

Research Article

# Estimation of Solidus and Liquidus Temperature of TIG Mild Steel (S275) Using Response Surface Methodology

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## Abstract

The solidus and liquidus temperatures are critical parameters in materials science, particularly for alloys, defining the boundaries between solid and liquid phases during melting and solidification. The solidus is the highest temperature at which an alloy is excellent, and the liquidus is the lowest temperature at which an alloy is completely liquid. Understanding these temperatures is crucial for processes like casting, brazing, and materials' behavior under high temperatures. This research aims to estimate the solidus and liquidus temperatures of mild steel (S275) weld metal by applying Response Surface Methodology (RSM) to the Tungsten Inert Gas (TIG) welding process. The input parameters considered in the study include welding current, welding voltage, and gas flow rate, while the output responses are the solidus and liquidus temperatures. The methodology helps identify the optimal combination of these input parameters that yields the most accurate values for the solidus and liquidus temperatures of the mild steel weld metal. The suggested model for solidus temperature has an  $R^2$  of 0.9984, an Adjusted  $R^2$  of 0.9970, and a Predicted  $R^2$  of 0.9306. In contrast, Liquidus temperature has an  $R^2$  of 0.9997, an Adjusted  $R^2$  of 0.9994, and a Predicted  $R^2$  of 0.9994, showing a significant model and indicating a desirability value of 91.5%.

## Keywords

Solidus Temperature, Liquidus Temperature, Current, Voltage, Desirability, Mild Steel

## 1. Introduction

The liquidus temperature denotes the upper threshold at which an alloy remains entirely in the molten state. As the temperature decreases below this point, solidification initiates but does not complete until the material reaches the solidus temperature. This parameter is critical in the solidification behavior of steel, as it directly impacts microstructural evolution and plays a significant role in determining the quality of the solidified material. In the steel making process, tapping temperature is confirmed based on the liquidus temperature. An appropriate liquidus temperature can ensure the running of the pouring process and significantly improve the quality of

the billet [1]. The solidus temperature specifies the temperature below a material is excellent and the minimum temperature at which a melt can coexist with crystals in thermodynamic equilibrium. Solidus and Liquidus temperatures are essential parameters in processes such as welding and heat treatment. The temperature ranges at which the liquid weld metal begins to solidify, and the base metal or filler material achieves its melting point by changing from a solid to a liquid state are crucial metrics in welding [2]. The quest for optimality and stability of the process is a significant concern to the industry's professionals.

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An interesting relation between the melting temperature and the alloy composition was discovered in Sn-based alloys by evaluating a series of experimental data on the liquidus temperatures (LTs) for 134 multicomponent Sn alloys. In these Sn alloys, the degree of liquidus temperature drop with alloying was not affected by the kind of individual elements but by their total atomic fraction alone. The equation could express the compositional dependence on the LT, LT (K)  $499.791.799X$ , where X was the total mole percentage of alloying elements. It was demonstrated that this equation would make it possible to develop Pb-free solder alloys more efficiently [3].

The liquidus temperature and corresponding temperature drop coefficients of medium manganese steel were thoroughly examined using FactSage software and differential scanning calorimetry (DSC) techniques. Findings revealed that the temperature drop coefficients for elements such as carbon (C), manganese (Mn), chromium (Cr), silicon (Si), and aluminum (Al) exhibited complex behavior, whereas those for molybdenum (Mo), vanadium (V), and niobium (Nb) remained constant. An empirical formula was developed to estimate the liquidus temperature of medium manganese steel based on these coefficients. The formula predicted a liquidus temperature of 1422.7 °C, closely matching the 1422.9 °C value determined through DSC analysis. Compared to other calculation methods, this new formula demonstrated superior precision, highlighting its reliability in estimating the liquidus temperature of medium manganese steel [4].

