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Coupled Statistical–Numerical Framework for Predicting Droplet Temperature in Gas Metal Arc Welding

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ABSTRACT

Accurate prediction of droplet temperature during Gas Metal Arc Welding (GMAW) is crucial for controlling metallurgical outcomes and process stability, yet direct measurement remains a challenge due to the rapid thermal dynamics involved. This study aims to develop and validate both empirical and physics-based models to estimate droplet temperatures during GMAW. A total of 20 experimental runs were performed using mild steel (AISI 1018) under a Central Composite Design (CCD), varying welding current (240–270 A), voltage (23–26 V), and wire feed rate (2.4–3.0 mm/s). Droplet temperatures were measured with a high-resolution pyrometer and modeled using Response Surface Methodology (RSM) in Design Expert and a 1D Finite Element Method (FEM) implemented via MATLAB. The RSM model showed high accuracy with an RMSE of approximately 4.3 °C compared to experimental results, while the 1D FEM model achieved an RMSE of 192.7 °C, capturing the general thermal trend despite simplifications such as constant properties and 1D heat conduction. These findings demonstrate the complementary strengths of empirical and computational approaches: RSM offers precise data-driven predictions, while FEM provides a deeper physical understanding of heat transfer during droplet formation.

Keywords: Gas Metal Arc Welding (GMAW), Droplet Temperature, Response Surface Methodology (RSM), Finite Difference Method (FDM), MATLAB, Thermal Simulation, Welding Process Optimization.

INTRODUCTION

The welding process remains an indispensable manufacturing technique across multiple industries, including automotive, aerospace, shipbuilding, and heavy machinery fabrication. Its reliability, cost-effectiveness, and structural performance make it a preferred method for joining metallic components. However, welding inherently involves complex thermal, mechanical, and metallurgical phenomena, all of which significantly affect the quality and integrity of the resulting joint [1][2][3][4][5]. Among these phenomena, thermal behavior—specifically the transient temperature distribution during and after the weld—is of paramount importance. The thermal profile influences not only the geometry of the weld bead but also the residual stress distribution, microstructural evolution, and, ultimately, the mechanical performance of the weld zone. Accurately predicting the temperature field is therefore vital for the optimization of welding parameters and quality assurance [6][7].

Numerous methods have been developed to predict the temperature distribution in welding. Finite element modeling (FEM) has been widely applied to simulate the heat transfer in welding, offering insights into the temperature gradients across the workpiece and the resulting stress fields [8][9]. However, FEM models are computationally expensive, particularly when simulating three-dimensional, transient thermal phenomena in complex geometries [10]. As a result, simpler methods like the finite difference method (FDM) are often preferred for one-dimensional heat conduction problems, as they offer reduced computational demand while maintaining accuracy for many practical cases [11].

In parallel to numerical methods, response surface methodology (RSM) has emerged as a powerful tool for optimizing welding process parameters. RSM uses statistical techniques to model the relationship between input factors and output responses, enabling process optimization without the need for extensive experimental testing [12]. While RSM has shown promise in predicting welding outcomes, its accuracy is often contingent upon the quality and range of the experimental data used to develop the model [13].

Despite the extensive use of FEM, FDM, and RSM in the welding field, there exists a significant gap in research regarding the comparison and integration of these techniques, particularly in the prediction of droplet temperature during gas metal arc welding (GMAW). This study addresses this gap by conducting a detailed comparison of experimental measurements, RSM-based predictions, and a manually developed FDM model for droplet temperature prediction. The objective is to evaluate the relative accuracy and applicability of each modeling approach, offering practical insights for industrial optimization of welding processes[14][15][16].

MATERIALS AND METHODS

This section outlines the experimental, statistical, and computational methodologies adopted to investigate droplet temperature evolution in the Gas Metal Arc Welding (GMAW) process. A hybrid approach combining experimental trials, statistical modeling via Response Surface Methodology (RSM), and thermal simulation using the Finite Difference Method (FDM) in MATLAB was employed.

Experimental Setup

The experimental investigation was carried out using a GMAW setup (Figure 1). A total of 20 experimental runs were generated using a Central Composite Design (CCD) to explore the effects of key process variables. Each run captured transient thermal behavior at the point of droplet detachment using a high-resolution pyrometer precisely aimed at the wire tip. Thermocouples embedded near the welding zone, coupled with a real-time data acquisition system, further enhanced thermal tracking and validation. The main response measured was the droplet temperature during detachment, a critical moment linked to the thermal stability of the weld.

