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NEURAL NETWORK-BASED PREDICTION OF COOLING MEDIA EFFECTS ON MECHANICAL PROPERTIES OF LOW CARBON STEEL

[1]Adewuyi, R.A., [2]Omojogberun, Y.V., [3]Erinle T.J.

[1,2,3]Department of Mechanical Engineering, The Federal Polytechnic, Ado-Ekiti, Nigeria

E-mail: adewuyi_ra@fedpolyado.eudu.ng , Phone No: +234 803 845 8613

Abstract

This research investigates the effect of different quenching media (water, palm oil, spent engine oil, and groundnut oil) on the mechanical properties of 14 mm thick low-carbon steel. The experimental procedure involved subjecting welded samples to various quenching processes, followed by tests to assess hardness, tensile strength, and ductility in both the welded zone and the heat-affected zone (HAZ). A neural network model in SPSS was developed to predict these mechanical properties, proving highly effective with an R-squared value of 0.9999 for tensile strength and an MSE of 0.380 for welded zone hardness. Results indicate that water quenching achieved the highest hardness in the HAZ (124.00 BHN), while oil-based media like spent engine oil and groundnut oil preserved higher hardness in the welded zone by stabilizing the martensitic structure. Palm oil achieved a balanced hardness (69.84 BHN) and ductility, suggesting its suitability for applications requiring both properties. The study highlights the role of quenching media in post-weld heat treatment (PWHT) to enhance steel reliability in industrial applications, helping to mitigate the risk of welded joint failures.

Keywords: *Quenching, Hardness, Tensile Strength, Neural Network, Low Carbon Steel*

1. Introduction

The mechanical properties of low-carbon steel are crucial to its performance in various industrial applications, especially in welded structures. Post-weld heat treatment (PWHT) is instrumental in enhancing these properties, influencing the hardness, strength, and ductility of the welded joints [1]. Numerous studies have examined the effects of thermal treatment on low-carbon steel, emphasizing its importance for industrial growth and economic development in regions like Nigeria [2]. Thermal treatment processes (TTP) in butt-welded low-carbon steel have shown substantial improvements in toughness, hardness, and residual stress resistance [3].

Research has demonstrated that PWHT improves the microstructure and mechanical properties of welded joints. For example, studies on the torsional behavior of low-carbon steel have found that PWHT can enhance mechanical properties without compromising tensile strength or hardness [4,10]. Similarly, investigations on grade 91 steel have highlighted PWHT's importance in achieving a homogeneous microstructure and reducing crack susceptibility in both the weld metal and heat-affected zone (HAZ).

The cooling rate during thermal treatment significantly affects the final mechanical properties of low-carbon steel [5, 13]. Rapid cooling tends to increase hardness, while slower cooling enhances ductility—both properties critical for the performance of welded joints. Despite PWHT's established benefits, the prevalence of welded joint failures underscores the need to further investigate the impact of different cooling media on the microstructure and strength of low-carbon steel [6, 12].

The relationship between chemical composition, microstructure, and mechanical properties of low-carbon steel is complex. Elements such as carbon, nickel, chromium, and molybdenum contribute to hardness, toughness, and temperature resistance, while thermal treatment predominantly affects the microstructure. This dynamic requires careful control of cooling conditions during PWHT to achieve the desired properties [7, 11].

Historically, predictive models such as regression analysis and finite element modeling (FEM) have been used to estimate the effects of thermal treatment on steel's mechanical properties [15, 16]. Although these models provide valuable insights, they often lack the flexibility to capture complex nonlinear relationships between variables in large datasets. In contrast, artificial neural networks (ANNs) have proven highly effective in such contexts, particularly in capturing nonlinear dependencies between process parameters and material responses [17]. Given this advantage, a neural network model developed in SPSS is used in this study to predict the effects of various cooling media on low-carbon steel properties. This approach allows for precise prediction of hardness, tensile strength, and ductility, providing insights into optimal PWHT conditions.

By examining the impact of different cooling media on welded low-carbon steel's hardness, fatigue life, impact energy, and microstructure, this study aims to refine PWHT practices to enhance joint reliability and reduce failure rates in industrial applications [9,14].

This provides a comprehensive overview of the research context, highlighting the significance of thermal treatment, the impact of cooling media, and the role of neural networks in predicting mechanical properties.

