

Research Article

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Optimize the corrosion behaviour and mechanical properties of AISI 316 stainless steel under heat treatment and previous cold working

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Abstract: Improving corrosion resistance in alloys made of stainless steel is an important innovation on the petroleum trade. The effect of heat treatments (HT) and cold working on the corrosion behaviour, surface hardness, and microstructure of 316 stainless steel was investigated experimentally. The corrosion environment is seawater and crude oil. The corrosion rates (CRs) were obtained using the mean loss of weight approach, which was then optimised using the Taguchi method. The specimens used in this study are made of 316 stainless steel rod, which is first annealed to obtain the qualities of the raw material before being put through a tensile test to assess the mechanical characteristics of the metal. After cold working, the hardness test, the corrosion test utilising the lost weight method, and the microstructure test are all carried out. By performing these tests, the metal show excellent mechanical properties such as yield stress, tensile stress, and hardness; in the corrosion test, the raw metal show higher resistance in both seawater and crude oil, while in cold working and HT with cold working, samples show higher corrosion. The HT samples had the lowest corrosion resistance as the cold working percentage increased. In this work, the input parameters such as ultimate corrosion media, HT and cold work (CW) are optimised utilising a multiple objective optimisation approach that uses weighted grey relational analysis. Two objectives, that are CR and Hardness (H), are simultaneously optimised. We suggested a quantitative approach to establish the weight factors of various responses for grey relational analysis called weighted grey relational analysis. The

optimum input parameters were determined using weighted grey relational analysis, and the outcomes showed that HT is the most relevant parameter. Cold working has been observed in association with stress-related twinning and austenite phase deformation, resulting in fast grain splitting and the production of a microstructure that resembles a ribbon composed of austenite and ferrite.

Keywords: cold working, AISI 316 stainless steel, mechanical properties, corrosion behavior, Taguchi methods

1 Introduction

Austenitic stainless steels (SS) are commonly used in many instances of industrial and construction industries due to their passivation feature and ability to tolerate environmental deterioration. Their outstanding mechanical performance and corrosion resistance at both high and low temperatures are largely responsible for this wide range of applications. However, intergranular corrosion poses a serious threat to them [1–3]. The majority of biomedical applications for austenitic stainless steels include implants, fittings, medicines, and surgical instruments. The biocompatibility, low cost, ease of manufacture, exceptionally high mechanical strength, and resistance to corrosion of 316L stainless steel contribute to its widespread application [4–6].

Heat treatment (HT) cannot harden 316 stainless steel. Rapid cooling can be used to perform annealing or solution treatment after heating to 1,010–1,120°C [7].

Rather than being heated, such stainless steel can be toughened by cold working. Intergranular corrosion can result from heat treating stainless steel as well as chromium and C depletion at grain boundaries [8]. However, by limiting the diffusion channel for carbon together with chromium in the fine granules, stainless steel grain refinement could significantly enhance corrosion resistance. Because of this, there is less chance of chromium depletion at grain boundaries, which would encourage the development of an identical

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passive oxide coating on the surface and prevent 316L stainless steel from dissolving [8–10].

The 316L steel has a very low strength. HTs cannot strengthen these steels since they do not go through any phase transformations. However, they may be made stronger by reducing the grain size to submicrometer levels [11,12].

Plastic deformation has the ability to alter the characteristics of a material by increasing the dislocation density, decreasing the percentage of coincidence site lattice barriers, introducing deformation bands, and even changing the phase [13,14]. The corrosion and cracking resistance of austenitic stainless steels in settings would be impacted by these modifications to the material and mechanical characteristics. Austenitic stainless steel achieves a passive state with high stability and strong corrosion resistance when chromium is present in some quantity [15,16]. It has been found that increasing the quantity of cold-working produced tensile and yield strength improvements for austenitic stainless steels. This can be done as a percentage, such as 10, 20%, and so on [17–19].

316 austenitic stainless steel has been the subject of several studies on corrosion rates (CRs); however, there has been little study on how pre-cold working and annealing temperature affect 316 CRs. These impacts at various levels and in diverse corrosive settings are made clear by the current investigation. In addition, each environment's mechanical properties and microstructure were examined, and the most efficient elements of the process were investigated.

2 Experimental work

2.1 Raw materials and HT

Three 316 stainless steel rods were selected, each measuring 1.87 m in length and 10 mm in diameter. As indicated in Table 1, a PECTROTEST TXC25 spectrometer was utilised to ascertain the chemical composition for a double check.

According to the ultimate corrosion media (CM), either saltwater or crude oil, the samples were split into two primary groups, each of which was further separated into three parts (without HT, annealing at 1,160°C and quenching

with water, and annealing at 1,160°C and quenching with oil). Three parts of each specimen group are divided into three smaller groups, each of which is subjected to 10, 20, and 30% cold working, respectively, according to ASTM E8M [19] utilising a universal tensile machine. Each group from 20 groups contains three specimens according to the cold working and immersion media environments as shown in Table 2.

The hardness test was performed in accordance with ASTM E384 [20]. After machining the metal as shown in Figure 1, in the first two cases, the specimens were kept unprocessed simply by being placed in seawater and crude oil, while the other examples were subjected to 10, 20, and 30% cold working, respectively, and annealing. The process of annealing was used to create 316 stainless steel. After being submerged at 1,160°C, Type 316 is quenched in either water or air.

2.2 Aggressive environments

The impact of annealing and pre-cold on the corrosion resistance of the 316 stainless steel was examined using two corrosive media. The corrosive environment consists of seawater and crude oil. Table 3 lists the characteristics of seawater, while Table 4 lists the characteristics of the crude oil utilised in the experiment.

The majority of the oil produced in Iraq is exported via the Arabian Gulf; therefore, sea water measurements from the Arabian Gulf must be taken. This is because there are numerous export platforms (including Khor al-Zubayr in the Basra Governorate and the port of Umm Qasr).

