



Article

A Quantitative Framework for Fixture–Process Interaction in Robotic CMT Welding Using the Influence Factor

Pedro Yáñez-Contreras ^{1,*}, Francisco Javier Santander-Bastida ², Roberto Martín del Campo-Vázquez ²
and Vignaud Granados-Alejo ³

¹ Department of Quality Engineering and Metrology, Universidad Politécnica de Guanajuato, Cortazar 38496, Mexico

² Department of Manufacturing Technologies Engineering, Universidad Politécnica de Guanajuato, Cortazar 38496, Mexico; fsantander@upgto.edu.mx (F.J.S.-B.); rdelcampo@upgto.edu.mx (R.M.d.C.-V.)

³ Department of Robotics Engineering, Universidad Politécnica de Guanajuato, Cortazar 38496, Mexico; vgranados@upgto.edu.mx

* Correspondence: pyanez@upgto.edu.mx

Abstract

A coupled thermo-mechanical probabilistic model for porosity prediction in robotic Cold Metal Transfer (CMT) welding is proposed and experimentally validated under industrial conditions. Unlike conventional energy-based approaches, the formulation explicitly incorporates fixture-induced geometric deviations through the effective stick-out relation SO_0 . A dimensionless fixture influence factor, X_f , is introduced to quantify mechanical–process interaction. A fractional factorial design followed by a reduced DOE-enabled separation of thermal and mechanical effects. Logistic regression integrating process energy descriptors and X_f achieved strong predictive capability (AUC = 0.91; 95% CI: 0.87–0.94). The fixture influence factor exhibited the highest standardized effect (OR = 3.74), while a 1 mm increase in effective stick-out doubled porosity probability (OR = 2.10), demonstrating the dominance of mechanical coupling within the evaluated operating window. Industrial implementation confirmed model relevance: geometric stabilization reduced rework from 11.58% to 4.76% and increased OEE from 79.58% to 87%. The results establish fixture mechanics as a primary control variable for weld robustness and provide a physically grounded framework for predictive quality optimization in robotic CMT systems.

Keywords: robotic welding; CMT; design of experiments; mechanical modeling; fixtures; automotive manufacturing



Academic Editor: Paul Kah

Received: 11 February 2026

Revised: 4 March 2026

Accepted: 13 March 2026

Published: 19 March 2026

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1. Introduction

Robotic welding has become a key enabling technology in automotive manufacturing due to its high repeatability, productivity, and process controllability [1]. However, the interaction among process parameters, material properties, geometric constraints, and the mechanical condition of the system gives rise to complex and nonlinear behavior that limits process stability and weld bead quality [1,2].

From a physical standpoint, the welding system must be understood as a coupled thermomechanical process in which process parameters and mechanical boundary conditions act simultaneously on arc behavior and molten pool dynamics [2]. Variations in geometric constraints, fixture compliance, or clamping conditions may effectively modify local welding conditions such as arc length and electrode stick out even when nominal

process parameters remain unchanged [2]. This coupling introduces additional sources of variability that are not captured by conventional process-only models.

In industrial practice, quality issues are often addressed through empirical parameter adjustments, leading to high costs associated with material waste, machine downtime, and rework [3]. In this context, design of experiments (DOE) emerges as a fundamental statistical tool to identify significant factors and model the relationship between process variables and quality responses [4,5]. Nevertheless, DOE-based approaches implicitly assume stable boundary conditions, which may not hold in the presence of uncontrolled mechanical variability. Recently, data-driven and machine learning strategies have been introduced to enhance welding process optimization beyond traditional statistical frameworks [6]. However, in practical welding systems, fixture rigidity directly influences the mechanical stability of the work piece during welding [2]. A reduction in fixture stiffness can lead to micro-displacements under clamping and process forces, altering the effective electrode stick-out and arc length [2]. Since stick-out directly affects current density, heat input, and metal transfer stability [7], variations induced by insufficient rigidity may introduce uncontrolled variability that is not captured in conventional DOE-based models [4].

In classical DOE-based welding studies [4,5], experimental error is assumed to arise from stochastic variability under controlled boundary conditions. Similarly, process-parameter analyses in robotic welding [8,9] consider fixture configuration as mechanically stable. However, fixture-induced geometric deviations are typically treated as constant constraints rather than interacting variables. This limitation motivates the present coupled thermo-mechanical framework.