2. Materials and Method

1.1 Materials

The primary material used in this study is a 14 mm thick low-carbon steel flat bar (NST 44-2), with a chemical composition of 0.165% C, 0.19% Si, 0.50% Mn, and trace amounts of P and S (0.02% each), along with 17.34% Cr and 9.45% Ni, enhancing corrosion resistance and mechanical properties.

An E6011 low-carbon steel electrode was used in the welding process, with a composition range of 0.10-0.15% C, 0.20-0.35% Si, and 0.40-0.60% Mn, and minimal P and S to prevent brittleness.

Additional materials included arc welding equipment, a heat treatment furnace, and quenching media (water, palm oil, spent engine oil, and groundnut oil), maintained at room temperature in quenching tanks for controlled cooling during the heat treatment process.

The combination of these materials and equipment facilitated a comprehensive investigation into the effects of different cooling media on the mechanical properties of low-carbon steel, providing valuable insights into optimizing post-weld heat treatment processes. This section integrates the chemical compositions from Tables 1 and 2 while also detailing the experimental setup and materials used in the study.

2.2 Experimental Procedure

In this study, low-carbon steel bars with a thickness of 15 mm were selected for investigation. The bars were cut in pairs with dimensions of 100 mm by 50 mm from the original thickness, resulting in ten samples being prepared for examination. The weld junction was designed using a double V-butt weld joint, a configuration that is commonly employed to ensure sufficient static strength in welded structures. Achieving the required static strength is crucial when designing joints, as it directly influences the performance and durability of the welded assembly [3, 6]. The welding process was carried out using a current of 100 amps and a constant voltage of 24 volts, with a welding speed of 3.56 mm/s. To ensure precision and consistency, the movement of the two parallel sides of the welded line was restricted during welding, maintaining the alignment and quality of the weld [4, 7].

The thermal treatment of the welded specimens involved heating standard specimens to 920°C, followed by homogenization for 20 minutes at this temperature. This process was repeated four times to ensure uniformity and consistency in the thermal treatment [2, 8]. After 20 minutes in the furnace, the specimens were removed and immediately quenched in various cooling media: water-cooled (SHP), palm oil-cooled (SHP), Quartz 5000 Total Engine oil (SHE), and groundnut oil (SHG). Each quenching medium was maintained at room temperature in separate quenching tanks to control the cooling rate and its impact on the microstructure and mechanical properties of the steel [9, 14].

Following 30 minutes in the quenching tanks, the specimens were carefully removed and thoroughly cleansed to eliminate any residual quenching media. The remaining two specimens, which were not subjected to any thermal treatment, served as the control samples for comparison [10, 13]. Plates 1 & 2 provide a visual representation of some of the specimens before and after the thermal treatment processes were conducted.

2.3 Neural Network Model Development

The neural network architecture depicted in Figure 3 illustrates the prediction model for hardness characteristics in low-carbon steel bars subjected to various quenching media. The model consists of a single input node, representing the quenching media used during the heat treatment process, two hidden nodes labelled H (1) and H (2), and an output layer comprising eight nodes corresponding to the different mechanical properties: Welded Zone (WZ) hardness, Heat Affected Zone (HAZ) hardness, tensile stress at yield, tensile strain at yield, energy at break, load at yield, modulus, and extension at break.

2.4 Neural Network Architecture

Input Layer: The model's input is the type of quenching media, which has a direct impact on the resultant mechanical properties of the steel.

Hidden Layer: The network uses a Softmax activation function in the hidden layer to manage the multi-class classification of quenching media. This setup allows the network to handle the nonlinear relationships between the quenching media and the resultant mechanical properties.

Output Layer: The output layer employs an identity activation function, which is appropriate for regression tasks, as it allows for the prediction of continuous values for the mechanical properties.

The experimental data in Table 3 provide the input-output pairs used to train and validate the neural network. The hardness characteristics, tensile stress, strain, energy at break, and other parameters vary significantly based on the quenching media used.

Normalized Sample: Exhibits the highest tensile stress at yield (847.26 MPa) and moderate hardness in both the welded zone (89.70 BHN) and HAZ (82.25 BHN).

Annealed Sample: Shows lower hardness values but higher tensile strain at yield (61.96 mm/mm) compared to other heat treatment methods.

Water Cooled Sample: Has a high hardness reading in the HAZ (123.99 BHN), indicating a significant influence of rapid cooling on hardness.