A research team conducted a study on determining the solidus and liquidus temperatures of the 100CrMo7 steel grade using two advanced thermal analysis techniques. They employed large sample experiments (22 g) with the NETZSCH JUPITER instrument for direct thermal analysis and examined much smaller samples (up to 210 mg) using differential thermal analysis with the Setaram SETSYS 18TM device. The study demonstrated the reliability of both high-temperature testing methods. The experimental results were then compared to industry-standard values and theoretical predictions generated by IDS and Thermo-Calc software. The findings revealed significant differences, with discrepancies reaching several tens of degrees for the liquidus temperature and over 100 °C for the solidus temperature [5].

An analytical micro-segregation model is frequently utilized to assess the impact of solid-state diffusion, offering predictions that lie between those of the Scheil approximation and the Lever rule. This model has been widely applied in forecasting micro-segregation patterns. In multicomponent steels, incorporating a liquidus temperature correlation into the model allows for evaluating the influence of individual alloying elements and examining the temperature–solid fraction relationship. However, prior investigations have identified inconsistencies in the predicted solidus temperature within this framework. Consequently, a fixed solidus temperature value is required to improve the accuracy of the model's calculations [6].

Response Surface Methodology (RSM) is used in TIG welding to optimize and predict parameters like solidus and liquidus temperatures by modeling the relationship between input parameters (welding current, voltage, gas flow rate) and output variables (temperatures). This approach helps determine the optimal combination of welding parameters to achieve desired weld properties [7].

## 2. Material and Method

### 2.1. Design of Experiment

The key input parameters considered in this study were welding current, welding voltage and gas flow rate, while the response or measured parameter was ambient temperature; the range and level [8] of the experimental variables were obtained and are presented in Table 1.

**Table 1.** Range and Levels of independent variables.

Independent Variables	Range and Levels of Input Variables	
	Lower Range (-1)	Upper Range (+1)
Welding Current (Amp) $X_1$	150	180
Welding Voltage (Volt) $X_2$	16	19
Gas flow rate (lit/min) $X_3$	13	16

Using the range and levels of the independent variables presented in Table 1, the statistical design of the experiment (DoE) using the central composite design (CCD) method was done. Experimental design was done with the aid of design expert version 13. The total number of experimental runs generated using the CCD, as defined [9]

$$N = 2k + nc + 2k \quad (1)$$

where,

N = the number of experimental runs based on the CCD design

2k = the number of factorial points

nc = the number of centre points

2k = the number of axial points

k = the number of input variables

Using Equation 1, twenty (20) experimental runs were generated based on the central composite design method and presented in Table 2.

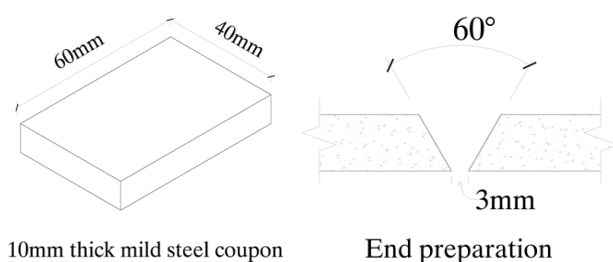
Where Std stands for Standard deviation

**Table 2.** Design of Experiment (DoE) Matrix.

Std	Run	Current (A)	Voltage (V)	Gas flow rate (lit/min)
15	1	165.000	17.500	14.500
16	2	180.000	16.000	16.000
17	3	150.000	19.000	16.000
18	4	165.000	17.500	14.500
19	5	165.000	17.500	14.500
20	6	165.000	20.023	14.500
9	7	180.000	19.000	16.000
10	8	165.000	17.500	14.500
11	9	150.000	19.000	13.000
12	10	165.000	17.500	14.500
13	11	180.000	16.000	13.000
14	12	139.773	17.500	14.500
1	13	180.000	19.000	13.000
2	14	165.000	14.977	14.500
3	15	190.227	17.500	14.500
4	16	165.000	17.500	11.977
5	17	165.000	17.500	17.023
6	18	150.000	16.000	13.000
7	19	150.000	16.000	16.000
8	20	165.000	17.500	14.500

## 2.2. Sample Preparation

According to the experimental matrix presented in Table 2, twenty sets of experiments were performed using five specimens for each run. The plate samples were 60mm long and had a wall thickness of 10mm [10]. They were cut longitudinally with a single-V joint preparation, as shown in Figure 1.

