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MODELING OF THE MIG WELDING PROCESS USING INTERVAL TYPE-2 FUZZY LOGIC SYSTEMS

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ABSTRACT: This study presents a model based on Interval Type-2 Fuzzy Logic Systems (IT2 FLS) applied to the Metal Inert Gas (MIG) welding process, aimed at representing and predicting weld bead behavior under uncertain conditions. The model considers six input variables: gas flow rate, work angle, wire feed speed, arc voltage (Trim), travel speed (IPM), and welding technique (push or pull), using experimental data obtained from an automated welding cell. Each variable was characterized by five membership functions (very low, low, medium, high, and very high), allowing the definition of the Footprint of Uncertainty (FOU) associated with experimental dispersion. Statistical validation through Analysis of Variance (ANOVA) showed a value of , confirming the statistical significance of the model, while the coefficient of determination indicated that the model explained 86.4% of the total variability in the experimental data. These results demonstrate that the IT2 FLS is a robust and accurate tool for modeling welding processes with nonlinear and uncertain behavior, providing a solid foundation for the development of intelligent systems for control and optimization of the MIG process.

KEYWORDS: MIG welding, type-2 fuzzy logic, uncertainty, process modeling, intelligent control.

Introduction

Metal Inert Gas (MIG) welding, also known as Gas Metal Arc Welding (GMAW), is one of the most widely used joining processes in the manufacturing industry due to its versatility, efficiency, and high degree of automation. Its performance depends on several operational variables such as current, voltage, wire feed speed, travel speed, shielding gas flow rate, and torch angle, whose nonlinear interaction directly affects penetration depth and the occurrence of defects [1, 2].

Accurate control of these parameters represents one of the main challenges of the GMAW process. Current and voltage determine arc stability and metal transfer, while wire feed speed and gas flow regulate the deposition rate and the protection of the molten pool. However, these variables exhibit strong dynamic interdependence, meaning that small variations in one parameter can alter bead geometry, penetration depth, or cause defects such as porosity and lack of fusion. In addition, the process response is highly sensitive to electrical noise, environmental thermal conditions, and base material properties, which limits process repeatability under industrial environments [3] .

From an operational standpoint, this complexity prevents the use of simple deterministic or linear models to predict weld bead quality, leading operators to empirically adjust process parameters. Recent studies have shown that even slight deviations in voltage or wire feed speed can significantly modify the penetration profile and microstructure of the deposited material [4]. According to Song and Hardt (1993), the dynamic nature of the welding process requires adaptive control strategies capable of adjusting parameters in real time to maintain arc stability and weld quality.

For this reason, adaptive and intelligent control of the GMAW process has become a priority research area to stabilize the arc, optimize energy efficiency, and enhance weld quality. In recent years, approaches based on nonlinear modeling, predictive control, and intelligent systems have shown substantial improvements in process stability and repeatability compared to conventional methods [4, 5].

Classical optimization methods such as Taguchi designs and Response Surface Methodology (RSM) have proven useful under controlled conditions, although their accuracy decreases when environmental fluctuations, noise, or arc instabilities occur [2, 6]. In this context, artificial intelligence (AI)-based approaches have gained relevance by offering tools capable of handling uncertain information and learning nonlinear relationships among process parameters [7].

Zhang, Mo, and Yu [8] implemented type-2 hierarchical fuzzy controllers in vehicular systems, demonstrating their robustness under uncertain and dynamic environments.

Fuzzy logic is particularly useful for representing expert knowledge through linguistic rules. However, Type-1 Fuzzy Logic Systems (T1 FLS) are sensitive to uncertainty in membership functions, which motivated the development of Type-2 Fuzzy Logic Systems (T2 FLS), proposed by Zadeh, allowing uncertainty representation through the *Footprint of Uncertainty (FoU)* [9, 10]. Within this framework, Interval Type-2 Fuzzy Logic Systems (IT2 FLS) provide a balance between computational complexity and representational capability and have been successfully applied to microgrid frequency regulation [11], vehicle tracking [8], and parameter adaptation using metaheuristic algorithms [12].

The robustness of IT2 FLS has also been validated in industrial contexts. Mittal et al. [7] and Shvedov [13] highlighted their usefulness in modeling nonlinear relationships under noisy environments. These findings support the suitability of type-2 fuzzy systems for modeling processes with high experimental variability.