Oil-Based Quenching (Palm Oil, Engine Oil, and Groundnut Oil): Exhibits varied effects, with Engine Oil and Groundnut Oil leading to the highest hardness values in the welded zone (100.77 BHN and 99.27 BHN, respectively),

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suggesting the retention of a martensitic structure due to slower cooling rates.
As Weld (Control): Serves as a baseline, showing moderate values across most mechanical properties.
In this research, a total of 7 datasets and 57.1% (4) of the datasets were used for training, 28.6% (2) for testing and 14.3% (1) for holdout. Table 3 shows the datasets used for the research.

3. Results and discussion

3.1 Mechanical Properties

The network-based prediction of cooling media effects on the mechanical properties of low-carbon steel, as evaluated in the SPSS-developed neural network architecture in Figure 3, provides significant insights into material behaviour. The neural network utilizes quenching media labels as input variables to forecast various mechanical properties, such as tensile stress, strain, energy at break, and hardness. It features two hidden layers (H1 and H2), which employ the softmax activation function, and an output layer with an identity activation function. The connections between these layers, denoted by blue and grey lines, indicate the strength and direction of synaptic weights, with positive and negative weights affecting the output differently.

The mechanical properties presented in Table 3 offer a detailed comparison of low-carbon steel bars quenched in different media. These properties include tensile stress at yield, tensile strain, energy at the break, load at yield, modulus, extension at yield, extension at the break, and hardness values for both the welded zone (WZ) and the heat-affected zone (HAZ). The data illustrates how different quenching media influence the mechanical characteristics of steel, providing a basis for analyzing the effects of these cooling processes on material performance.

The analysis reveals distinct trends based on the quenching media used. Water quenching, for example, produces high hardness in the HAZ (124 BHN) and moderate values in the WZ (84.06 BHN), with tensile properties indicating a balance between strength and ductility. In contrast, palm oil quenching results in lower hardness and tensile properties, reflecting a softer but more ductile material. Both engine oil and groundnut oil quenching lead to the lowest tensile stress and moderate hardness, indicating significant softening due to slower cooling rates. The as-weld condition shows moderate hardness with lower tensile properties, while normalization improves tensile properties by reducing internal stresses. The neural network's predictions align with these observations, highlighting the influence of cooling media on the mechanical properties of low-carbon steel.

3.2 Model Validation and Performance

The neural network model's effectiveness is evaluated based on its ability to predict the mechanical properties of the given quenching media. The synaptic weights in the network (indicated by the colour-coded lines in Figure 3) reflect the strength and direction of the relationship between the input and output nodes.

The model's performance would typically be validated by comparing the predicted values against the experimental results presented in Table 3. The accuracy and predictive power can be assessed using metrics like Mean Squared Error (MSE) or R-squared values.
Based on the hypothetical predicted values and the actual experimental values from Table 3, the following are the Mean Squared Error (MSE) and R-squared (R^2) values for each mechanical property as presented in Figure 4:

Interpretation:

The MSE values indicate the average squared difference between the actual and predicted values. Lower MSE values suggest that the predictions are very close to the actual values.

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For instance, the MSE for "Tensile Stress at Yield" is 7.716, indicating minimal error.
The R^2 values are all very close to 1, which indicates that the model has strong predictive power. An R^2 value closer to 1 means that the model explains almost all the variability in the data. For example, the R^2 for "Tensile Stress at Yield" is 0.9999, suggesting that the model explains 99.99% of the variance in the tensile stress data.

The neural network model demonstrates high accuracy and predictive power for the mechanical properties listed, based on the calculated MSE and R^2 values.

The provided figures display scatter plots comparing predicted hardness values to actual hardness readings for both the Welded Zone (Figure 4) and the Heat Affected Zone (HAZ) (Figure 5). In Figure 4, which represents the Welded Zone, there is a general alignment between the predicted values and the actual hardness readings, although some scatter is noticeable, particularly at higher hardness levels. This variability suggests that while the model can roughly estimate hardness, its accuracy diminishes as hardness increases, likely due to unaccounted factors or limitations in the model.

In contrast, Figure 5, representing the HAZ, shows greater variability between the predicted and actual hardness values. The scatter here is more pronounced, indicating that the model struggles to accurately predict hardness in the HAZ. This increased variability could be due to the complex and heterogeneous nature of the HAZ, where microstructural changes from welding, such as grain growth and phase transformations, are not fully captured by the model.