2.3 Corrosion test

The corrosion of the samples was examined using the loss-weight method in conformity with ASTM G31 [21], a standard. The specimens were cleaned correctly, with the use of chemical and mechanical cleaners to eliminate any contaminants and any oxidation layer (if present). To avoid the inaccurate and deceptive findings of short-period tests, a certain container was used, and the appropriate test period was picked. The tests were set up as cases

Table 1: Lists the chemical constitution of 316 stainless steel in percentages

	Fe	C	Si	Mn	Cr	Ni	Cu	P	S	Co
Measured	Bal.	0.037	0.215	1.19	17.13	11.89	0.45	0.0187	0.012	0.154
Maximum (%)	Bal.	0.07	1	2	18.5	13		0.045	0.03	

Table 2: Specimen classification based on cold working and immersion media

Group	HT	Cold working	Quenching media	Ultimate CM
1	Without	Without	Without	Crude oil
2	Without	Without	Without	Seawater
3	Without	10%	Without	Seawater
4	Without	20%	Without	Seawater
5	Without	30%	Without	Seawater
6	Without	10%	Without	Crude oil
7	Without	20%	Without	Crude oil
8	Without	30%	Without	Crude oil
9	Annealing at 1,160°C	10%	Oil	Crude oil
10	Annealing at 1,160°C	20%	Oil	Crude oil
11	Annealing at 1,160°C	30%	Oil	Crude oil
12	Annealing at 1,160°C	10%	Oil	Seawater
13	Annealing at 1,160°C	20%	Oil	Seawater
14	Annealing at 1,160°C	30%	Oil	Seawater
15	Annealing at 1,160°C	10%	Water	Seawater
16	Annealing at 1,160°C	20%	Water	Seawater
17	Annealing at 1,160°C	30%	Water	Seawater
18	Annealing at 1,160°C	10%	Water	Crude oil
19	Annealing at 1,160°C	20%	Water	Crude oil
20	Annealing at 1,160°C	30%	Water	Crude oil

**Figure 1:** Tension test specimen.**Table 3:** Properties of sea water

Test	Seawater
Temperature (°C)	16
Mass density (kg/m ³)	1027.03
Kinematic viscosity (m ² /s)	1.1978×10^{-6}
PH	8.12
Dynamic viscosity (Pa s)	0.001324

submerged in settings including seawater and crude oil. The container was shut tightly and kept for a week. To determine the weight lost, the specimens were taken out and cleaned every week. The CR was calculated using the following equation [22]:

$$CR = \frac{\Delta m \times 24 \times 365 \times 10}{\rho \times A \times t}, \quad (1)$$

Table 4: Crude oil's characteristics

Test	Results	Method
Density (g/cm ³) at 15°C	0.95	ASTM D-1298
Flash point (°C)	139.00	ASTM D-93
Kinematic viscosity (m ² /s)	371.20	ASTM D-445
Pour point (°C)	−3.00	ASTM D-97
Sulphur contact (wt%)	4.53	ASTM D-4294
Carbon residue (RAMS) (wt%)	9.54	ASTM D-524
Water and sediment (vol%)	0.11	ASTM D-1796

where ρ is the metal density in grams per cubic centimetre, A is the specimen's area in square centimetres (cm²), t is the exposure duration in hours, m is weight loss in milligrams, and CR is the CR in millimetres per year (MPY). In Table 5, a portion of the weight loss calculations is shown.

2.4 Analysis and design of experimental data

The total number of the input parameters, their involvement in research, as well as their levels, influence the design of experiments (DOE) that will be utilised to perform the experiments. The L20 array is created in the current experiment using the Taguchi approach, and subsequent processing is progressed correspondingly. Furthermore, the strength of the chosen design is guaranteed. A powerful

Table 5: Weight loss for sea water samples

Sample	Week zero	Week 1	Week 2	Week 3	Week 4	Weight loss week 1	Weight loss week 2	Weight loss week 3	Weight loss week 4
Shaft without	12.2625	12.2618	12.2613	12.261	12.2608	0.0007	0.0007	0.0015	0.0017
Without HT 10%	12.4981	12.4979	12.4977	12.4975	12.4973	0.0002	0.0002	0.0006	0.0008
Without HT 20%	12.4482	12.448	12.4479	12.4477	12.4476	0.0002	0.0002	0.0005	0.0006
Without HT 30%	12.5585	12.558	12.5577	12.557	12.5549	0.0005	0.0005	0.0015	0.0036
1,160°C → cooling in oil 10%	12.6498	12.6492	12.6476	12.6449	12.6411	0.0006	0.0006	0.0049	0.0087
1,160°C → cooling in oil 20%	12.615	12.6131	12.6122	12.6118	12.6113	0.0019	0.0019	0.0032	0.0037
1,160°C → cooling in oil 30%	12.2255	12.2252	12.2232	12.222	12.2214	0.0003	0.0003	0.0035	0.0041
1,160°C → cooling in water 10%	12.5063	12.5045	12.5043	12.5031	12.5022	0.0018	0.0018	0.0032	0.0041
1,160°C → cooling in water 20%	12.4495	12.449	12.4478	12.4471	12.4466	0.0005	0.0005	0.0024	0.0029
1,160°C → cooling in water 30%	12.5789	12.5771	12.5767	12.5729	12.5721	0.0018	0.0018	0.006	0.0068

design is one that noise or other uncontrolled events have the least impact possible on the response variables. The next sections provide specifics on the experiment and analytic method utilised in the current study for multi-response optimisation.

2.4.1 Optimisation parameters

The input parameters used in the current analysis are ultimate CM, HT, and cold work (CW). The parameters, units, and levels as indicated in Table 6.

2.4.2 Response variables

CR and hardness (H) were examined as two response variables. CR minimisation and Hardness (H) maximisation were the goals. Table 7 displays the response variables along with the abbreviations and units.

2.4.3 Experimental data array

With fewer experiments, the experimental data array may be used to examine how a system's or process's input parameters impact the response variables. The Taguchi technique is used to do this. The number of input parameters utilised in the experiment, together with their levels, determine the experimental data array. The L20 data array was used for the current investigation, as indicated in Table 8. The data analysis may be carried out using a standard statistical programme like Minitab; in the current study, the tool used for this was Minitab18.