In the case of MIG welding, the use of type-2 fuzzy models is particularly promising due to the complex behavior of the arc and the process's sensitivity to small parameter variations. However, most previous studies have focused on empirical or statistical models that do not incorporate the uncertain nature of experimental data. Therefore, this study proposes a model based on Interval Type-2 Fuzzy Logic Systems (IT2 FLS) for the MIG welding process, aiming to capture parameter variability and improve the prediction of weld bead penetration.

Materials and Methods

Description of the MIG Welding Process

The Metal Inert Gas (MIG) welding process, also known as Gas Metal Arc Welding (GMAW), depends on a set of operational parameters whose interaction directly influences arc stability, metal transfer, and weld bead quality. Figure 1 illustrates the six input parameters considered in this study and their physical relationship with bead formation, providing a conceptual framework for the experimental procedure and fuzzy modeling approach.

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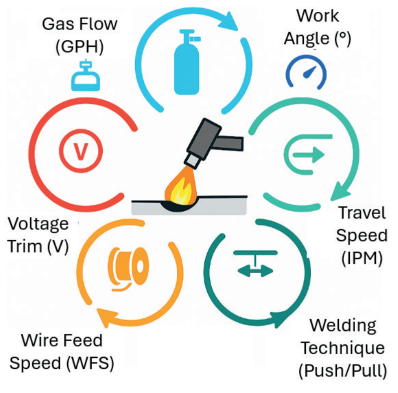

Figure 1. Diagram of the six key parameters of the MIG welding process.

The gas flow rate (GPH) protects the molten pool from atmospheric contamination. Excessive flow can cause turbulence, while insufficient flow increases the likelihood of porosity. The work angle (°) affects the arc direction and thus influences both the penetration depth and the filler metal distribution along the joint. The wire feed speed (WFS) determines the amount of filler material deposited; higher values increase bead size but also raise the risk of overheating.

The arc voltage (Trim) regulates the total energy and effective length of the arc. Higher voltages generate longer and less penetrating arcs, whereas lower voltages produce shorter and more stable arcs, leading to more uniform penetration. The travel speed (IPM) determines the heat input per unit length; higher speeds result in narrow beads with limited penetration, while lower speeds cause excessive heat input and material accumulation. Finally, the welding technique (push/pull) affects the thermal profile and geometry of the bead: the push technique produces wider and shallower beads, whereas the pull technique promotes deeper penetration.

The base materials used were GMW3031 STSCR182 and ASTM A503 steels, joined using a solid wire AWS A5.18 ER70S-3 (ISO 14341 EN440 G2 SI 1) with a diameter of 0.035 inches. The shielding gas consisted of an Ar–CO_2 mixture with a flow rate maintained between 32 and 38 GPH, ensuring proper protection of the molten pool and minimizing porosity formation.

Experimental Design

The experiments were conducted in an automated GMAW welding cell equipped with a three-axis programmable manipulator, ensuring high precision, arc stability, and repeatability between trials. The experimental objective was to analyze the influence of six operational parameters on the weld bead penetration, which was considered the main response variable.

A reduced factorial design (6^2) was adopted to explore representative combinations of parameter levels while maintaining an effective balance between experimental space coverage and efficiency in the number of runs. The parameters and levels considered are summarized in Table 1.

Table 1. Experimental parameters and levels.

Input variable	*Symbol*	*Unit*	*Minimum level*	*Maximum level*
Gas flow	X_1	GPH	32	38
Work angle	X_2	°	41	49
Wire feed speed (WFS)	X_3	IPM	260	270
Voltage (Trim)	X_4	V	0.7	0.9
Travel speed	X_5	IPM	29	32
Technique (Push–Pull)	X_6	—	1 (Pull)	2 (Push)

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Each experimental combination was evaluated by measuring the weld bead penetration, obtained from metallographic cross-sections and optical analysis using a calibrated digital measurement system.

Interval Type-2 Fuzzy Logic System (IT2 FLS)

The IT2 FLS model was formulated to represent the nonlinear and uncertain relationships inherent to the GMAW process, considering as input variables the six parameters described in Table 1 (X_1–X_6) and a single output variable corresponding to weld bead penetration (Y). The system was structured to capture experimental variability and to model the combined effects of welding parameters on the resulting response.

Each input variable was characterized by five membership functions (MFs) with the linguistic labels *Very Low (VL)*, *Low (L)*, *Medium (M)*, *High (H)*, and *Very High (VH)*. Two trapezoidal functions were assigned to the lower and upper extremes of the domain, while three triangular functions were used in the intermediate region, ensuring continuous coverage of the universe of discourse and smooth transitions between adjacent levels.

