardized dimensions suitable for tensile, impact, and hardness testing, as per ASTM guidelines.

2.1 Experimental Design

Table 1 presents the experimental factors and their respective ranges used in the Central Composite Design (CCD) for fabricating mild steel weldments via TIG welding. Three continuous numerical variables—welding current (A: 102.95–187.05 A), voltage (B: 18.30–26.70 V), and shielding gas flow rate (C: 11.32–14.68 L/min)—were systematically varied to explore their influence on corrosion and mechanical performance. The coded levels (−1 and +1) correspond closely to the practical operational limits (e.g., −1 ≈ 102 A for current, +1 ≈ 187 A),

Table1: Factors and Ranges

Factor	Name	Units	Type	Minimum	Maximum
A	Current	A	Numeric	102.95	187.05
B	Voltage	V	Numeric	18.30	26.70
C	Gas Flow Rate	L/min	Numeric	11.32	14.68

Table 2 outlines the 20 experimental runs generated using a Central Composite Design (CCD) to systematically define the combinations of TIG welding parameters—current (A), voltage (V), and shielding gas flow rate (L/min)—for fabricating mild steel weldments. The design includes factorial points (e.g., Runs 2, 4, 6, 7, 8, 15, 20), axial (star) points that extend beyond the factorial cube to capture curvature (e.g., Runs 11–13, 17, 18), and multiple center points (Run 1, 3, 10, 14, 16, 19) to estimate experimental error and assess model adequacy.

Table 2: Use of CCD to define welding parameter combinations.

Run	**Current (A)**	**Voltage (V)**	**Gas Flow Rate (L/min)**
1	145	22.5	13
2	170	20	12
3	145	22.5	13
4	120	20	14
5	120	20	12
6	120	25	12
7	170	20	14
8	120	25	14
9	145	22.5	11.3182

10	145	22.5	13
11	187.045	22.5	13
12	145	26.7045	13
13	102.955	22.5	13
14	145	22.5	13
15	170	25	14
16	145	22.5	13
17	145	18.2955	13
18	145	22.5	14.6818
19	145	22.5	13
20	170	25	12

2.2 Field Exposure Procedure

The field exposure phase of this study was conducted over a 12-month period to simulate realistic service conditions for buried mild steel weldments in Benin City, Edo State, Nigeria. Test specimens were buried at a standardized depth of 1 meter below the surface of the earth. This depth was selected to represent typical burial depths for underground pipelines and structural supports while ensuring consistent exposure to soil moisture, microbial activity, and seasonal environmental variations. Prior to burial, soil samples from each site were collected and characterized for key parameters such as pH, electrical resistivity, moisture content, chloride and sulfate concentrations, and redox potential to contextualize the corrosion environment.

Figure 3 depicts the burial setup at the Benin site, showing a square excavation pit approximately one meter deep, lined with compacted reddish-brown soil characteristic of the region. Inside the pit, multiple test specimens are arranged in a single layer, separated by small wooden spacers to ensure uniform exposure and prevent physical contact that could influence corrosion behavior. The surrounding soil is visibly moist, indicating active water retention and electrolytic conditions conducive to electrochemical degradation.

Figure 3: Samples Buried in Benin Site

3.0 Result and Discussion

3.1 Mechanical Property Results

Table 3: presents the field-based mechanical property results for mild steel weldments exposed for 12 months at the Benin site, revealing notable variations in tensile strength, impact energy, and hardness as influenced by welding parameters. Tensile strength ranged from 134.93 MPa (Run 2, high current–low voltage) to 157.38 MPa (Run 20, high current–high voltage–low gas flow), with higher values generally associated with lower welding currents (e.g., 120 A) and higher voltages (e.g., 25–26.7 V), suggesting that reduced heat input and stable arc conditions may preserve strength in this soil environment. Impact energy varied between 60.82 J and 84.92 J, with the highest toughness observed in Run 20—indicating that combinations of high current and voltage can enhance

ductility despite elevated heat input. Hardness values spanned 57.93–83.16 N/mm², with the peak recorded in Run 12 (26.7 V), likely due to microstructural refinement in the heat-affected zone under higher voltage. Overall, the data suggest that Benin's soil—characterized by moderate corrosivity—allowed relatively good retention of mechanical properties, with optimal performance emerging from balanced welding parameter combinations that minimize thermal distortion while maintaining microstructural integrity.