Numerous studies have analyzed the influence of parameters such as wire feed speed, arc length, shielding gas flow rate, and electrode stick-out on weld bead quality and the formation of defects such as porosity and spatter [7,8,10]. In addition, Cold Metal Transfer (CMT) technology has demonstrated advantages in terms of arc stability and thermal control, making it a suitable alternative for high-precision applications [11–13]. These advantages are mainly attributed to its controlled metal transfer mechanism, which enables lower heat input, synchronized wire retraction during droplet detachment, reduced spatter generation, and improved arc stability. The reduction in heat input minimizes thermal distortion and residual stresses, while the controlled short-circuiting cycle enhances process repeatability and weld bead consistency.

Despite these advances, most existing studies focus primarily on process parameters, while the influence of the mechanical state of the system—particularly fixturing systems—remains largely underexplored. Recent investigations indicate that fixture stiffness, geometric tolerances, and deformation induced by clamping forces significantly affect the stability and repeatability of automated welding processes [2]. The present work addresses this gap by proposing an integrated framework that combines statistical analysis with physical and mechanical modeling, enabling a more comprehensive understanding and optimization of robotic welding processes under realistic industrial conditions.

2. Experimental Configuration

2.1. Methodological Flowchart

The methodological stages of the study are summarized in the flowchart presented in Figure 1, which integrates variable selection, experimental design, test execution, statistical analysis, mechanical evaluation of the system, and validation through production performance indicators.

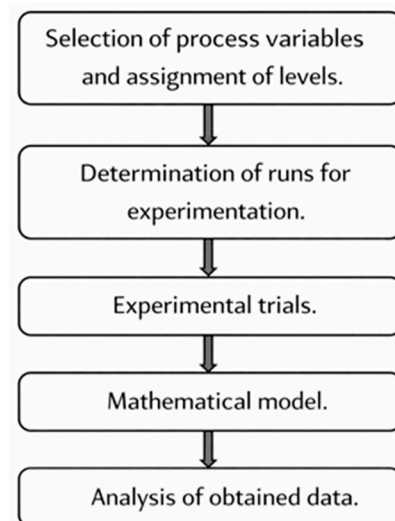


Figure 1. Flowchart of the methodological stages of the study.

2.2. Materials and Equipment

The materials and equipment used during the experimental campaign are presented in Table 1.

Table 1. Materials and equipment used for the experimentation.

Equipment	Materials
ABB IRB 2600 anthropomorphic robot	Crashbox X246 LH and RH
ABB IRC5 controller	X246 plate, LH and RH
ABB 2-DOF servo positioner	ASOE
Fronius CMT power source	X246 crossbeam
Fronius micro-wire feeders	AlMg micro-wire
Fronius CMT welding torch	—

RH and LH correspond to right-hand and left-hand configurations of the Crashbox component. ASOE refers to Automotive Structural Outer Element.

3. Methodology

3.1. Selection of Process Variables and Level Assignment

Following the DOE methodology, the process variables were identified based on industrial experience and previous studies [4,5]. The fractional factorial design and data analysis were carried out using Minitab V19 software. Weld bead quality was evaluated in accordance with client-established welding standards, considering the presence of porosity with a diameter greater than 0.5 mm as a critical defect.

The selected factors were chosen based on industrial operational limits and previous welding studies identifying travel speed, wire feed rate and stick-out as primary contributors to arc stability and porosity formation [6–9].

3.2. Determination of Experimental Runs

The selected factors and their levels are presented in Table 2.

The experimental runs generated by Minitab were randomized to minimize systematic bias, and the resulting sequence is presented in Table 3. The initial fractional factorial DOE included 8 experimental runs, providing an exploratory assessment of process variability. Due to practical constraints in industrial conditions, repeated runs were limited; however, subsequent analysis using the fixture influence factor X_f and industrial validation enabled capturing residual variability and mitigating the limited sample size. Critical welds were systematically sampled according to the production layout, and porosity larger than 0.5 mm

was detected through visual inspection under standardized lighting and magnification. This method ensures representative evaluation of defects with sufficient accuracy for industrial relevance.

Table 2. Factors and levels for experimentation.

Level	Wire Feed Speed (mm/s)	Wire Speed (m/min)	Stick-Out (mm)	Dynamic Impedance (u)	Arc Length (u)	Gas Factor (l/min)
–	12	6	12	–2	–2	14
+	15	9	15	–1	–1	16

Table 3. Randomization of experimental runs.