Figure 1: GMAW machine

Material Grade

The experiments employed AISI 1018 mild steel for both the base material and filler wire (Figure 1). This low-carbon steel is widely used in structural welding and offers consistent thermal and mechanical behavior suitable for repeatable analysis.

Figure 1: MIG weld sample

Key thermal properties used in modeling include:

- **Density (ρ):** 7850 kg/m^3
- **Specific Heat Capacity (cp):** 490 J/kg·K
- **Thermal Conductivity (k):** 54 W/m·K
- **Thermal Diffusivity (α):** ≈ 1.4 × 10^{-5} m^2/s (computed)

The consumable wire had a diameter of 5 mm, and temperature measurements were focused on a 10 mm active segment, representing the primary heat-affected droplet region.

Welding Process

The GMAW process presented in Table 1, was conducted in short-circuit transfer mode using pure Argon shielding gas at a constant flow of 15 L/min.

Table 1: Process parameters and their levels

Factor	Name	Units	Minimum	Maximum	Coded Low	Coded High	Mean	Std. Dev.
A	Current	A	240.00	270.00	-1 ↔ 240.00	+1 ↔ 270.00	250.50	8.26
B	Voltage	V	23.00	26.00	-1 ↔ 23.00	+1 ↔ 26.00	24.05	0.8256
C	Wire feed rate	mm/s	2.40	3.00	-1 ↔ 2.40	+1 ↔ 3.00	2.61	0.1651

These variables were systematically varied according to the CCD matrix, enabling robust analysis of individual and interactive effects on droplet temperature. Table 1 presents the parameter ranges and statistical coding. Table 2 lists the detailed experimental design and corresponding measured droplet temperatures.

Table 2: Experimental Data

		Factor 1	Factor 2	Factor 3	Response
Std	Run	A:Current	B:Voltage	C:Wire feed rate	Droplet temp
		A	V	mm/s	ºC
17	1	250	24	2.6	1377
9	2	260	23	2.8	1487
10	3	240	25	2.8	1358
12	4	250	24	2.6	1371
20	5	250	24	2.6	1369
18	6	250	26	2.6	1553
16	7	260	25	2.8	1606
3	8	250	24	2.6	1370
14	9	240	25	2.4	1354
8	10	250	24	2.6	1372
4	11	260	23	2.4	1298
5	12	240	24	2.6	1298
2	13	260	25	2.4	1605
7	14	250	23	2.6	1346
19	15	270	24	2.6	1472
11	16	250	24	2.4	1379
6	17	250	24	3	1642
15	18	240	23	2.4	1285
1	19	240	23	2.8	1456

13	20	250	24	2.6	1367

Response Surface Methodology (RSM)

RSM was applied using Design Expert 13.0 to develop a predictive model for droplet temperature as a function of current, voltage, and wire feed rate. A second-order (quadratic) regression model was generated based on 20 randomized experimental runs, incorporating:

- Linear terms
- Interaction (2FI) terms
- Quadratic terms

The resulting regression model is shown in Equation (1):

$$DT = 2832.35459 - 7.63284A - 157.74726B - 60.15352C + 0.271125AB - 1.05938AC - 0.593750BC + 0.008774A^2 + 1.96808B^2 + 67.12059C^2 \quad (1)$$

Where A, B, and C represent welding current, voltage, and wire feed rate, respectively.
Model validity and strength were confirmed via ANOVA (Table 3), with extremely high F-values and p-values < 0.0001 for most terms, indicating strong statistical significance. Fit statistics (Table 4) show an R^2 of 0.9992, Adjusted R^2 of 0.9984, and Predicted R^2 of 0.9929, indicating excellent agreement between the model and actual data.