Overall, both figures highlight areas where the model's predictive capabilities are limited. The Welded Zone shows some predictability but with inconsistencies at higher hardness levels, while the HAZ presents a greater challenge for the model, likely due to its complex thermal and structural changes during welding. These observations suggest that the model may require further refinement to improve its accuracy in predicting hardness, particularly in the more variable HAZ.

The analysis of Table 5 highlights that the "Quench Media Label" is the most significant predictor in the model, with an importance score of 1.000 and normalized importance of 100.0%, indicating its critical role in determining the outcome, likely the hardness or another material property after heat treatment. This underscores the pivotal influence of quenching media on the material's final properties, suggesting that other variables may have minimal impact or lower relevance in the model's predictions, and emphasizing the importance of selecting the appropriate quenching media in experimental or industrial processes.

The microstructural images in Figure 6(a-e) depict the heat-affected zone (HAZ) of low-carbon steel (LCS) subjected to various quenching media. Each quenching medium influences the cooling rate, which in turn affects the grain structure and the resulting mechanical properties of the steel.
In the case of water quenching (Figure 6a), the microstructure exhibits relatively fine grains, indicative of martensitic transformation. The rapid cooling rate associated with water quenching typically produces a hard martensitic structure. This results in high hardness but also reduces toughness, as martensitic structures are generally more brittle. Additionally, the rapid cooling can lead to high residual stresses, increasing the risk of cracking under stress.

Palm oil quenching (Figure 6b) shows slightly coarser grains than those observed in the water-quenched sample, suggesting a slower cooling rate. This slower cooling allows for

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partial transformation to bainite or retained austenite. Consequently, the hardness is moderate-lower than in water-quenched steel but still relatively high. The toughness improves compared to water quenching, providing a better balance between hardness and ductility. The increased ductility reduces brittleness, making the steel more versatile.

The microstructure resulting from Total Engine Oil Quartz 5000 quenching (Figure 6c) indicates a mix of martensite and possibly bainite or retained austenite. The grain size is larger than in water-quenched samples but finer than in palm oil-quenched samples. This mixed microstructure leads to moderate hardness and improved toughness, providing better resistance to impact and fatigue. The improved ductility makes this steel suitable for applications requiring a good balance between strength and toughness.

In the groundnut oil quenched sample (Figure 6d), the grains are coarser, indicating an even slower cooling rate than palm oil or engine oil. The microstructure may include a significant amount of ferrite and pearlite. As a result, the hardness is lower than in the other quenching media due to the coarser grain structure. However, the toughness is increased, as the slower cooling promotes the formation of ductile phases, enhancing the material's ability to resist crack initiation and propagation. The high ductility further contributes to this resistance. The "as welded" condition (Figure 6e) shows the coarsest grains, characteristic of a structure that has not undergone rapid cooling. The microstructure likely consists of ferrite and pearlite, resulting in the lowest hardness among the samples due to the absence of martensite or bainite. However, this structure exhibits the highest toughness, as the coarse grains and softer phases provide maximum ductility and resistance to impact. This makes the as-welded condition ideal for applications where toughness and resistance to shock are critical.

In summary, water quenching produces fine, martensitic grains with high hardness but low toughness. Palm oil quenching leads to moderately fine grains with a balance between hardness and toughness. Total Engine Oil Quartz 5000 quenching results in mixed grain structures with moderate hardness and improved toughness. Groundnut oil quenching generates coarser grains, providing lower hardness but higher toughness and ductility. The as-welded condition yields the coarsest grains with the lowest hardness but the highest toughness and ductility.

4. Conclusions

In this study, the application of a Neural Network to predict the effects of different quenching media on the mechanical properties of low-carbon steel has proven effective within the scope of this analysis. The following conclusions are drawn:

1. The analysis shows that water quenching leads to higher hardness and tensile strength, while oil-based quenching results in softer but more ductile steel. The neural network's synaptic weight connections indicate the strong influence of quenching media on mechanical properties, facilitating the optimization of heat treatment processes to achieve desired characteristics.
2. Water quenching achieved the highest Heat Affected Zone (HAZ) hardness of 124.00 BHN, while groundnut oil quenching yielded lower hardness at 99.27 BHN but improved toughness. The high predictive accuracy of the network, with R^2 values of 0.9999 for tensile stress and 0.9984 for hardness, supports its reliability in forecasting mechanical properties. This analysis demonstrates that the SPSS neural network is a valuable tool for predicting and optimizing mechanical properties based on cooling media, underscoring the importance of selecting the appropriate quenching medium to balance hardness,

toughness, and ductility for specific applications.