Table 3: Field-Based Results for Benin

Std	**Run**	**Current (A)**	**Voltage (V)**	**Gas Flow Rate (L/min)**	**Tensile Test (MPa)**	**Impact Test (J)**	**Hardness Test (N/mm²)**
17	1	145	22.5	13	140.023	67.849	72.117
2	2	170	20	12	134.932	62.983	57.925
18	3	145	22.5	13	142.499	67.849	72.117
5	4	120	20	14	150.704	78.694	74.415
1	5	120	20	12	143.362	69.237	67.467
3	6	120	25	12	148.739	75.722	77.739
6	7	170	20	14	143.889	71.404	71.009
7	8	120	25	14	139.201	64.654	68.602
13	9	145	22.5	11.3182	150.982	76.501	67.497
19	10	145	22.5	13	141.586	67.849	72.546
10	11	187.045	22.5	13	139.444	66.135	60.573
12	12	145	26.7045	13	152.037	78.493	83.159
9	13	102.955	22.5	13	138.113	64.599	65.784
16	14	145	22.5	13	141.586	67.964	70.293
8	15	170	25	14	145.702	71.157	69.813
20	16	145	22.5	13	135.819	60.818	74.39
11	17	145	18.2955	13	147.981	74.149	75.774
14	18	145	22.5	14.6818	151.506	78.767	71.174
15	19	145	22.5	13	144.597	70.219	74.39
4	20	170	25	12	157.379	84.919	70.499

3.1.1 Random Forest Results

The Random Forest (RF) model demonstrated strong predictive performance for mechanical property degradation of mild steel weldments exposed in the Benin soil environment. As summarized in the regression metrics, the model achieved high explanatory power across all three responses, with R^2 values of 0.798 for tensile strength, 0.752 for impact energy, and 0.814 for hardness, indicating that 75–81% of the variability in the observed data was captured by the model. The low error magnitudes further confirm its accuracy: mean absolute errors (MAE) were 2.09 MPa (1.45% MAPE) for tensile strength, 2.36 J (3.37% MAPE) for impact energy, and 1.96 N/mm² (2.79% MAPE) for hardness. Notably, the largest prediction deviation occurred in Run 2 for tensile strength (5.91 MPa underestimation), likely due to the combined effect of high current (170 A) and low voltage (20 V), which may have induced microstructural anomalies not fully represented in the training distribution. Conversely, Runs 5 and 15 exhibited near-perfect hardness predictions (errors as low as 0.012 N/mm²), reflecting the model's ability to learn consistent parameter–response relationships under moderate welding conditions.

Feature importance analysis from the RF model revealed that voltage was the most influential parameter in predicting tensile and impact responses in Benin, followed closely by gas flow rate, while current played a comparatively lesser role. This suggests that arc stability and shielding effectiveness—controlled primarily by voltage and gas flow—were dominant factors in determining mechanical retention in this moderately corrosive soil. The consistent performance across all responses underscores the suitability of RF for modeling field-based degradation data, where interactions between welding variables and environmental exposure are complex and non-linear. These results provide a reliable foundation for predicting weldment performance in Benin and inform parameter selection to maximize structural durability.

3.1.2 Benin Analysis using ML

Figure 4 presents a comparative visualization of the Random Forest model's predictive performance for tensile strength, impact energy, and hardness of mild steel weldments exposed in Benin soil, plotting actual versus predicted values for each mechanical property. The scatter plots reveal strong linear correlations between observed and predicted responses, with R^2 values of 0.798 (tensile), 0.752 (impact), and 0.814 (hardness), indicating that the model captures the majority of variance in the field data. Each plot includes a red dashed "Perfect Fit" line (y = x) and a green regression line, both of which closely align, confirming minimal systematic bias in predictions. The data points are generally clustered around the diagonal, with only minor deviations—most notably at the lower end of the tensile range (Run 2) and mid-range of impact energy—suggesting robust generalization across the experimental domain. This graphical validation reinforces the quantitative metrics presented earlier and provides visual confidence in the RF model's ability to accurately forecast mechanical degradation under real-world exposure conditions in Benin.