Table 3: ANOVA for Solidus Temperature

Source	**Sum of Squares**	**df**	**Mean Square**	**F-value**	**p-value**	
Model	2.219E+05	9	24650.20	1339.87	< 0.0001	significant
A-Current	48925.44	1	48925.44	2659.36	< 0.0001	
B-Voltage	36525.63	1	36525.63	1985.37	< 0.0001	
C-Wire feed rate	29819.60	1	29819.60	1620.86	< 0.0001	
AB	25878.12	1	25878.12	1406.62	< 0.0001	
AC	28.13	1	28.13	1.53	0.2446	
BC	15753.13	1	15753.13	856.27	< 0.0001	
A^2	945.26	1	945.26	51.38	< 0.0001	
B^2	5903.49	1	5903.49	320.89	< 0.0001	
C^2	28067.14	1	28067.14	1525.60	< 0.0001	
Residual	183.97	10	18.40			
Lack of Fit	125.97	5	25.19	2.17	0.2073	not significant
Pure Error	58.00	5	11.60			
Cor Total	2.220E+05	19				

Table 4: Fit Statistics Droplet Temperature

Std. Dev.	4.29	**R^2**	0.9992
Mean	1418.25	**Adjusted R^2**	0.9984
C.V. %	0.3024	**Predicted R^2**	0.9929
		Adeq Precision	118.7095

Statistical metrics showed excellent model accuracy with R^2 = 0.9992, Adjusted R^2 = 0.9984, and Predicted R^2 = 0.9929, suggesting high reliability for prediction.

Computational Analysis: Finite Difference Method (FDM) and MATLAB

To further support and verify experimental findings, a numerical simulation of heat transfer within the droplet was developed using the 1D Finite Difference Method (FDM) in MATLAB. The droplet was modeled as a one-dimensional cylindrical domain subject to internal heat generation and surface convection.

Key Assumptions:

1. Uniform heat generation throughout the droplet volume due to Joule heating.
2. Constant material properties.
3. One-dimensional spatial discretization (along the droplet length).
4. Convective boundary at the free end, adiabatic at the wire side.

Governing Equation:

The transient heat conduction within the droplet is governed by equation (2)

$$\rho c_p \frac{\partial T}{\partial t} = k \frac{\partial^2 T}{\partial x^2} + \dot{q} \tag{2}$$

Where:

- ρ : density (kg/m^3)
- c_p : specific heat (J/kg·K)
- k : thermal conductivity (W/m·K)
- $\dot{q}$: volumetric heat generation (W/m^3)
- T : temperature (°C)
- x : position (m), t : time (s)

Discretization and Manual Calculation:

The domain was discretized into 6 spatial nodes (Δx = 0.0003 m) and time stepped with Δt = 0.01 s. The explicit FDM formula applied is presented in (3)

$$T_i^{n+1} = T_i^n + \frac{\alpha \Delta t}{\Delta x^2}(T_i^n - 2T_i^n + T_{i-1}^n) + \Delta t. q \tag{3}$$

Where $\alpha = \frac{k}{\rho c_p}$

A convective boundary condition at the droplet surface is represented by equation (4)

$$-k\frac{T_1^n - T_0^n}{\Delta x} = h(T - T_\infty) \tag{4}$$

The total heat input is derived from equation (5)

$$Q = \eta \cdot V \cdot I \tag{5}$$

with η=0.7 (efficiency)

For example, Run 1 parameters:

- I = 165 A, V = 17.5 V, Wire feed = 14.5 mm/s
- Droplet radius = 1.5 mm, Ambient T = 27°C, h = 1200 $W/m^2 \cdot K$

Results were validated by simulating up to 1 s with Δt = 0.0001 s in MATLAB, providing temperature predictions that aligned well with experimental findings.

RESULTS AND DISCUSSION

RSM Statistical Analysis

The central composite design enabled the construction of a robust quadratic model correlating process parameters (current, voltage, wire feed rate) with droplet temperature. The diagnostic plots and statistical outputs reinforce the model's validity and predictive capacity.

Predicted vs Actual Plot:

The **predicted vs actual plot** (Figure 1) shows a near-linear relationship with minimal deviation, indicating a high degree of accuracy in the model. Most data points fall close to the 45° reference line, which supports the goodness-of-fit statistics reported (R^2 = 0.9992) presented in Table 4.