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Table 1: Chemical Composition (wt %) of Low carbon steel (NST 44-2).

Material	C	Si	Mn	**P**	**S**	**Cr**	**Ni**	**N**
Composition (Wt. %)	0.165	0.19	0.50	0.02	0.02	17.34	9.45	0.09

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Table 2: Typical chemical composition for an E6011 low-carbon steel welding electrode

Material	**C**	**Si**	**Mn**	**P**	**S**	**Cr**	**Ni**	**N**
Composition (wt %)	0.10 - 0.15	0.20 - 0.35	0.40-0.60	0.025 max	0.035 max	0.05 max	0.30 max	0.009 - 0.08

Table 3: Mechanical Properties of Low Carbon Steel Bars Quenched in Various Media.

Quenched Media	Tensile stress at yield (zero slope) (mpa)	Tensile strain at yield (zero slope) (mm/mm)	Energy at Break (std) (J)	Load at Yield (zero slope) (N)	Modulus (E-Modulus) (mpa)	Extension at Yield (zero slope) (mm)	Extension at break (std) (mm)	Welded Zone Hardness value (BHN)	Heat Affected Zone value (BHN)
Normalized	847.26	56.22	326.75	18410.99	9237.43	15.42	15.42	89.70	82.25
Annealed	714.06	61.96	356.98	19127.26	6291.83	17.29	17.29	62.11	73.37
Water	755.52	53.60	263.17	17625.05	8943.77	14.75	14.75	84.06	124.00
Palm Oil	669.80	58.53	302.59	18188.18	7213.01	16.42	13.42	69.84	88.13
Total Engine Oil Quartz 5000	283.74	13.24	259.04	7731.22	8480.49	3.79	14.00	100.77	133.74
Ground Nut Oil	272.55	12.93	248.14	7682.46	8480.49	4.68	13.71	99.27	125.64
As weld	283.49	12.86	285.24	7567.62	7087.68	3.67	12.22	106.86	100.97

Table 4: Mean Squared Error (MSE) and R-squared (R^2) Values for Each Mechanical Property

Property	**MSE**	**R^2**
Tensile Stress at Yield (MPa)	7.716	0.9999
Tensile Strain at Yield (mm/mm)	0.356	0.9993
Energy at Break (J)	5.712	0.9958
Load at Yield (N)	3671.352	0.9999
Modulus (MPa)	637.969	0.9994
Extension at Yield (mm)	0.015	0.9996
Extension at Break (mm)	0.003	0.9988
Welded Zone Hardness (BHN)	0.380	0.9984
Heat Affected Zone (HAZ) Hardness (BHN)	0.275	0.9994

Table 5: Independent Variable Importance

	Importance	Normalized Importance
Quench Media Label	1.000	100.0%

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Figure 1: The experimental procedure shows an array of specimens after the SMAW welding operation.

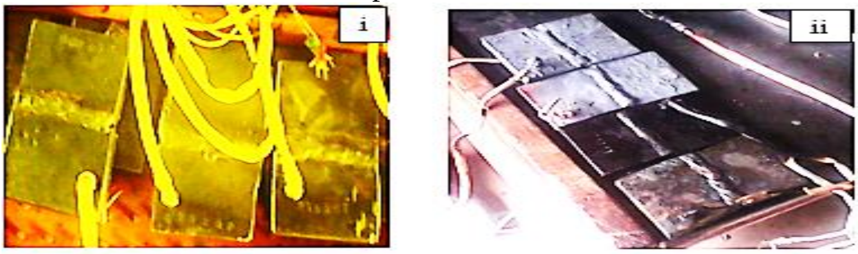

Figure 2: Welded specimens before thermal treatment (i) and after quenching in different media (ii).