**Figure 1.** Weld specimen design.

Preparing the mild steel coupons for welding required tools,

including power hacksaw cutting and grinding machines, a mechanical vice, emery (sand) paper, and a sander.

## 3. Results and Discussion

This study used the response surface methodology (RSM) as an expert method to analyze the data collected from the experiments performed.

The experimental results utilized in the Response Surface Methodology are presented in Table 3.

**Table 3.** Experimental results for Solidus and Liquidus temperature.

S/N	Input parameters			Responses	
	I, Amp	E, Volts	GFR, L/Min	Solidus Temp °C	Liquidus Temp °C
1	165.000	17.500	14.500	1076.000	1453.000
2	180.000	16.000	16.000	1178.000	1569.000
3	150.000	19.000	16.000	1091.000	1468.000
4	165.000	17.500	14.500	1084.000	1446.000
5	165.000	17.500	14.500	1087.000	1444.000
6	165.000	20.023	14.500	1221.000	1615.000
7	180.000	19.000	16.000	1380.000	1722.000
8	165.000	17.500	14.500	1080.000	1445.000
9	150.000	19.000	13.000	1043.000	1435.000
10	165.000	17.500	14.500	1078.000	1447.000
11	180.000	16.000	13.000	1033.000	1369.000
12	139.773	17.500	14.500	1018.000	1320.000
13	180.000	19.000	13.000	1293.000	1693.000
14	165.000	14.978	14.500	1047.000	1420.000
15	190.227	17.500	14.500	1257.000	1542.000
16	165.000	17.500	11.978	1086.000	1501.000
17	165.000	17.500	17.023	1222.000	1698.000
18	150.000	16.000	13.000	1037.000	1356.000
19	150.000	16.000	16.000	1121.000	1559.000
20	165.000	17.500	14.500	1078.000	1442.000

To validate the suitability of the quadratic model [11] for analyzing the experimental data, the sequential model sum of squares was calculated for solidus temperature and Liquidus Temperature responses, as presented in Tables 4 and 5. The Quadratic vs. 2FI source was selected as the highest-order polynomial source where the additional terms are significant and the model is not aliased.

**Table 4.** Sequential model sum of square for Solidus Temperature.

Source	Sum of Squares	Df	Mean Square	F-value	p-value	
Mean vs Total	2.534E+07	1	2.534E+07			
Linear vs Mean	1.372E+05	3	45717.66	14.61	< 0.0001	
2FI vs Linear	31879.00	3	10626.33	7.59	0.0035	
Quadratic vs 2FI	17898.32	3	5966.11	199.73	< 0.0001	Suggested
Cubic vs Quadratic	204.53	4	51.13	3.26	0.0957	Aliased
Residual	94.18	6	15.70			
Total	2.552E+07	20	1.276E+06			

**Table 5.** Sequential model sum of square for Liquidus Temperature.

Source	Sum of Squares	Df	Mean Square	F-value	p-value	
Mean vs Total	4.483E+07	1	4.483E+07			
Linear vs Mean	1.529E+05	3	50963.37	8.55	0.0013	
2FI vs Linear	44431.37	3	14810.46	3.78	0.0376	
Quadratic vs 2FI	50817.35	3	16939.12	2161.72	< 0.0001	Suggested
Cubic vs Quadratic	3.38	4	0.8459	0.0677	0.9894	Aliased
Residual	74.98	6	12.50			
Total	4.508E+07	20	2.254E+06			

Tables 6 and 7 presents the model statistics computed for solidus temperature and liquidus Temperature responses based on the model sources. The suggested model for solidus temperature has an  $R^2$  of 0.9984, an Adjusted  $R^2$  of 0.9970, and a Predicted  $R^2$  of 0.9306. In contrast, the Liquidus temperature has  $R^2$  of 0.9997, an Adjusted  $R^2$  of 0.9994, and a Predicted  $R^2$  of 0.9994, showing a significant model.