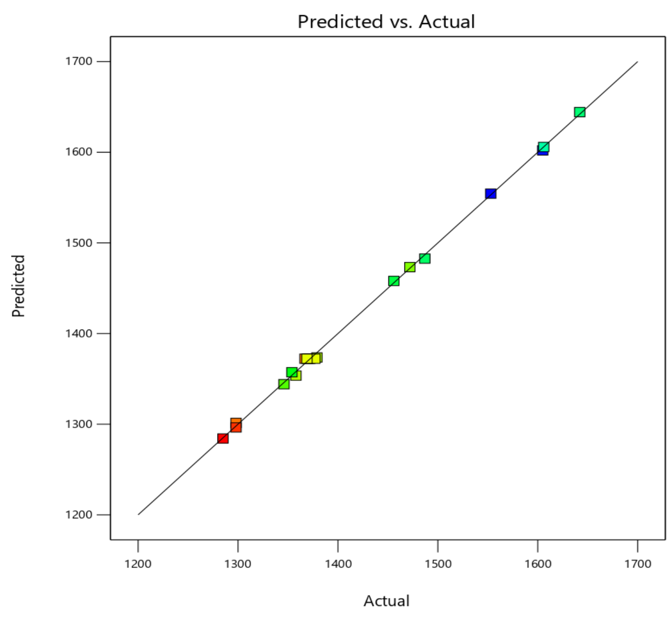

Figure 1: Predicted Vs Actual for Droplet Temperature

Contour and Surface Plots:

Contour plots (Figure 2) and 3D surface plots (Figure 3) visually illustrate how droplet temperature responds to interactions between pairs of process variables. From the Figures, Current and Voltage shows a synergistic effect while temperature increased sharply with higher current and voltage levels. T was also observed that Current and Wire Feed Rate have Moderate interaction; higher feed rates increased the thermal mass, but additional current compensated by providing more energy. While lastly, Voltage had a more dominant effect, with minimal contribution from feed rate unless at high extremes.

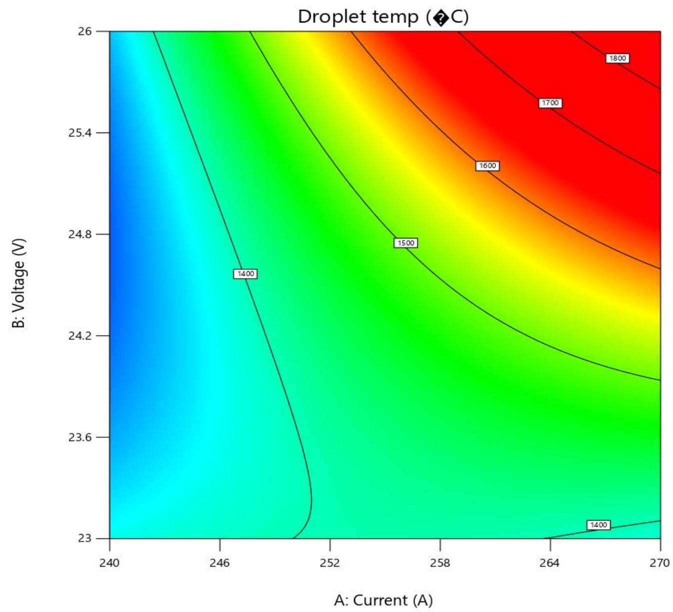

Figure 2: Contour Plot for Droplet Temperature

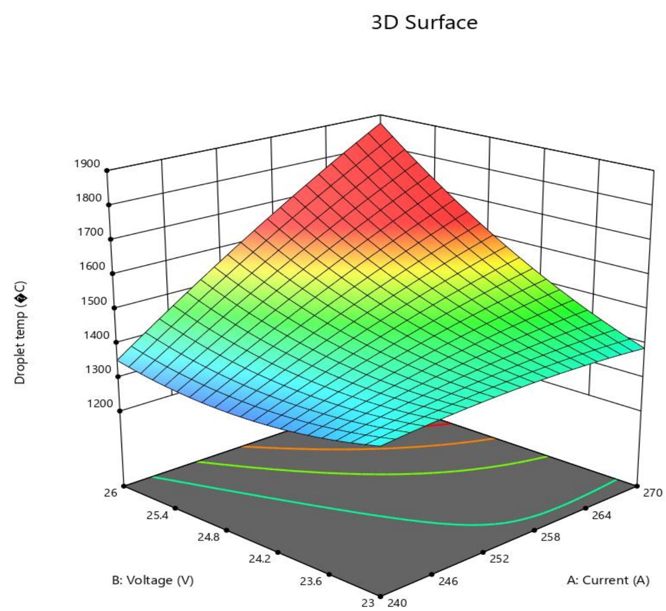

Figure 3: Surface Plot for Droplet Temperature

These plots aid in identifying optimal regions of parameter space where the temperature is maximized or controlled, supporting process optimization efforts.