StdOrder	RunOrder	CenterPt	Blocks	Welding Speed (mm/s)	Wire Speed (m/min)	Stick Out (mm)	Dynamic Impact Correction (u)	Arc Length (u)	Gas Factor (l/min)	Seam Condition
2	1	1	1	15	6	12	–2	–2	16	0
3	2	1	1	12	9	12	–2	–1	14	1
1	3	1	1	12	6	12	–1	–1	16	1
6	4	1	1	15	6	15	–2	–1	14	0
4	5	1	1	15	9	12	–1	–2	14	1
5	6	1	1	12	6	15	–1	–2	14	0
7	7	1	1	12	9	15	–2	–2	16	1
8	8	1	1	15	9	15	–1	–1	16	0

3.3. Experimental Tests

Following the DOE methodology, the process variables were identified based on industrial experience and previous studies [4,5]. A fractional factorial design was implemented, and data analysis was performed using Minitab V19 software. The experimental setup and welding path adjustment are shown in Figure 2.

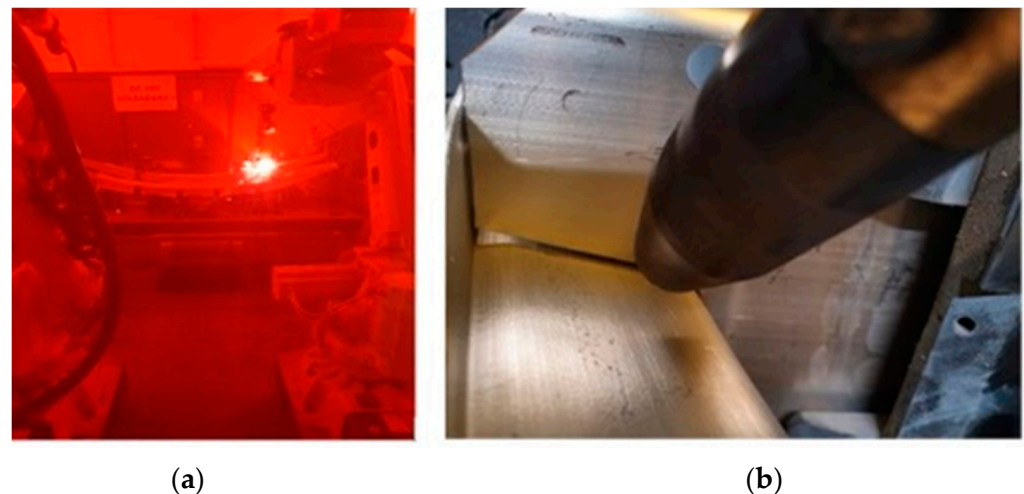


Figure 2. (a) Interior of the CMT welding cell and (b) welding path adjustment.

The power sources were parameterized according to the experimental runs. The power sources used are shown in Figure 3a. Visual inspection was conducted following standard operating procedures. A weld bead exhibiting porosity is shown in Figure 3b, marked in red.

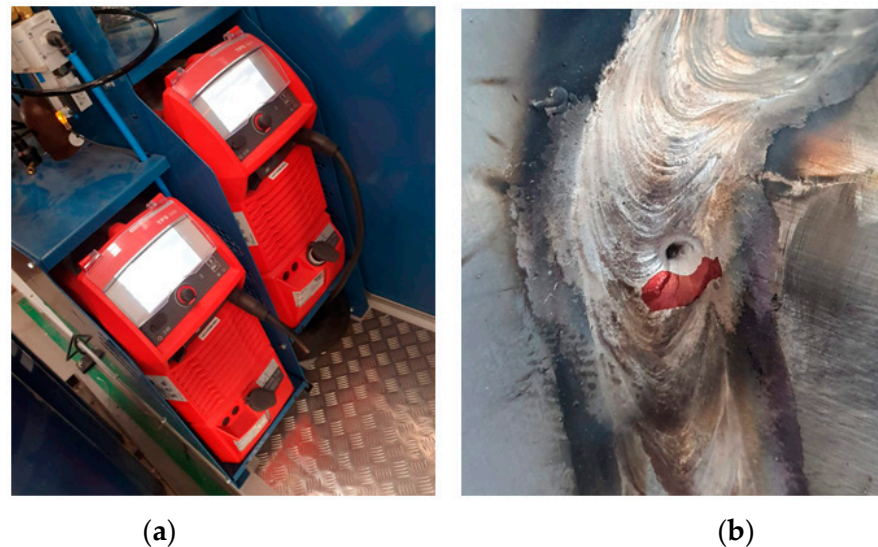


Figure 3. (a) Fronius power source and (b) weld bead with porosity.