2.4.4 Signal-to-noise ratio calculation and analysis

The signal-to-noise (S/N) ratio for each factor level combination is calculated. Since the goal was to reduce the CR, the smaller-is-better criteria was applied, and Eq. (2) is utilised to obtain the S/N ratio. Similarly, as the goal was to maximise hardness (H), the larger-is-better criteria was applied, and the S/N ratio is determined using Eq. (3).

The following is the S/N ratio for the smaller-the-better characteristic:

$$S/N = -10 \log \left(\frac{1}{n} \sum_i^n y_i \right). \quad (2)$$

The S/N ratio for the larger-the-better feature is also written as follows:

Table 6: Parameters of input and their levels

Input parameters	Symbol	Unit	Level 1	Level 2	Level 3	Level 4
Ultimate CM	CM		Sea Water CM1	Crude Oil CM2		
HT	HT		without HT1	Annealing at 1,160°C	Annealing at 1,160°C	
				Quenching in oil	Quenching in water	
				HT2	HT3	
Cold work	CW		0	10	20	30

Table 7: Response variables

No	Response variables	Abbreviation	Unit
1	CR	CR	mpy
2	Hardness	H	N/mm ²

Table 8: Experimental data array

Exp. No	CM	HT	CW	Exp. No	CM	HT	CW
1	CM1	HT1	0	11	CM2	HT1	0
2	CM1	HT1	10	12	CM2	HT1	10
3	CM1	HT1	20	13	CM2	HT1	20
4	CM1	HT1	30	14	CM2	HT1	30
5	CM1	HT2	10	15	CM2	HT2	10
6	CM1	HT2	20	16	CM2	HT2	20
7	CM1	HT2	30	17	CM2	HT2	30
8	CM1	HT3	10	18	CM2	HT3	10
9	CM1	HT3	20	19	CM2	HT3	20
10	CM1	HT3	30	20	CM2	HT3	30

$$S/N = -10 \log \left(\frac{1}{n} \sum_{i=1}^n \frac{1}{y^i} \right). \quad (3)$$

where y^i stands for the observed response values for each run, and n stands for the experimental sets. Table 9 shows the S/N ratio for CR and H depending on Eqs. (2) and (3).

2.4.5 Grey-Taguchi optimisation technique

We have used a multi-objective optimisation approach since two response parameters are thought to be optimised concurrently. In the current experimental study, we are using grey and Taguchi to optimise the process parameters, and depending on their grade, Taguchi approach is then used to optimise them.

2.4.6 Grey relational technique

Grey relational methodology is a technique for combining many quality factors into one, allowing for the implementation

of Taguchi single objective optimisation techniques and multi-objective quality parameter conversions. To do this, grey relational analysis (GRA) is used to determine the grey relational grade (GRG). Less data and multifactor analysis are its defining qualities, and these two traits might outweigh the drawbacks of statistical regression analysis. This single goal optimisation strategy makes advantage of the performance feature known as GRG. A step-by-step description of the GRA process and its outcome is presented [22,23].

2.4.6.1 GRA methodology

The following stages are the order in which GRA is conducted.

2.4.6.1.1 Normalising the S/N ratios

The study's initial data, which is used to convert the original sequence into an identical sequence, is prepared by normalising the S/N ratio in Taguchi-based GRA. The information in the 0–1 range of values, often known as the “grey relational generation,” are transformed by normalising the S/N ratio. In this study, the smaller the better criterion for CR and the larger the better criterion for normalisation of Hardness (H) are employed, respectively, utilising the equations found in Eqs. (4) and (5) [23].

Smaller the better:

$$u_i(p) = \frac{\max z_i(p) - z_i(p)}{\max z_i(p) - \min z_i(p)}. \quad (4)$$

Larger the better:

$$u_i(p) = \frac{z_i(p) - \min z_i(p)}{\max z_i(p) - \min z_i(p)}, \quad (5)$$

where $\max z_i(p)$ is the largest value of $z_i(p)$ for the p th respond, $\min z_i(p)$ is the lowest value of the S/N ratio, $u_i(p)$ is the outcome of grey relational generation. The normalised data are presented in Table 10.

2.4.6.1.2 Determining the deviation sequence

The difference between the reference sequence $y_o(p)$ and the comparability sequence $y_i(p)$, following normalisation,

Table 9: S/N ratio for CR and H with their calculated values

Exp. No	CM	HT	CW	CR	H	CR S/N ratio	H S/N ratio
1	CM1	HT1	0	0.143876781	184	16.8402	45.2964
2	CM1	HT1	10	0.066716407	198.5	23.5153	45.9552
3	CM1	HT1	20	0.050352548	203	25.9596	46.1499
4	CM1	HT1	30	0.300293095	229	10.4491	47.1967
5	CM1	HT2	10	0.71948974	96	2.8595	39.6454
6	CM1	HT2	20	0.306930175	103	10.2592	40.2567
7	CM1	HT2	30	0.345052859	94	9.2423	39.4626
8	CM1	HT3	10	0.345731672	100	9.2252	40.0000
9	CM1	HT3	20	0.242799663	127	12.2950	42.0761
10	CM1	HT3	30	0.582217968	90	4.6983	39.0849
11	CM2	HT1	0	0.138065687	152	17.1983	43.6369
12	CM2	HT1	10	0.051667957	200	25.7356	46.0206
13	CM2	HT1	20	0.135684539	221	17.3494	46.8878
14	CM2	HT1	30	0.070028183	231	23.0945	47.2722
15	CM2	HT2	10	0.141415624	94	16.9901	39.4626
16	CM2	HT2	20	0.049263307	127	26.1495	42.0761
17	CM2	HT2	30	0.36404637	111	8.7769	40.9065
18	CM2	HT3	10	0.17342484	103	15.2178	40.2567
19	CM2	HT3	20	0.28751917	120	10.8267	41.5836
20	CM2	HT3	30	0.126789336	110	17.9383	40.8279

is represented by the deviation sequence Δ_{oi} [23]. Eq. (6) is used to determine it as follows:

$$\Delta_{oi} = |y_0(p) - y_i(p)|. \quad (6)$$

The deviation sequence is presented in Table 11.

$$x_i(p) = \frac{\Delta_{\min} + \varphi \Delta_{\max}}{\Delta_{oi}(p) + \varphi \Delta_{\max}}, \quad (7)$$

where φ is the distinctive coefficient, which has a value between 0 and 1, but is often considered to be 0.5. The value of Δ_{oi} are $\Delta_{\min}$ (smallest value) and $\Delta_{\max}$ (biggest value). Table 12 presents the grey relational coefficient (GRC) (Tables 13 and 14).