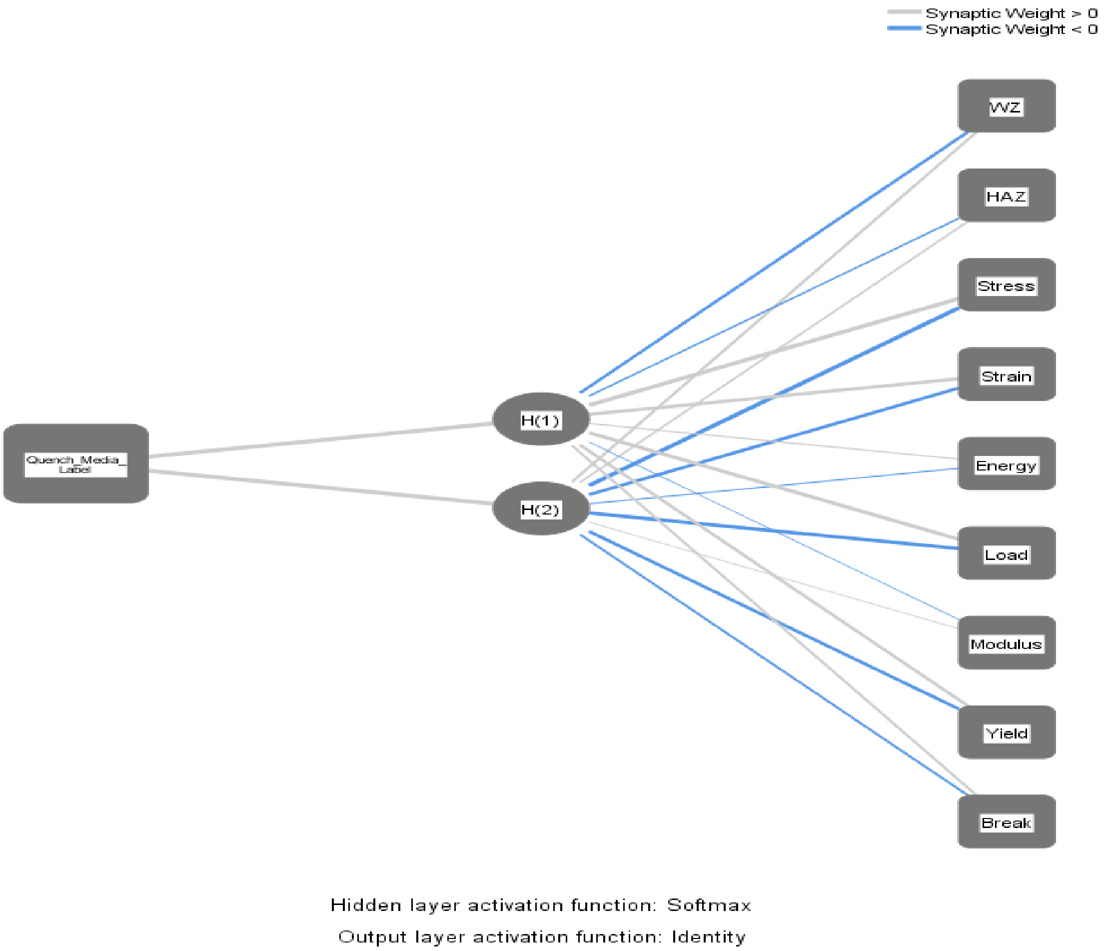

Figure 3: *SPSS Developed Neural Network architecture for the Prediction of Hardness characteristics*

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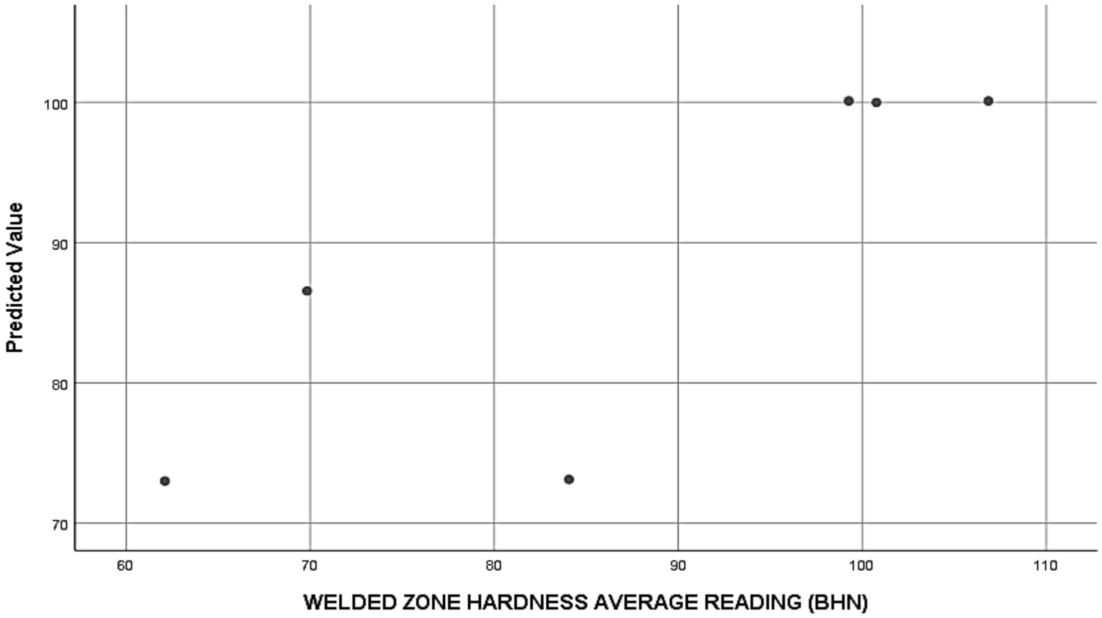