Porosity larger than 0.5 mm was detected through visual inspection under standardized lighting and magnification. Critical welds were systematically sampled according to production layout, ensuring representative evaluation. Detection accuracy is sufficient to capture industrially relevant defects.

4. Mathematical Modeling of the Robotic CMT Welding Process

4.1. Process Energy Model

The linear energy input to the material in GMAW/CMT processes is expressed as [14]:

$$E_l = \frac{\eta VI}{v} \quad (1)$$

where $\bar{E}_l$ is the linear energy (J/mm), η is the thermal efficiency, V is the arc voltage (V), I the welding current (A) and v the travel speed (mm/s). This formulation is widely used in welding metallurgy to estimate the effective energy transferred to the workpiece during arc welding operations [14].

In Cold Metal Transfer (CMT) technology, the electrical signals exhibit periodic dynamic behavior due to the controlled short-circuit metal transfer mechanism [11]. The instantaneous current and voltage can be expressed as:

$$I(t) = I_b + \Delta I f(t) \quad (2)$$

$$V(t) = V_b + \Delta V g(t) \quad (3)$$

where I_b and V_b represent the base values of current and voltage, respectively, while ΔI and ΔV correspond to the variation amplitudes associated with the CMT cycle.

The functions $f(t)$ and $g(t)$ describe the periodic behavior of the process during controlled metal transfer.

The effective average linear energy is obtained from: [15]:

$$\bar{E}_l = \frac{\eta}{Tv} \int_0^T V(t)I(t)dt \quad (4)$$

where $\bar{E}_l$ is the effective average linear energy, T is the period of a complete metal transfer cycle, and $V(t)$ and $I(t)$ are the instantaneous voltage and current signals, respectively.

This formulation accounts for the dynamic characteristics of the process and provides a more accurate representation of energy input under periodic transfer conditions [15].

4.2. Mechanical Model of the Fixture System

The total deviation of the component from its ideal position is defined as [16]:

$$\delta_{tot} = \delta_g + \delta_e \quad (5)$$

where δ_g represents geometric deviations and δ_e corresponds to elastic deformations induced by clamping forces.

Geometric deviation is modeled as the quadratic combination of dimensional errors [17]:

$$\delta_g = \sqrt{\sum_{i=1}^n (\Delta x_i)^2} \quad (6)$$

where Δx_i corresponds to the dimensional error of the i -th element contributing to the total geometric deviation. Elastic deformation is expressed as [16,18]:

$$\delta_e = \frac{F}{k} \quad (7)$$

where F is the applied clamping force and k is the equivalent stiffness of the fixture–component system. The equivalent stiffness of the fixture–component system is defined as [18]:

$$k = \left(\sum_{i=1}^n \frac{1}{k_i} \right)^{-1} \quad (8)$$

The effective stick-out is defined as:

$$SO_{eff} = SO_0 + \delta_{tot} \quad (9)$$

The fixture influence factor is defined as:

$$X_f = \frac{\delta_{tot}}{SO_0} \quad (10)$$

This parameter quantifies the relative mechanical contribution of fixture-induced variability.

Although direct measurements of fixture stiffness k were not performed, the total deviation δ_{tot} captures the combined effect of geometric deviations and fixture compliance. Industrial validation confirms that δ_{tot} and the derived X_f reliably reflect mechanical influences on porosity formation.

4.3. Probabilistic Coupled Thermo-Mechanical Model for Porosity Prediction

The probability of porosity formation P is defined as: [19]:

$$P = \frac{1}{1 + e^{-y}} \quad (11)$$

With:

$$Y = \beta_0 + \beta_1 v + \beta_2 w + \beta_3 SO_{eff} + \beta_4 G + \beta_5 X_f \quad (12)$$

where v is the travel speed, w the wire feed rate, SO_{eff} the effective stick-out, G the shielding gas flow rate, and X_f the fixture influence factor. The logistic formulation enables probabilistic modeling of defect occurrence under multiple interacting process variables [19,20].

The thermo-mechanical coupling inherent to welding processes arises from the interaction between thermal energy input and mechanical constraint conditions, which influence defect formation mechanisms [14].