2.4.6.1.3 Grey relational coefficient

The grey relational coefficient (GRC) is a measure of the connection between the ideal (optimal) and actual normalised S/N ratio for all sequences. The two sequences have a grey relational coefficient of 1 if they agree at every points [23,24]. Eq. (7) may be used to represent the grey relational coefficient GRC.

2.4.6.1.4 Weight factor calculations

For an actual engineering challenge, different approaches have varying degrees of relevance. The GRG varies significantly when different responses have differing weights,

Table 10: S/N ratio normalised value for CR and H

No.	CR $u_i(p)$	H $u_i(p)$	No.	CR $u_i(p)$	H $u_i(p)$
1	0.399713812	0.758667502	11	0.384338166	0.55597961
2	0.113103449	0.839139277	12	0.0177739	0.847125913
3	0.008156188	0.862921038	13	0.377850071	0.953050465
4	0.674127162	0.990774843	14	0.131171455	1
5	1	0.068468036	15	0.393279023	0.046132762
6	0.682280218	0.143134062	16	0	0.365345299
7	0.72594359	0.046132762	17	0.74592732	0.222489648
8	0.726676553	0.111775533	18	0.469375053	0.143134062
9	0.594868095	0.365345299	19	0.657915463	0.305197983
10	0.921048588	0	20	0.352562299	0.212888801

Table 11: Deviation sequence for CR and H

No.	CR Δ_{oi}	H Δ_{oi}	No.	CR Δ_{oi}	H Δ_{oi}
1	0.600286188	0.241332498	11	0.615661834	0.44402039
2	0.886896551	0.160860723	12	0.9822261	0.152874087
3	0.991843812	0.137078962	13	0.622149929	0.046949535
4	0.325872838	0.009225157	14	0.868828545	0
5	0	0.931531964	15	0.606720977	0.953867238
6	0.317719782	0.856865938	16	1	0.634654701
7	0.27405641	0.953867238	17	0.25407268	0.777510352
8	0.273323447	0.888224467	18	0.530624947	0.856865938
9	0.405131905	0.634654701	19	0.342084537	0.694802017
10	0.078951412	1	20	0.647437701	0.787111199

indicating that weight considerations are crucial for attaining the best outcomes. In most cases, researchers employ equal weight to calculate the GRG of numerous replies [25,26] or use a weight to subjectively emphasise or de-emphasize the aim. To provide acceptable values to various responses under optimisation, a sensible criterion for weight factor computation can be utilised [27]. To estimate the weight factors, this technique depends on how much the alterations in the parameters have an impact on the responds. Using Eqs. (8) and (9) correspondingly, the grey relational coefficient ranges and weight factors are calculated. The weighting variables for each response are also shown in the last row of Table 15.

$$R_{ij} = \max\{K_{i,j,1}, K_{i,j,2}, \dots, K_{i,j,k}\} - \min\{K_{i,j,1}, K_{i,j,2}, \dots, K_{i,j,k}\}, \quad (8)$$

$$w_i = \frac{\sum_{j=1}^p R_{i,j}}{\sum_{i=1}^m \sum_{j=1}^p R_{i,j}}, \quad (9)$$

$j = 1, 2, \dots, p$, $i = 1, 2, \dots, m$, and $k = 1, 2, \dots, l$. w , weights, m , responses, p , parameters, l , experimental levels, R , ranges of grey relational coefficients, K , average grey relational coefficients for

Table 13: Mean value for the CR parameter at each level

Level	CR		
	CM	HT	CW
1	0.607552035	0.418983027	0.45129585
2	0.455918913	0.617598102	0.546889198
3		0.596209442	0.478614836
4			0.596515596
max	0.607552035	0.617598102	0.596515596
min	0.455918913	0.418983027	0.45129585
Range = max-min	0.151633122	0.198615075	0.145219745
Sum	0.495467942		

each parameter at each level of each response, and m , responses. There are specified weighting parameters for the responses, and the calculation for the GRG is provided by

$$\text{GRG} = 0.471183231\text{GRC}_{\text{CR}} - 0.528816769\text{GRC}_{\text{H}}, \quad (10)$$

where GRC_{CR} stands for the grey relational coefficient of CR and GRC_{H} is that for the hardness. Table 16 lists the values for two responses grey relationship grades.