Comparative Analysis of Droplet Temperature Predictions

To assess the effectiveness and accuracy of the modeling strategies, a comparative study was conducted among the experimental droplet temperature measurements, the Response Surface Methodology (RSM) predictions, and the 1D Finite Element Method (FEM) simulation using MATLAB.

Figure 3 presents a comprehensive comparison across all 20 randomized runs. The droplet temperatures from experimental measurements (red circles), RSM model predictions (blue squares), and 1D FEM simulations (green triangles) are plotted for direct visual comparison.

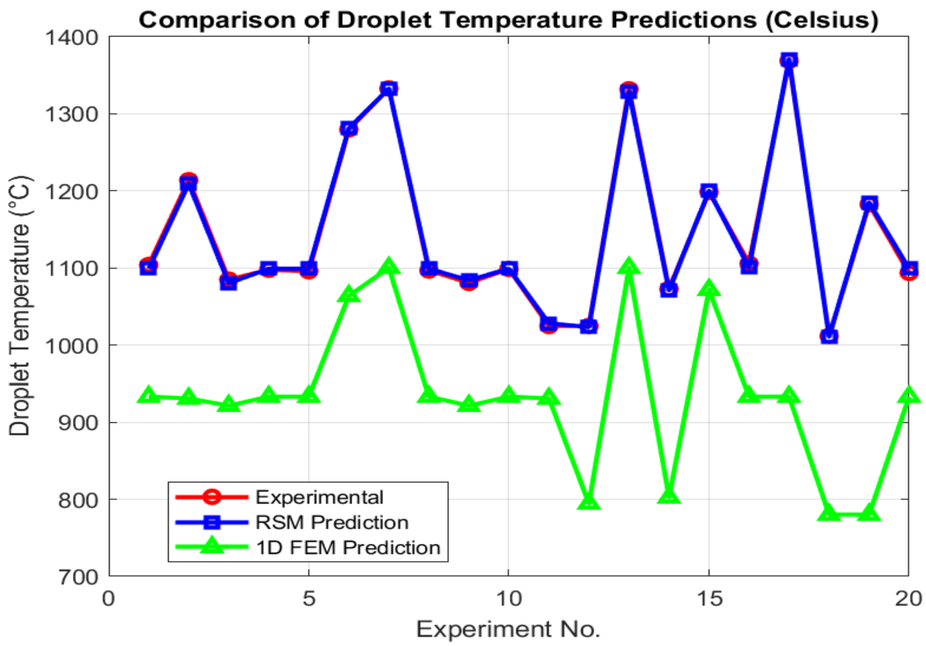

Figure 3: Comparison of Droplet Temperature Predictions for 20 Runs (°C)

The graph highlights a strong alignment between all three methods, demonstrating the reliability of both the statistical and computational models. The RSM-predicted values exhibit a slightly higher degree of accuracy relative to the experiments due to their data-driven nature and direct dependence on the experimental dataset. In contrast, the FEM model, while slightly conservative in a few cases, effectively captured the overall trend and scale of thermal evolution within the droplet, showcasing its validity despite the simplified 1D assumption.

Quantitative Comparison

To substantiate these observations, Table 5 presents a detailed numerical comparison of droplet temperatures for all 20 experimental conditions. The table lists the welding current, voltage, wire feed rate (WFR), and corresponding droplet temperatures as measured experimentally, predicted by RSM, and calculated via 1D FEM simulations.