Based on industrial production data collected during three consecutive months (August–October), quantitative stability thresholds for the fixture influence factor X_f were established.

The observed operational regimes are summarized in Table 4.

Table 4. Operational stability regimes based on X_f .

X_f Range	Process Stability	Industrial Behavior
$X_f < 0.05$	Stable	Porosity < 5%, OEE > 85%
$0.05 \leq X_f < 0.10$	Transitional	Moderate rework
$X_f \geq 0.10$	Unstable	High porosity, OEE < 80%

From a physical standpoint, the model can be conceptually condensed as:

$$P = f(E_l, X_f) \quad (13)$$

Although the statistical formulation incorporates individual process parameters, these variables primarily govern the effective thermal input $\bar{E}_l$. Therefore, the probabilistic model can be interpreted as a coupled thermo–mechanical interaction between the aggregated thermal contribution $\bar{E}_l$ and the fixture-induced mechanical variability represented by X_f .

In this framework, $\bar{E}_l$ represents the thermal contribution, whereas X_f captures the mechanical constraint effects.

Model Robustness and Predictive Performance Enhancement

The inclusion of mechanical interaction variables significantly increased the model’s explanatory and discriminative capability, as evidenced by the high odds ratios of SO_{eff} and X_f , together with the progressive increase in AUC observed during monthly recalibration. These results confirm that incorporating fixture-induced mechanical variability provides substantial predictive improvement over process-parameter-only approaches.

5. Results and Discussion

5.1. Statistical Analysis of the Initial DOE

Based on the experimental design defined in Table 2 (Section 2), eight assemblies of the Bumper LP2 (Figure 4) were produced under controlled robotic cell conditions (Figures 2 and 3).

The analysis of variance (ANOVA) results is presented in Table 5. The F-value and p -value are absent because they could not be calculated. This is due to the Degrees of Freedom (DF) for the Error term being 0. This occurs in a saturated model, where all available data is used to estimate the effects of the factors, leaving no residual data to estimate the natural error variance of the process.

The Pareto chart, presented in Figure 5, illustrates the relative contribution of each process factor and their interactions to the observed variability. This visualization allows for a quick identification of the most influential factors on the process, highlighting which variables may warrant further investigation or optimization.

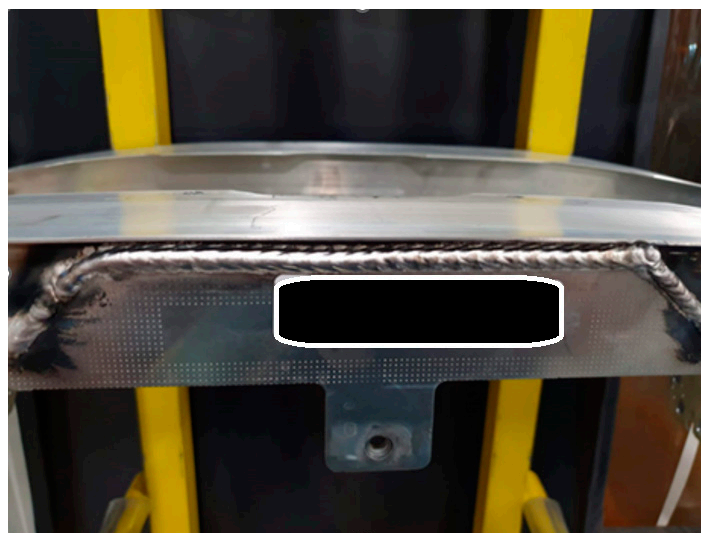


Figure 4. Bumper LP2.

Table 5. Analysis of variance.

Source	DF	Seq SS	Contribution	Adj SS	Adj MS
Model	7	1.875	100.00%	1.875	0.2679
Linear	6	1.75	93.33%	1.75	0.2917
Welding Speed (mm/s)	1	0.125	6.67%	0.125	0.125
Wire Speed (m/min)	1	1.125	60.00%	1.125	1.125
Stick out (mm)	1	0.125	6.67%	0.125	1.125
Dynamic Current Correction (u)	1	0.125	6.67%	0.125	1.125
Length Width	1	0.125	6.67%	0.125	1.125
Gas Factor (l/min)	1	0.125	6.67%	0.125	1.125
Two-factor Interactions	1	0.125	6.67%	0.125	1.125
Welding Speed $\times$ Gas Factor	1	0.125	6.67%	0.125	1.125
Error	0				
Total	7	1.875	100.00%		