**Table 6.** Model summary statistics for Solidus Temperature.

Source	Std. Dev.	$R^2$	Adjusted $R^2$	Predicted $R^2$	PRESS	
Linear	55.94	0.7325	0.6824	0.5494	84365.68	
2FI	37.41	0.9028	0.8580	0.7453	47680.18	
Quadratic	5.47	0.9984	0.9970	0.9903	1825.23	Suggested
Cubic	3.96	0.9995	0.9984	0.9915	1598.28	Aliased

**Table 7.** Model summary statistics for Liquidus Temperature.

Source	Std. Dev.	$R^2$	Adjusted $R^2$	Predicted $R^2$	PRESS	
Linear	77.19	0.6160	0.5439	0.3362	1.648E+05	
2FI	62.57	0.7950	0.7003	0.5579	1.097E+05	

Source	Std. Dev.	R <sup>2</sup>	Adjusted R <sup>2</sup>	Predicted R <sup>2</sup>	PRESS	
Quadratic	2.80	0.9997	0.9994	0.9994	159.08	Suggested
Cubic	3.53	0.9997	0.9990	0.9959	1015.08	Aliased

Based on the coded variables in equation 2, the optimal equation shows the individual effects and combined interactions of the selected input variables (current, voltage, and gas flow rate) against the measured solidus temperature.

$$Y_s = 1080.45 + 72.78A + 53.50B + 43.40C + 60.75AB + 12.50AC - 11.75BC + +20.46A^2 + 19.22B^2 + 26.29C^2 \quad (2)$$

Where,  $Y_s$  = Solidus temperature

Based on the coded variables in equation 3, the optimal equation shows the individual effects and combined interactions of the selected input variables (current, voltage, and gas flow rate) against the measured liquidus temperature.

$$Y_L = +1446.13 + 66.51A + 58.06B + 58.31C + 61.12AB - 0.8750AC - 42.63BC - 5.12A^2 + 25.46B^2 + 54.45C^2 \quad (3)$$

Where,  $Y_L$  = Liquidus temperature

Table 8 presents the diagnostics case statistics, which show the observed values of solidus temperature against their predicted values.

**Table 8.** Diagnostic case statistics for Solidus Temperature.

Run Order	Actual Value	Predicted Value	Residual	Leverage	Internally Studentized Residuals	Externally Studentized Residuals	Cook's Distance	Influence on Fitted Value DFFITS	Standard Order
1	1076.000	1080.450	-4.450	0.166	-0.892	-0.882	0.016	-0.394	16
2	1178.000	1172.600	5.400	0.670	1.718	1.941	0.598	2.764 <sup>(1)</sup>	6
3	1091.000	1085.540	5.460	0.670	1.738	1.973	0.612	2.810 <sup>(1)</sup>	7
4	1084.000	1080.450	3.550	0.166	0.711	0.692	0.010	0.309	17
5	1087.000	1080.450	6.550	0.166	1.312	1.368	0.034	0.611	19
6	1221.000	1224.790	-3.790	0.607	-1.107	-1.121	0.189	-1.394	12
7	1380.000	1377.600	2.400	0.670	0.763	0.746	0.118	1.062	8
8	1080.000	1080.450	-0.453	0.166	-0.091	-0.086	0.000	-0.039	20
9	1043.000	1047.240	-4.240	0.670	-1.350	-1.416	0.370	-2.017	3
10	1078.000	1080.450	-2.450	0.166	-0.492	-0.472	0.005	-0.211	18
11	1033.000	1037.300	-4.300	0.670	-1.370	-1.442	0.381	-2.053	2
12	1018.000	1015.920	2.080	0.607	0.609	0.588	0.057	0.732	9
13	1293.000	1289.300	3.700	0.670	1.178	1.204	0.281	1.715	4
14	1047.000	1044.840	2.160	0.607	0.630	0.610	0.061	0.759	11
15	1257.000	1260.720	-3.720	0.607	-1.085	-1.096	0.182	-1.363	10
16	1086.000	1081.820	4.180	0.607	1.219	1.253	0.230	1.559	13
17	1222.000	1227.810	-5.810	0.607	-1.696	-1.906	0.445	-2.370 <sup>(1)</sup>	14
18	1037.000	1038.240	-1.240	0.670	-0.395	-0.378	0.032	-0.538	1
19	1121.000	1123.540	-2.540	0.670	-0.810	-0.795	0.133	-1.132	5
20	1078.000	1080.450	-2.450	0.166	-0.492	-0.472	0.005	-0.211	15

The diagnostics case statistics, which show the observed values of liquidus temperature against their predicted values are presented in Table 9.