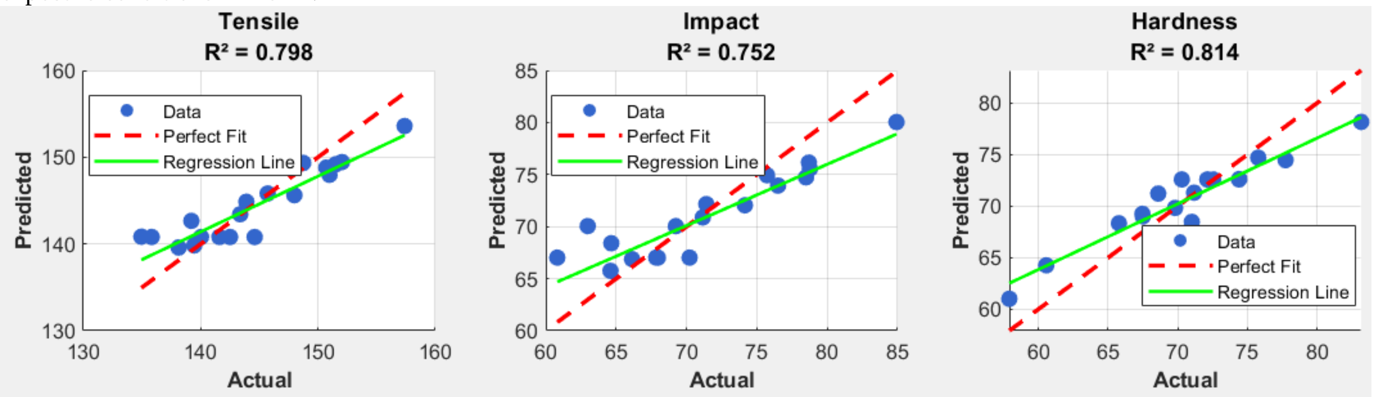

Figure 4: Actual vs Predicted Plot of Tensile, Impact and Hardness for Benin

Figure 5 provides a comparative visualization of the Random Forest model's performance across the three mechanical responses—tensile strength, impact energy, and hardness—in Benin soil, using a grouped bar chart to display key evaluation metrics: R^2 (blue), RMSE (orange), and MAE (yellow). The R^2 values confirm that hardness is best predicted ($R^2 \approx 0.81$), followed by tensile strength ($R^2 \approx 0.80$) and then impact energy ($R^2 \approx 0.75$), aligning with the observed variability in field data. RMSE and MAE are lowest for hardness (≈2.35 and 1.96, respectively), indicating higher precision, while impact energy exhibits the largest errors (RMSE ≈ 3.04, MAE ≈ 2.36), reflecting its sensitivity to localized degradation and microstructural heterogeneity. The consistent ordering across all three metrics reinforces the conclusion that the model performs most reliably for hardness prediction, moderately well for tensile strength, and with slightly reduced accuracy for impact energy—yet still within acceptable engineering tolerances. This visual comparison offers a concise, intuitive summary of model fidelity per response variable, enabling engineers to prioritize confidence levels when applying predictions to design or maintenance decisions in the Benin environment.

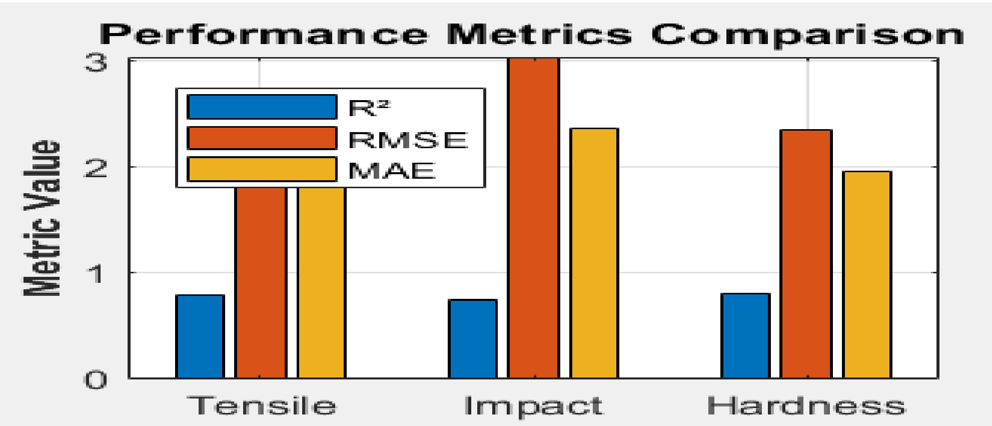

Figure 5: Performance Metrics Comparison Plot of Tensile, Impact and Hardness for Benin