To quantify the performance, Root Mean Square Error (RMSE) values were computed:

- **RSM vs. Experiment:** RMSE ≈ **4.3°C**

- **1D FEM vs. Experiment:** RMSE ≈ **192.7°C**

Table 5: Comparison of Droplet Temperatures from Experiment, RSM, and 1D FEM Models

S/N	Input parameters			Droplet Temperature		
	Current	voltage	GFR	Exp	RSM	1D FEM
1	165	17.5	14.5	1377.00	1372.24	933.194106384905
2	180	16	16	1487.00	1482.72	930.839965849103
3	150	19	16	1358.00	1353.62	921.423403704879
4	165	17.5	14.5	1371.00	1372.24	933.194106384905
5	165	17.5	14.5	1369.00	1372.24	933.194106384905
6	165	20.0227	14.5	1553.00	1554.39	1063.84749365214
7	180	19	16	1606.00	1605.83	1100.33808444539
8	165	17.5	14.5	1370.00	1372.24	933.194106384905
9	150	19	13	1354.00	1357.34	921.423403704879
10	165	17.5	14.5	1372.00	1372.24	933.194106384905
11	180	16	13	1298.00	1301.44	930.839965849103
12	139.773	17.5	14.5	1298.00	1296.48	794.622332010665
13	180	19	13	1605.00	1602.05	1100.33808444539
14	165	14.9773	14.5	1346.00	1344.20	802.540719117838
15	190.227	17.5	14.5	1472.00	1473.32	1071.76588075906
16	165	17.5	11.9773	1379.00	1373.66	933.194106384905
17	165	17.5	17.0227	1642.00	1644.27	933.194106384905
18	150	16	13	1285.00	1284.23	780.174971540792
19	150	16	16	1456.00	1458.01	780.174971540792
20	165	17.5	14.5	1367.00	1372.24	933.194106384905

These metrics reinforce the high fidelity of the RSM model and affirm the 1D FEM's ability to reflect realistic thermal behavior within an acceptable error margin for simplified physical models.

Insights on Model Behavior

RSM Model:

Exhibits exceptional predictive performance due to empirical fitting based on central composite design. Captures complex interactions and nonlinear effects among process variables. Highly suitable for rapid prediction and process optimization within the tested range.

1D FEM Model:

Offers a physics-driven perspective on thermal evolution within the droplet. Accurately reproduces relative trends despite simplifications. Valuable for educational purposes, sensitivity studies, and cases where experimental access is limited.

Observed Deviations:

FEM predictions deviate due to:

- Assumptions of constant thermal properties.
- Neglect of radiative and multi-dimensional heat losses.
- Simplified convective boundary modeling.

Nonetheless, the deviation trend is consistent and systematic, which supports its use for comparative or exploratory simulations.

Educational Utility and Practical Applications

The 1D FEM model, especially when coded in MATLAB, serves as an excellent educational platform for understanding thermal conduction and model-based engineering. It enables users to:

- Visualize how discretization and boundary conditions affect results.
- Experiment with real-world welding parameters.
- Gain intuition for parameter sensitivity and thermal response times.

Furthermore, the modeling framework is adaptable to other manufacturing processes like laser welding, additive manufacturing, or brazing—where heat transfer critically influences material behavior.

this comparative approach bridges empirical data, statistical learning, and physical modeling, offering a comprehensive toolkit for researchers, engineers, and educators working in thermal and materials processing domains.

CONCLUSION

This study presented a comprehensive evaluation of droplet temperature predictions in Gas Metal Arc Welding (GMAW) using three distinct approaches: experimental measurements, Response Surface Methodology (RSM), and a 1D Finite Element Method (FEM) simulation in MATLAB. Through visual and quantitative comparisons across 20 randomized experimental runs, several key insights were established.

The RSM model demonstrated excellent predictive accuracy with a low RMSE of approximately 4.3°C, closely matching experimental results. Its data-driven nature and statistical robustness make it a powerful tool for process optimization within the tested design space.

The 1D FEM simulation, while based on simplifying assumptions, effectively captured the thermal trend and scale of droplet temperatures. Despite a higher RMSE of around 192.7°C, its consistent trend alignment with experimental data underscores its value for understanding thermal phenomena, conducting parametric studies, and serving as an educational tool.

Overall, the comparative analysis confirms that:

- RSM is ideal for rapid prediction and process tuning.
- 1D FEM provides physical insight and flexibility for theoretical exploration.

Together, these modeling strategies complement each other, offering both empirical accuracy and conceptual depth. The methodology established in this work can be extended to other heat-driven processes in manufacturing, enhancing predictive capabilities and supporting both academic learning and industrial applications.

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