Figure 2 shows the membership functions corresponding to variable X_1 (gas flow), which are representative of the structure adopted for all input variables. This configuration accurately described the gradual variability of each parameter and defined the Footprint of Uncertainty (FOU) associated with the experimental dispersion observed in the welding process.

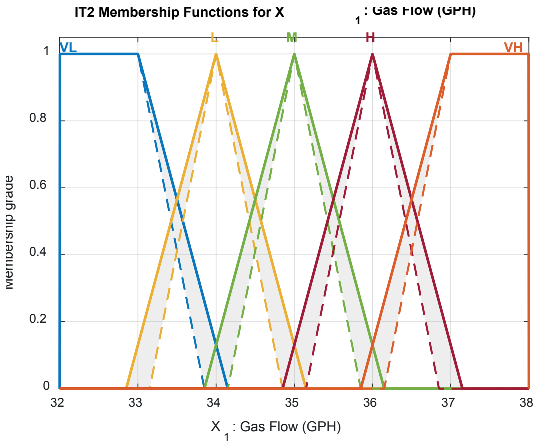

Figure 2. Interval Type-2 membership functions for variable X_1 (Gas Flow).

The triangular membership function is defined according to Equation (1):

$$\mu(x;a,b,c)=\max(\min(\frac{x-a}{b-a},\frac{c-x}{c-b}),0) \quad (1)$$

In an interval type-2 fuzzy logic system, the membership degree of an element is not described by a single value but by an interval of membership bounded by an upper membership function $\bar{\mu}_{\tilde{A}}(x)$ and a lower membership function $\underline{\mu}_{\tilde{A}}(x)$. This concept is formally expressed in Equation (2):

$$\tilde{A}=\{(x,u)\mid x\in X,\ u\in J_x\subseteq[0,1]\},\ J_x=[\underline{\mu}_{\tilde{A}}(x),\bar{\mu}_{\tilde{A}}(x)] \quad (2)$$

The region enclosed between these two functions represents the FOU, defined as:

$$\mathrm{FoU}(\tilde{A})=\bigcup_{x\in X}[\underline{\mu}_{\tilde{A}}(x),\bar{\mu}_{\tilde{A}}(x)] \quad (3)$$

The FOU constitutes the core of type-2 reasoning, as it explicitly models the uncertainty associated with the boundaries of the membership functions. In this study, the width of the FOU for each variable was established proportionally to the experimental dispersion observed, enabling a more realistic representation of welding conditions and their influence on penetration.

The knowledge base was constructed from the technical expertise of welding specialists and the analysis of experimental results. The fuzzy rules were formulated following the classical IF–THEN linguistic structure proposed by Zadeh. A representative example of a rule is:

***IF Gas flow** is medium AND **Work angle** is medium AND **Wire feed speed (WFS)** is high AND **Voltage (Trim)** is medium AND **Travel speed** is low AND **Technique** is Pull THEN **Penetration** is high .*

The inference process followed the Mamdani approach, using *min–max* operators for rule activation and aggregation. Subsequently, type-reduction was performed using the *centroid of sets* method to transform the resulting type-2 sets into equivalent type-1 sets. Finally, defuzzification was carried out using the *centroid* method, yielding a single numerical value corresponding to the predicted weld penetration.

This architecture allowed the IT2 FLS model to integrate experimental uncertainty, process parameter variability, and expert knowledge coherently, providing a robust, continuous, and physically interpretable representation of the MIG welding process behavior.

Model Evaluation and Validation

The statistical evaluation of the model was performed through Analysis of Variance (ANOVA) and computation of the coefficient of determination (R^2), in order to validate the overall significance of the model and its explanatory capacity regarding experimental variability.

The equations employed are expressed as follows:

$$SS_{Mod} = \sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2 \quad (4)$$

$$SS_{Tot} = \sum_{i=1}^{n} (y_i - \bar{y})^2 \quad (5)$$

$$SS_{Res} = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \quad (6)$$

$$MS_{Mod} = \frac{SS_{Mod}}{k} \quad (7)$$

$$MS_{Res} = \frac{SS_{Res}}{n-p} \quad (8)$$

$$R^2 = 1 - \frac{SS_{Res}}{SS_{Tot}} \quad (9)$$

The F-statistic was computed as:

$$F_0 = \frac{MS_{Mod}}{MS_{Res}} \quad (10)$$

and was compared with the critical F-value *F (k, n - p)* at a 95 % confidence level. A *p*-value < 0.05 was considered evidence of a statistically significant fit, confirming that at least one input variable exerts a relevant influence on weld bead penetration.