Table 12: GRC for CR and H

No.	CR GRC	H GRC	No.	CR GRC	H GRC
1	0.454427226	0.674461192	11	0.448164475	0.529649577
2	0.360517156	0.756589071	12	0.337330452	0.765844455
3	0.335155729	0.78483207	13	0.445573258	0.914161121
4	0.60542008	0.981883934	14	0.365275842	1
5	1	0.349276169	15	0.451785057	0.343910356
6	0.611456407	0.368496243	16	0.333333333	0.440662696
7	0.645947755	0.343910356	17	0.663066059	0.391386261
8	0.64655999	0.3601723	18	0.485142536	0.368496243
9	0.552405674	0.440662696	19	0.593764614	0.418479374
10	0.863630332	0.333333333	20	0.435753505	0.388466824

Table 14: Mean value for the H parameter at each level

Level	H		
	CM	HT	CW
1	0.539361736	0.800927677	0.602055384
2	0.556105691	0.372940347	0.490714766
3		0.384935128	0.5612157
4			0.573163451
max	0.556105691	0.800927677	0.602055384
min	0.539361736	0.372940347	0.490714766
Range = max-min	0.016743954	0.42798733	0.111340618
Sum	0.556071903		

Table 15: Grey relational coefficients weighing factors

	CR	H
Sum	0.495467942	0.556071903
Total sum	1.051539845	
Weight	0.471183231	0.528816769

2.4.6.1.5 GRG and rank determination

The GRG provides the foundation for the overall assessment of the many performance aspects. The highest rank is given to the grade with the highest value. The computation of the GRG, which acts as a basis for the overall assessment of the multiple-performance feature, is the next stage of GRA and is performed using Eq. (11) [23,28]:

$$\delta_i = \sum_{p=1}^n w_p x_i(p), \quad (11)$$

where w_p is the weighted factor for each grey relational coefficient and n is the total number of response variables. For each of the response variables, the total weighting factors should equal 1.

3 Results and discussion

3.1 Microhardness

Results for the microhardness of the 316 austenitic stainless steels as received and after HT and cold working are shown in Figure 2 for the groups in Table 2. At room temperature, the microhardness values were determined. As a result, cold work was the sole factor in all of the microhardness variations. The percentage of cold working affects the work-hardening capacity [22,29].

When the hardness values are observed, they increase directly with the value of cold operation and reach their maximum when the cold working rate is 30%, as seen in groups 5

Table 16: Grey relational grade and rank

No.	GRG	Rank	No.	GRG	Rank
1	0.570784877	7	11	0.491255163	14
2	0.569966626	8	12	0.563935843	9
3	0.572952118	6	13	0.693370378	3
4	0.804500479	1	14	0.700928621	2
5	0.655886326	4	15	0.394739106	19
6	0.482974998	16	16	0.3900909	20
7	0.486225314	15	17	0.519397226	10
8	0.495113377	12	18	0.42345802	17
9	0.493314114	13	19	0.50107084	11
10	0.583200387	5	20	0.410747515	18

and 8 with hardness value 229 and 231, respectively. 316 stainless steel hardness usually reduced relatively considerably when annealing up to 1,120°C, when it dropped significantly due to recrystallisation and the formation of equated grains [30].

3.2 Microstructure

The chemical, physical, and mechanical properties of a specimen can be significantly influenced by its microstructure. For metallographic investigation, samples were taken from the experimental AISI 316 stainless steel. Each of the samples were done by grinding with emery paper measuring 250, 600, 1,000, and 1,200, then polishing with 3 µm diamond, and etching for 50 s in a certified and tested hood with 10 mL HNO₃, 10 mL acetic acid, 15 mL HCl, and 2–5 drops glycerin to define the microstructure according to ASTM E 407 [28]. As shown in Figure 3a, the microstructure of the specimen as it was received was mostly made up of equiaxed austenite grains, with just a little amount of annealing twins. Parallel lamellar structures and many dislocations were produced by cold working. The lamellar structure is extended mostly in the cold working direction [31]. When demonstrated in the insets in Figure 3b and when cold working increases, the deformation and lamellar structure become increasingly apparent as a difference between Figure 3c and d.

Furthermore, as cross-sectional metallographic structures indicated, distortion morphologies became thinner and more uniform. Cold working causes considerable deformation and the production of a lamella rough grain, as shown in Figure 3d. The density of dislocations increases over time with cold working, which can improve micro-hardness.

3.3 Surfaces analysis

Photography of high resolution to the surface morphology of the 316 stainless steel samples was examined using a NanoSEM

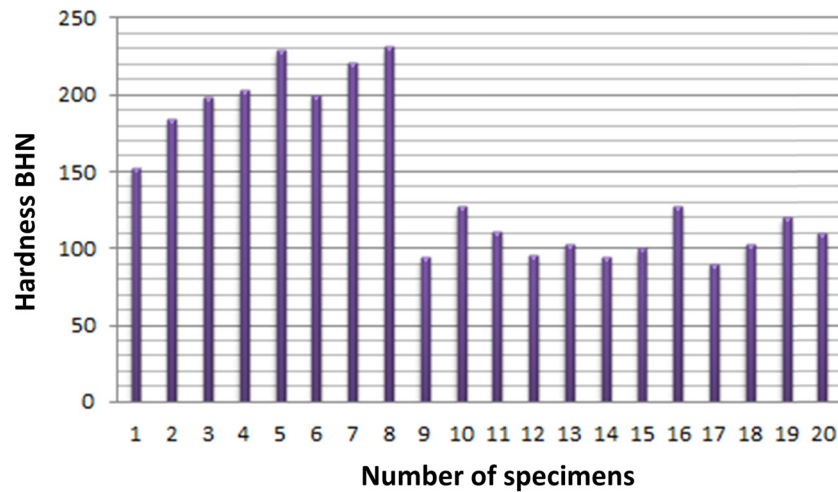


Figure 2: Hardness of 316 stainless steel of the as-received and after heat treatment, cold working/aggressive environments classified by groups.

450 scanning electron microscope (SEM) [32]. Figure 4 indicates the differences in the morphology of polished surfaces for steel that has had 10, 20, and 30% cold working in addition to HT. Examining the micro scanner images makes it clear how cold-working in various proportions has affected the internal

structure and the HT process. As the metal is cold worked more quickly, it deforms more and changes its mechanical properties, especially its ability to resist, *i.e.*, corrosion. The internal structure of the metal is more significantly affected by HT, and this is seen by the metal's ability to resist corrosion.