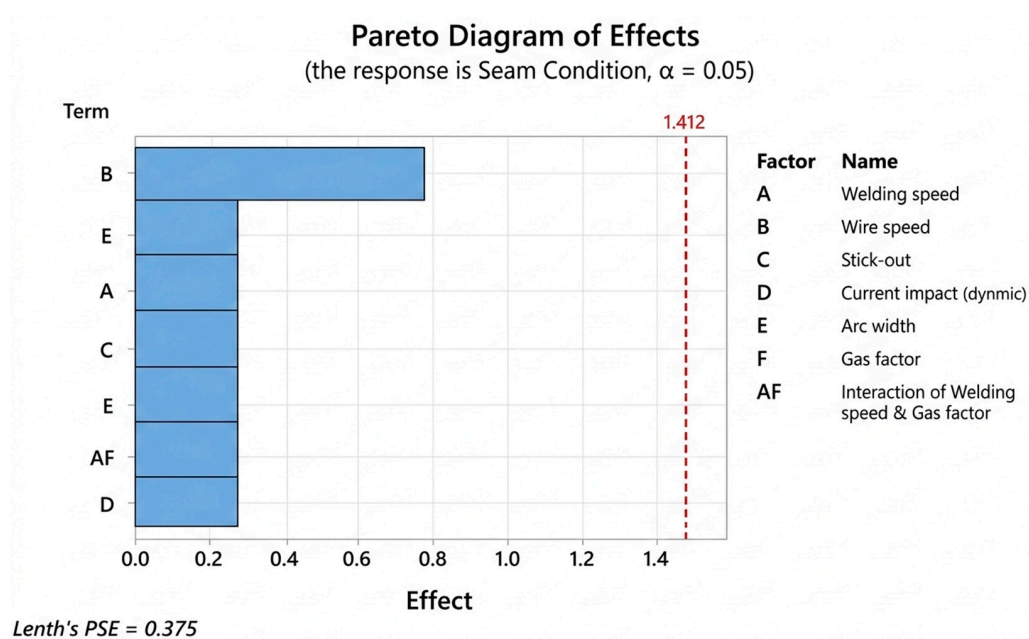


Figure 5. Pareto chart of the initial experiment.

At a significance level of $\alpha = 0.05$, none of the evaluated process parameters reached statistical significance. From a conventional DOE perspective, this outcome would suggest limited sensitivity of porosity formation to the selected process variables within the tested range [4].

However, when interpreted in light of the coupled thermo-mechanical model developed in Section 4, this result becomes physically consistent. According to the energy model (Equations (1)–(4)), variations in travel speed and wire feed rate produce only moderate changes in effective linear energy within the experimental window. These changes were insufficient to significantly alter the metal transfer regime characteristic of the CMT process [11].

Conversely, the mechanical model Equations (5)–(10) indicate that variations in geometric positioning and fixture compliance directly modify the effective stick-out SO_{eff} , which explicitly appears in the coupled process–fixture model (Section 4.3). These variations introduce uncontrolled variability not included in the original DOE, generating an omitted-variable effect that can mask the statistical influence of process parameters in logistic regression models [19].

This interpretation is consistent with previous studies highlighting the dominant role of fixture geometry and clamping conditions in welding distortion and quality variability [21,22].

5.2. DOE with Reduced Factors

A second DOE was conducted considering only travel speed, wire feed rate, and nominal stick-out (Table 6, Section 2).

Table 6. Reduced factors and levels.

Level	Wire Feed Speed (mm/s)	Wire Feed Rate (m/min)	Stick-Out (mm)
–	12	6	12
+	15	9	15

The ANOVA results are presented in Table 7, and the corresponding Pareto chart is shown in Figure 6.