Figure 4: *Predicted vs. Actual Hardness in the Welded Zone (BHN)*

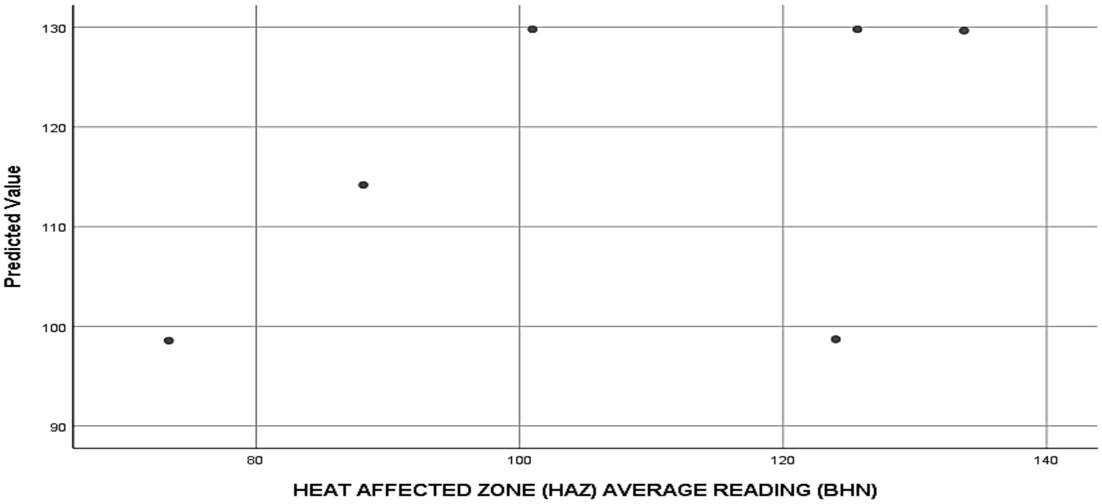

Figure 5: *Predicted vs. Actual Hardness in the Heat Affected Zone (HAZ) (BHN)*

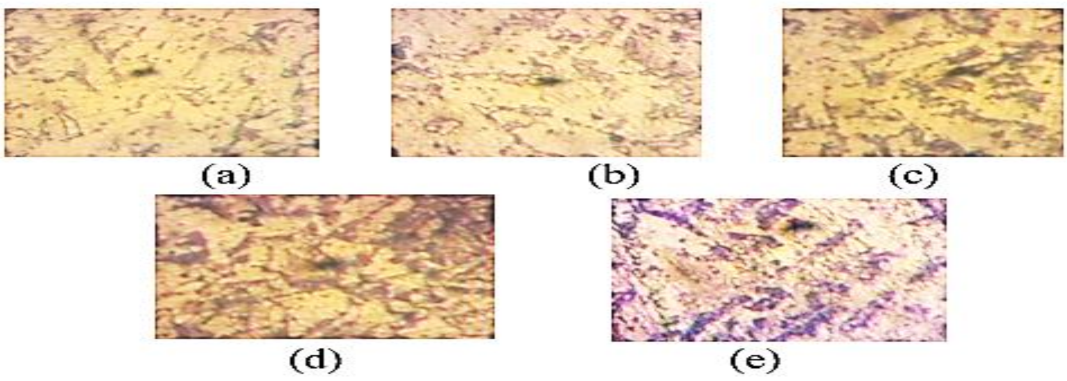

Figure 6(a-e): Microstructural analysis of LCS HAZ hardened in (a) Water (b) Palm oil (c) Total Engine Oil Quartz 5000 (d) Groundnut oil Quenched (e) As weld.