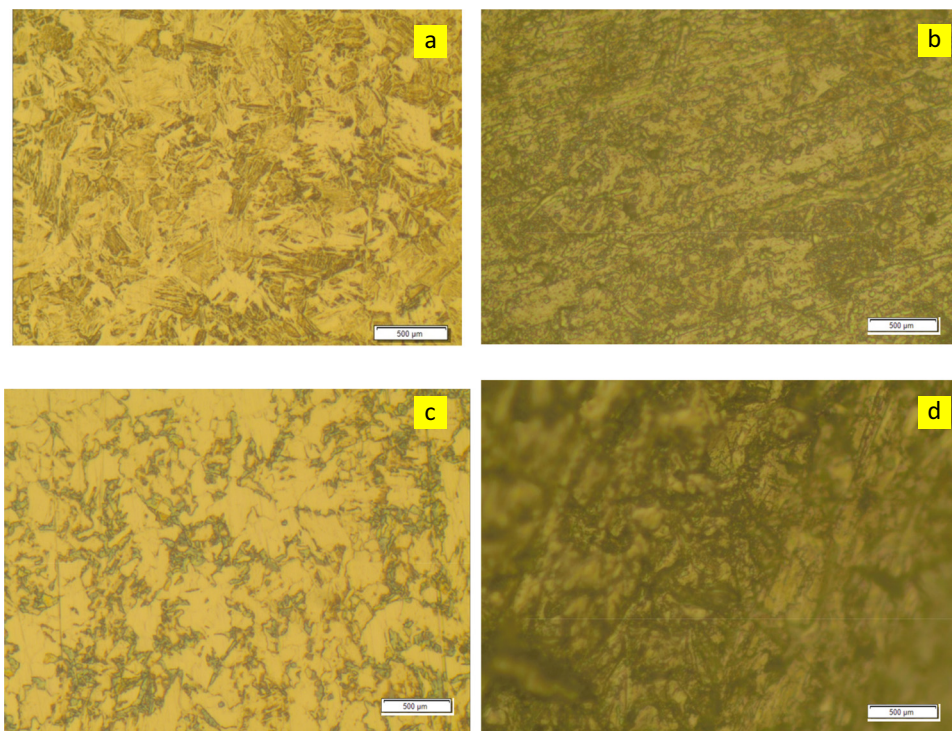


Figure 3: Investigate of the 316 stainless steel microstructure (a) in its as-received state; (b) 20% cold working quenching in a hostile environment in oil/crude oil; (c) 10% cold working quenching in a harsh environment water/sea water; (d) 20% cold functioning without heat treatment in a hostile environment seawater.

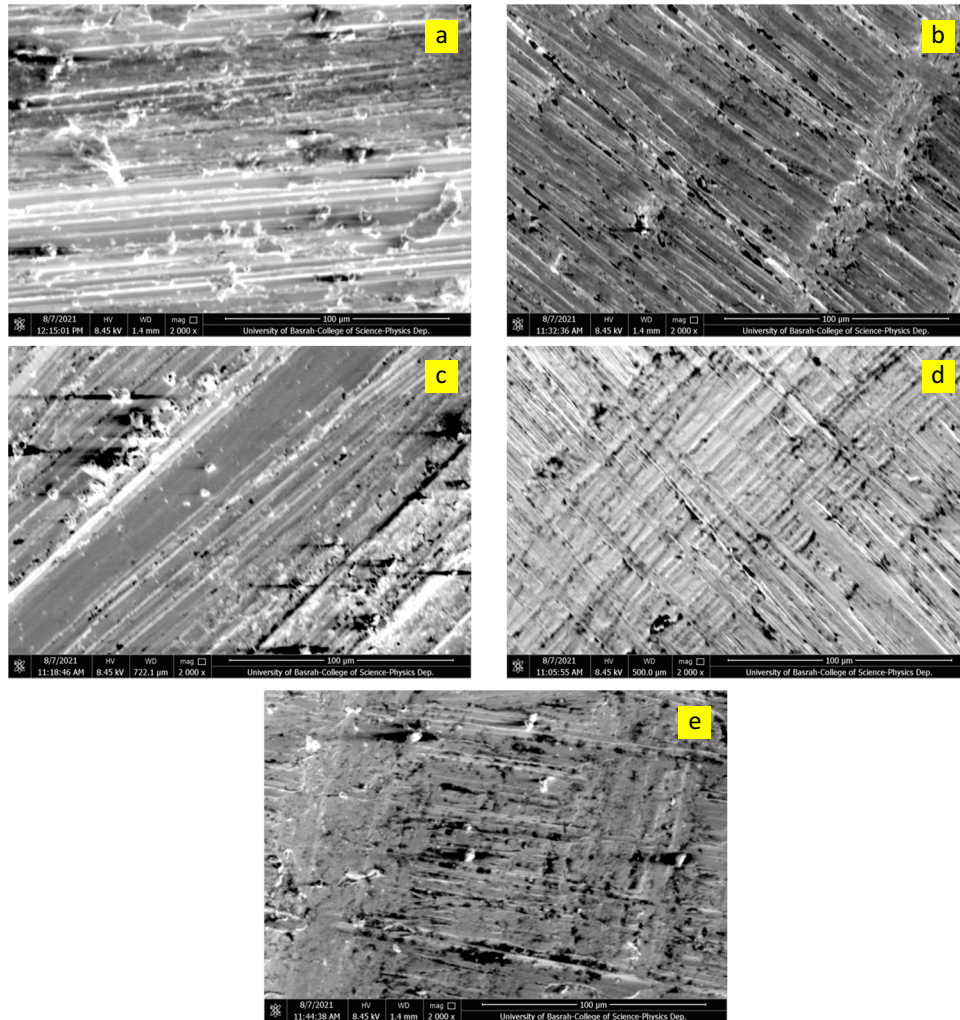


Figure 4: SEM pictures of AISI 316 stainless steel (a) as received, (b) 10% cold work, (c) 20% cold work, (d) 30% cold work, and (e) annealing, 10% cold working, crude oil.