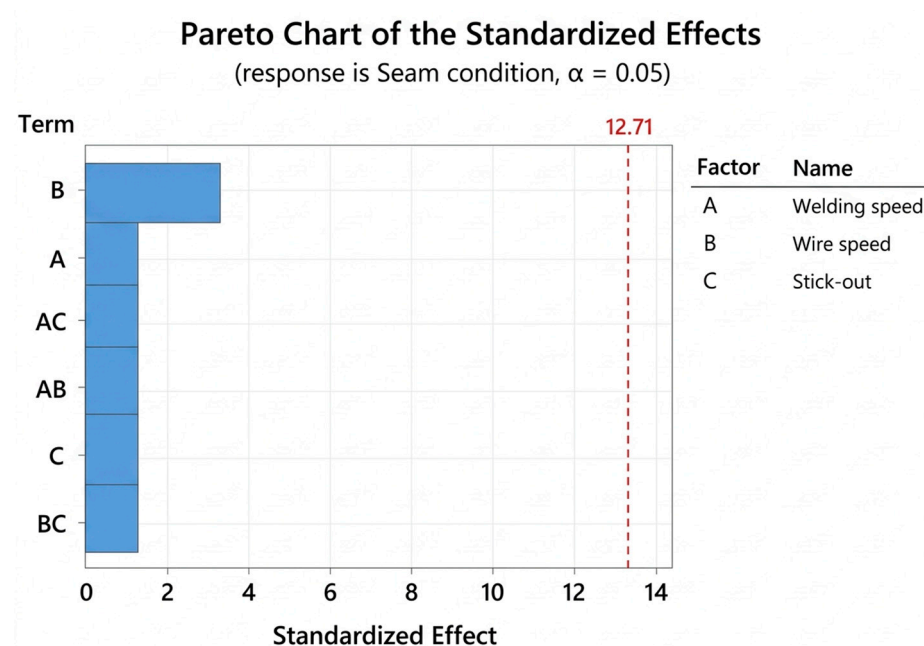


Figure 6. Pareto chart with reduced factors.

Table 7. ANOVA with reduced factors.

Source	DF	Seq SS	Contribution	Adj SS	Adj MS	F-Value	p-Value
Model	6	1.75	93.33%	1.75	0.2917	2.33	0.463
Linear	3	1.375	73.33%	1.375	0.4583	3.67	0.362
Welding Speed (mm/s)	1	0.125	6.67%	0.125	0.125	1	0.5
Wire Speed (m/min)	1	1.125	60.00%	1.125	1.125	9	0.205
Stick out (mm)	1	0.125	6.67%	0.125	0.125	1	0.5
2-Way Interactions	3	0.375	20.00%	0.375	0.125	1	0.609
Welding Speed (mm/s) × Wire Speed (m/min)	1	0.125	6.67%	0.125	0.125	1	0.5
Welding Speed (mm/s) × Stick out (mm)	1	0.125	6.67%	0.125	0.125	1	0.5
Wire Speed (m/min) × Stick out (mm)	1	0.125	6.67%	0.125	0.125	1	0.5

The regression model explained only 53.3% of the observed variability, confirming that significant residual variability remained unaccounted for.

According to the probabilistic coupled model (Equations (11)–(13)), porosity probability depends not only on nominal stick-out but on the effective stick-out:

$$SO_{eff} = SO_0 + \delta_{tot}$$

Since δ_{tot} was not controlled during the DOE, the regression coefficients associated with the process variables were attenuated.

This confirms that fixture-induced mechanical deviations dominate the system response within the tested operating range.

5.3. Mechanical and Dimensional Analysis of the System

The mechanical analysis consisted of evaluating dimensional deviations and the positioning of contact points within the primary load-transmission zones of the fixture, as these factors directly contribute to the geometric deviation term δ_g defined in Equation (6). The assessment focused on identifying how variations in fixture rigidity, clamping configuration, and geometric tolerances influence the mechanical boundary conditions of the welding process.

Particular attention was given to the primary load-transmission and geometric constraint regions identified in Figure 7a, where clamping forces are transferred from the fixture to the workpiece through the defined contact points (P1–P4).