Thus, the IT2 FLS model not only captured the inherent uncertainty of welding parameters but also quantified their impact on the experimental response through statistically validated performance metrics.

Results and Discussion

An Analysis of Variance (ANOVA) was applied to evaluate the statistical significance of the Interval Type-2 Fuzzy Logic System (IT2 FLS) model and to determine the influence of operational parameters on weld bead penetration. The results are summarized in Table 2, showing that the calculated value $F_0 = 5.73$ exceeds the critical table value $F_{tablas} = 3.37$ at a 95% confidence level. Moreover, the value $p = 0.0104 < 0.05$ confirms the existence of a significant relationship between the input variables and the response, thereby rejecting the null hypothesis of independence.

Table 2. ANOVA results for the IT2 FLS model.

Source of variation	*Sum of squares*	*df*	*Mean squares*	F_0	*F table*	*p-value*
Model	1.3717	6	0.2286	5.726	3.374	0.0104
Residual	0.3593	9	0.0399	–	–	–
Total	1.5998	15	–	–	–	–

The model sum of squares (SS_{Mod} = 1.37) represents 85.7% of the total variation (SS_{Tot} = 1.60), which demonstrates good fitting capability. In contrast, the residual sum of squares (SS_{Res} = 0.36) indicates that the dispersion of errors between experimental and predicted values is moderate and shows no evidence of lack of fit. The ratio between the model and residual mean squares (MS_{Mod}/MS_{Res} = 5.73) reflects a substantial effect size, confirming that the model is not only statistically significant but also practically relevant for predicting process behavior.

The coefficient of determination obtained was R^2 = 0.8640, meaning that the model explains 86.4% of the total variability in the experimental data. This value indicates a strong relationship between the input variables and the predicted response, validating the fuzzy system's structure. The remaining 13.6% is attributed to experimental noise and interaction effects not captured by the rule base.

Residual analysis revealed a random distribution around the mean with no systematic patterns, supporting the statistical validity of the fit and the consistency of the model. This behavior indicates that the designed rules and membership functions successfully represented the relationship between welding parameters and weld bead penetration, even under conditions of experimental uncertainty.

Overall, the ANOVA and R^2 results indicate that the IT2 FLS model achieves an appropriate balance between accuracy and generalization. Its stability under small variations in input parameters is attributed to the *Footprint of Uncertainty (FOU)*, which enables a realistic representation of the inherent uncertainty of the MIG process. This behavior, distinct from conventional linear models, demonstrates the capability of the IT2 FLS to describe process variability and predict weld penetration. Furthermore, its adaptability under changing process conditions suggests favorable potential for integration into adaptive control systems designed to maintain arc stability and weld quality without requiring constant operator intervention.

Conclusions

The Interval Type-2 Fuzzy Logic System (IT2 FLS) model applied to the MIG welding process proved to be an effective tool for representing and predicting weld bead penetration and overall weld quality under uncertain conditions. Its formulation, based on six input variables associated with process parameters, successfully captured the nonlinear behavior and inherent variability of welding with statistically verified accuracy.

The Analysis of Variance (ANOVA) confirmed the statistical significance of the model with a p-value of 0.0104 < 0.05, while the coefficient of determination R^2 = 0.8640 indicated that it explained 86.4% of the total experimental variability. These results validate the relationship between the input parameters and the fuzzy response, demonstrating the IT2 FLS's ability to accurately estimate weld bead penetration.

The type-2 fuzzy logic approach explicitly incorporated uncertainty into the membership functions, yielding a model robust to data dispersion and experimental noise. Unlike deterministic or linear approaches, the interval fuzzy system provided the flexibility to represent multivariable relationships without imposing rigid functional constraints, thus reproducing the physical behavior of the MIG process with greater realism.

From an industrial perspective, the IT2 FLS model constitutes a solid foundation for developing intelligent welding control systems. Its modular structure and linguistic interpretability facilitate integration into automated welding cells, where it could be employed to adjust critical variables such as voltage, gas flow, and travel speed, contributing to more uniform penetration and greater process stability.

Finally, it is recommended to validate the model under industrial production conditions to assess its performance in real environments, taking into account factors such as thermal variations, differences in consumables, and environmental changes. It is also suggested to explore optimization through evolutionary algorithms such as Particle Swarm Optimization (PSO) or Genetic Algorithms (GA) to fine-tune membership function parameters and fuzzy rule weights. Integrating these techniques with the IT2 FLS model could lead to the development of more adaptive and reliable control systems for welding processes subject to high levels of uncertainty.

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