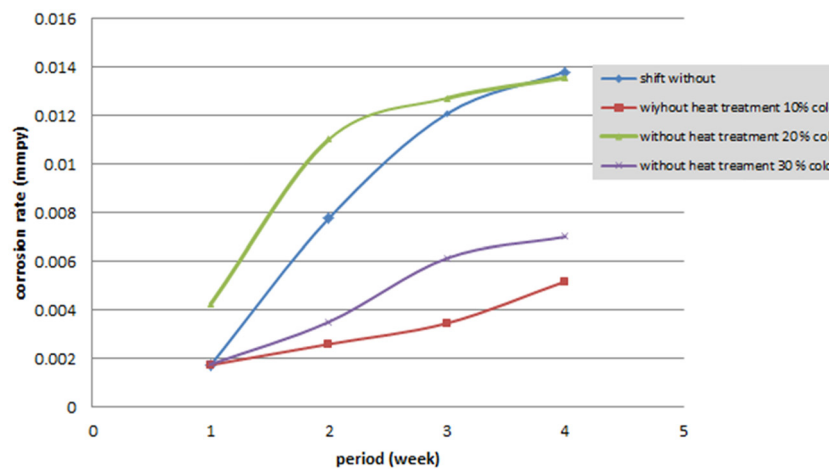


Figure 5: Corrosion rate for different cold working without heat treatment.

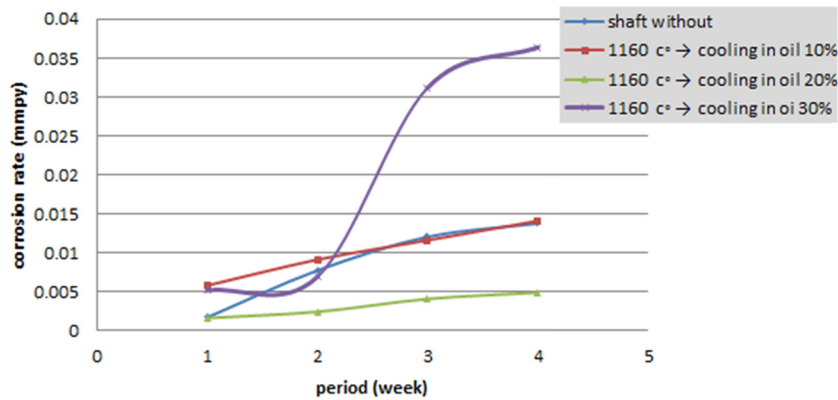


Figure 6: Corrosion rate for different cold working quenching in oil.

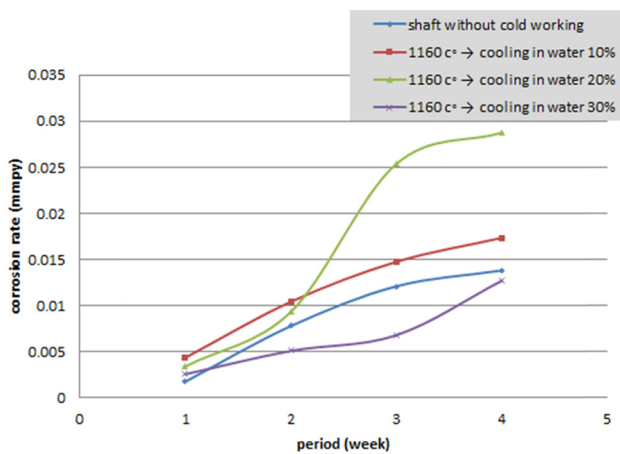


Figure 7: Corrosion rate for different cold working quenching in water.

Table 17: S/N ratio response table (larger is better)

Level	CM	HT	CW
1	-4.966	-4.237	-5.522
2	-6.055	-6.365	-5.861
3		-6.354	-5.776
4			-4.890
Delta	1.090	2.128	0.971
Rank	2	1	3

3.4 CRs

It was previously explained how the sample surfaces experienced a mass difference due to the hostile environment. Time affects how much each specimen's mass changes during a

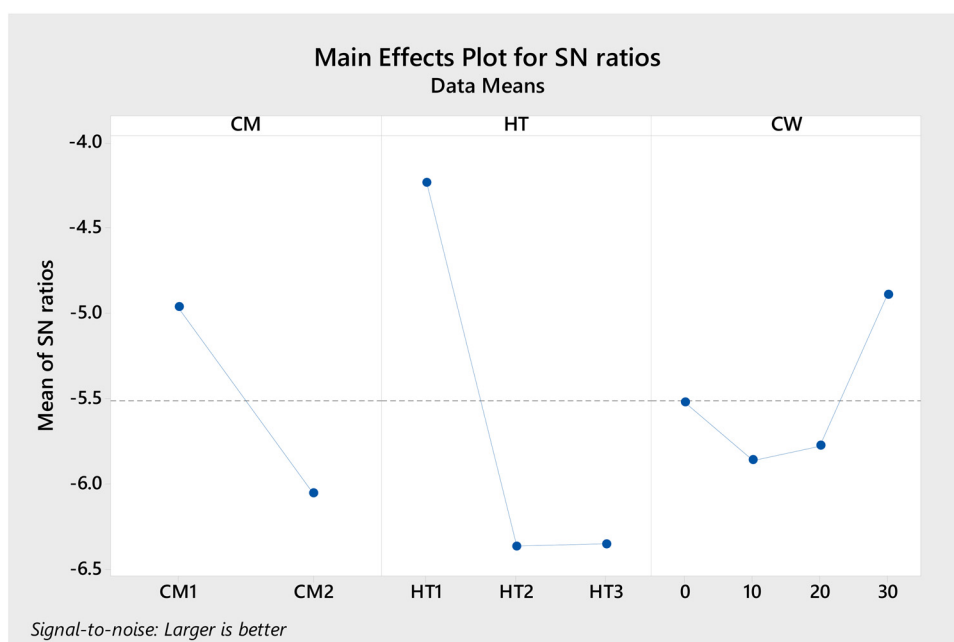


Figure 8: S/N ratio for GRG main influence plot.