**Table 9.** Diagnostic case statistics for Liquidus Temperature.

Run Order	Actual Value	Predicted Value	Residual	Leverage	Internally Studentized Residuals	Externally Studentized Residuals	Cook's Distance	Influence on Fitted Value DFFITS	Standard Order
1	1453.000	1446.13	6.87	0.166	2.688	4.841 <sup>(1)</sup>	0.144	2.162 <sup>(2)</sup>	16
2	1569.000	1568.300	0.695	0.670	0.432	0.414	0.038	0.590	6
3	1468.000	1467.900	0.097	0.670	0.060	0.057	0.001	0.081	7
4	1446.000	1446.130	-0.130	0.166	-0.051	-0.048	0.000	-0.022	17
5	1444.000	1446.130	-2.130	0.166	-0.833	-0.820	0.014	-0.366	19
6	1615.000	1615.790	-0.792	0.607	-0.451	-0.433	0.032	-0.538	12
7	1722.000	1721.430	0.571	0.670	0.355	0.339	0.026	0.482	8
8	1445.000	1446.130	-1.130	0.166	-0.442	-0.424	0.004	-0.189	20
9	1435.000	1434.790	0.214	0.670	0.133	0.126	0.004	0.180	3
10	1447.000	1446.130	0.870	0.166	0.340	0.325	0.002	0.145	18
11	1369.000	1368.190	0.813	0.670	0.505	0.486	0.052	0.692	2
12	1320.000	1319.780	0.218	0.607	0.124	0.118	0.002	0.147	9
13	1693.000	1691.810	1.190	0.670	0.739	0.721	0.111	1.026	4
14	1420.000	1420.490	-0.494	0.607	-0.282	-0.268	0.012	-0.334	11
15	1542.000	1543.500	-1.500	0.607	-0.857	-0.845	0.114	-1.051	10
16	1501.000	1502.080	-1.080	0.607	-0.616	-0.595	0.059	-0.740	13
17	1698.000	1698.210	-0.206	0.607	-0.118	-0.112	0.002	-0.139	14
18	1356.000	1355.660	0.339	0.670	0.211	0.200	0.009	0.285	1
19	1559.000	1559.280	-0.279	0.670	-0.173	-0.165	0.006	-0.234	5
20	1442.000	1446.130	-4.130	0.166	-1.616	-1.783	0.052	-0.797	15

mizing and predicting the target responses.

## 4. Conclusion

The study has developed and applied predictive expert models to optimize and predict TIG mild steel (S275) weld solid and liquidus temperature using the response surface methodology. Consequently, a central composite design matrix having twenty (20) experimental runs (refer to Table 1) was developed second-order polynomial equations were developed for each of the responses that can be used by welding practitioners to make predictions about the response forgiven levels of each factor response (refer to equations 2 and 3) the results of numerical optimization indicated a desirable value of 91.5%, showing that the RSM model possesses satisfactory statistical indices, making it a highly effective tool for opti-

## Abbreviations

DF	Degree of Freedom
CCD	Central Composite Design
DSC	Differential Scanning Calorimetry
DoE	Design of Experiment
EXP	Experiment
GFR	Gas Flowrate
RSM	Response Surface Methodology
TIG	Tungsten Inert Gas
STD	Standard Deviation

## Author Contributions

Augustine Oghenekevwe Igbinate is the sole author. The author read and approved the final manuscript.

## Conflicts of Interest

The author declares no conflicts of interest.

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