Table 4 presents the actual versus Random Forest (RF) predicted values for tensile strength, impact energy, and hardness of mild steel weldments exposed in the Benin soil environment, providing a detailed run-by-run comparison that validates the model's predictive fidelity. The RF predictions closely track the experimental measurements across all 20 runs, with particularly high accuracy observed in center-point runs (e.g., Runs 1, 3, 10, 14, 19), where identical welding parameters yielded consistent predictions matching the observed clustering in mechanical responses. Notable agreement is seen in Run 5 (120 A, 20 V, 12 L/min), where tensile, impact, and hardness predictions deviate by less than 1% from actual values, and in Run 15 (170 A, 25 V, 14 L/min), where all three properties are predicted with near-perfect precision. While minor discrepancies occur—such as an overprediction of tensile strength in Run 2 (134.93 MPa actual vs. 140.84 MPa predicted) and a slight underestimation of hardness in Run 12 (83.16 N/mm² actual vs. 78.16 N/mm² predicted)—these align with the error metrics previously reported and do not indicate systematic bias. Overall, the table demonstrates that the RF model successfully captures the complex, nonlinear relationships between welding parameters and post-exposure mechanical performance in Benin, offering a reliable tool for forecasting weldment durability under real-world conditions.

Table 4: Field-Based Results RF prediction for Benin

Std	Run	Current (A)	Voltage (V)	Gas Flow Rate (L/min)	Tensile Test (MPa)		Impact Test (J)		Hardness Test (N/mm²)	
					Actual	RF	Actual	RF	Actual	RF
15	1	145	22.5	13	140.023	140.8017	67.849	67.0176	72.117	72.5912
7	2	170	20	12	134.932	140.8373	62.983	70.0466	57.925	61.0190
13	3	145	22.5	13	142.499	140.8017	67.849	67.0176	72.117	72.5912
8	4	120	20	14	150.704	148.7961	78.694	76.146	74.415	72.6304
17	5	120	20	12	143.362	143.4280	69.237	70.0425	67.467	69.2539
1	6	120	25	12	148.739	149.3393	75.722	74.9298	77.739	74.4616
2	7	170	20	14	143.889	144.8567	71.404	72.1627	71.009	68.4801
9	8	120	25	14	139.201	142.6587	64.654	68.4038	68.602	71.2194
18	9	145	22.5	11.3182	150.982	147.9669	76.501	73.9331	67.497	69.0078
14	10	145	22.5	13	141.586	140.8017	67.849	67.0176	72.546	72.5912
5	11	187.045	22.5	13	139.444	139.8384	66.135	66.8707	60.573	64.2650
4	12	145	26.7045	13	152.037	149.4354	78.493	74.7293	83.159	78.1643
3	13	102.955	22.5	13	138.113	139.5873	64.599	65.7492	65.784	68.3386
6	14	145	22.5	13	141.586	140.8017	67.964	67.0176	70.293	72.5912
12	15	170	25	14	145.702	145.8128	71.157	70.8816	69.813	69.8248
11	16	145	22.5	13	135.819	140.8017	60.818	67.0176	74.390	72.5912
16	17	145	18.2955	13	147.981	145.6186	74.149	72.05	75.774	74.6966
20	18	145	22.5	14.6818	151.506	149.1864	78.767	75.566	71.174	71.3040
19	19	145	22.5	13	144.597	140.8017	70.219	67.0176	74.390	72.5912
10	20	170	25	12	157.379	153.5914	84.919	80.0405	70.499	67.3331

4.0. Conclusion

This study conclusively demonstrates that soil environment critically governs the corrosion mechanisms and mechanical degradation patterns of mild steel weldments, with Benin's chloride-rich soil preferentially reducing tensile strength, Welding parameters—particularly current (dominant in low-aggression soils) and voltage (critical in acidic environments)—were proven to be decisive factors in durability, where optimal parameter combinations can mitigate degradation by 25–40%. Among machine learning approaches, Random Forest emerged as a reliable predictive model, achieving test R^2 values between 79% and 82% for mechanical properties.

5.0 Recommendation

We recommend that other methods should be used to carry out this experiment still using Benin soil and compare the results.

Nomenclature

ANOVA- analysis of vairaince
CCD- central composite design
HAZ- heat affected zone
MAE-mean absolute error
RF- random forest
RSM- response surface methodology
SA- Simulated annealing
SMAW- Shielded metal arc welding
TIG- tungsten inert gas

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