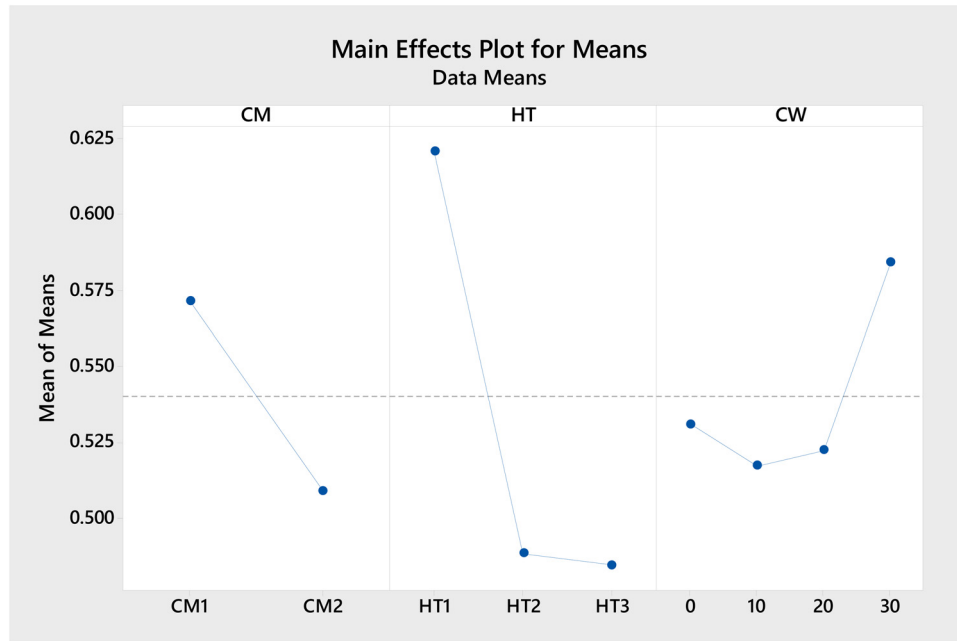


Figure 9: Mean of means of GRG main effect plot.

Table 18: Response table for means

Level	CM	HT	CW
1	0.5715	0.6210	0.5310
2	0.5089	0.4882	0.5172
3		0.4845	0.5223
4			0.5842
Delta	0.0626	0.1365	0.0670
Rank	3	1	2

corrosion test. Calculations of weight loss offer an accurate assessment of CRs. Using Eq. (1), the weights before and after exposure to the corrosive liquid were computed.

The CR for different cold working percentage with and without HT for oil and water as aggressive environments are shown in Figures 5–7. According's to Figure 5, where it is clear that the received sample experienced the greatest weight loss, this graph investigates the impact of cold working alone, without consideration of HT conditions.

3.5 GRG analysis using Taguchi

The main effects analysis is utilised to examine the influence and impacts of input parameters on the GRG, as shown in Figure 8. It is clear from Figure 8 that as CM changed from sea water to crude oil, the S/N ratio decreases [33]. Also the S/N ratio decreases when the HT is applied. But in the case of cold work, the S/N ratio also decreases and then increases at 30%. Figure 8 shows how to estimate CM at level 1, HT at level 1, and cold work at level 4, which means CM1-HT1-CW4 will concurrently give the optimal output characteristics (CR and surface hardness).

3.5.1 Signal-to-noise ratio response table

Based on the rank value shown in Table 17, the response table shows that the control factors affecting the response variable (GRG) follow the prescribed sequence in descending order: HT > CM > CW.

Table 19: Variance analysis

Source	DF	Seq SS	Contribution (%)	Adj SS	Adj MS	F-Value	P-Value
CM	1	0.01959	8.64	0.01959	0.019589	3.11	0.101
HT	2	0.08702	38.39	0.10840	0.054201	8.61	0.004
CW	3	0.03825	16.87	0.03825	0.012751	2.03	0.160
Error	13	0.08184	36.10	0.08184	0.006295		
Total	19	0.22670	100.00				

3.5.2 Analysis of mean

The optimal amount for the process parameters was calculated using the analysis of means (ANOM). The collection of input parameters is presented in Figure 9's ANOM graph for response variable optimisation (GRG). We must go with the higher values of input parameters under the larger, better criteria used for optimisation of GRG since we are improving the process parameters under multi-objective optimisation such that sea water may be used as the corrosive medium, without HT, and with 30% cold work, which is the ideal combination of input parameters.

The response table indicates that the control variables that affect the response variables follow a decreasing order HT > CW > CM based on the rank value presented in Table 18.

3.6 Variance analysis for GRG

The *P* value for the HT parameters is less than 0.05, which is considered significant (lower probabilities give greater proof against the null hypothesis), and its percentage of contribution is also high, being 38.39%. This indicates that HT is the most important variable, followed by CW and CM, which have 16.87 and 8.64% influence, respectively, in the GRG ANOVA table. The *F*-value, a test statistic used to establish if a term is related to a response, also demonstrates that the HT is the aspect that has the greatest impact on the GRG response (Table 19).

4 Conclusions

In this work, two techniques were used to strengthen AISI 316 stainless steel. In the first instance, the specimens were immersed in two hostile environments (crude oil and sea-water) after having gone through many cold working actions on the tensile machine. In the second instance, the specimens were sliced before being heated. These samples were afterward subjected to the same circumstances as the initial case. The most important conclusions are as follows:

1. Cold action has been accompanied by stress-related twinning and austenite phase deformation, which resulted in fast grain splitting and the creation of an austenite and ferrite ribbon-type microstructure.
2. The hardness values increase in direct proportion to the intensity of cold working. Since a decline in hardness values was noticeable as a result of the microstructure changes that took place throughout the annealing process,

it is also possible to see how the annealing HT affected hardness values.

3. The multi-objective optimisation technique we suggested reveals that HT is the element with the greatest influence, followed by CW and CM.
4. The order of the descending importance of the control variables impacting the response variable (GRG) is as stated: CW > HT > CM.
5. The combined set of the resultant parameters (CR and surface hardness) will be the best possible when CM are at level 1, HT is at level 1, and cold work is at level 4, which provided by CM1-HT1-CW4.

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