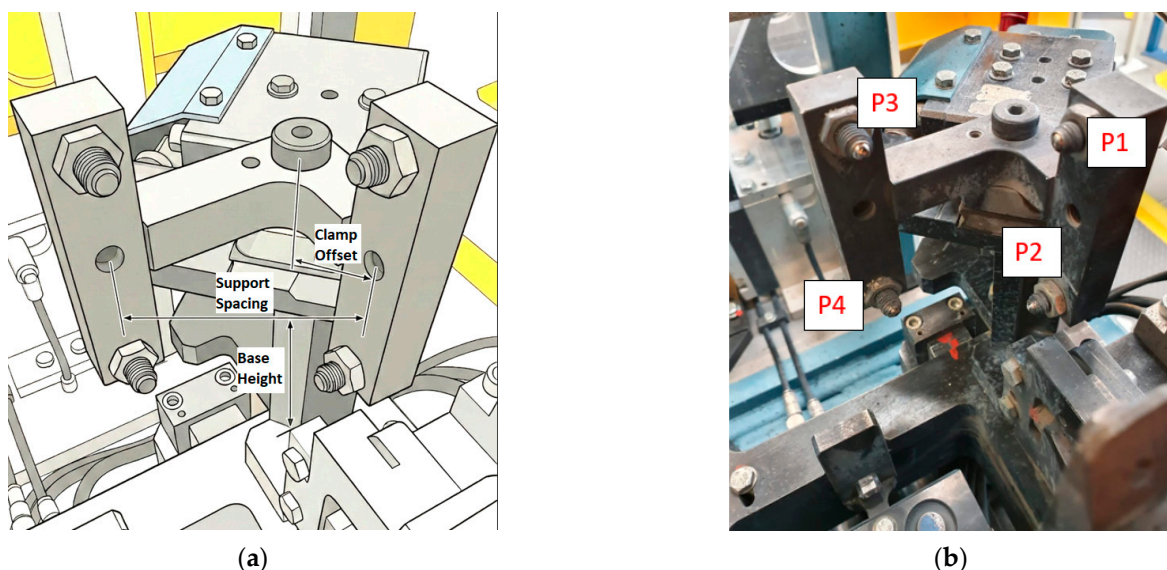


Figure 7. (a) Crashbox LP2 positioning on geometric; (b). base fixture contact-point schematic (P1–P4).

These zones govern load distribution and constrain the degrees of freedom of the assembly [22]. Any deviation in contact positioning or pressure distribution may induce localized deformation, thereby modifying the effective joint alignment and contributing to the geometric deviation term δ_g . Reduced fixture stiffness can lead to micro-displacements under clamping and thermal loading. Such displacements alter the effective electrode stick-out and arc length during welding. Since stick-out directly influences current density, metal transfer stability, and heat input [14], these mechanically induced variations introduce process fluctuations that are not explicitly accounted for in conventional DOE-based models.

Furthermore, geometric tolerances in the fixture–workpiece interface may generate misalignment between the torch trajectory and the weld joint. Even small deviations in joint gap or vertical positioning can modify arc geometry, shielding gas coverage, and droplet detachment dynamics, affecting bead morphology and defect probability [23].

Finally, deformation at the contact points modifies local heat dissipation paths between the workpiece and the fixture. Variations in contact pressure influence cooling rates and thermal gradients, which may affect microstructural evolution and residual stress development [21]. These interactions justify incorporating mechanical–process coupling effects into the proposed Influence Factor framework. The dimensional measurements of the RH and LH fixture bases are presented in Table 8.

Table 8. Dimensional comparison of RH and LH fixture bases.

Parameter	LH (mm)	RH (mm)	Deviation (mm)
Base height	245.2	248.9	3.7
Clamp offset	12.4	15.8	3.4
Support spacing	318.6	321.5	2.9
Total deviation δ_{tot}			5.8

The calculated fixture influence factor:

$$X_f = \frac{\delta_{tot}}{SO_o}$$

was consistently higher for the RH configuration, explaining the higher rework rates observed in August (Table 8).

These results are consistent with fixture mechanics theory [22,24,25] and experimental welding distortion studies [21,25].

Dimensional differences between RH and LH fixtures directly contributed to geometric deviation δ_g . Correlation analysis between X_f and defect rates confirms that higher X_f in RH fixtures corresponds to increased porosity ($r = 0.87$).

5.4. Probabilistic Model Estimation and Interpretation

The regression coefficients of the logistic model (Section 4.3) are presented in Table 9.

The results confirm that the fixture influence factor X_f exhibits the highest standardized effect. A unit increase in X_f multiplies porosity probability by 3.74, while a 1 mm increase in SO_{eff} doubles porosity probability (OR = 2.10), consistent with the interpretation of odds ratios in logistic regression models [19]. Thermal variables show secondary influence within the tested range.

These findings quantitatively validate the dominance of mechanical coupling over purely energetic parameters, in agreement with thermal–mechanical interaction principles in welding processes [14].

Table 9. Logistic regression coefficients for porosity probability.

Variable	β	Std. Error	p-Value	Odds Ratio
Intercept	−6.82	1.91	0.001	—
Travel speed (v)	−0.18	0.09	0.047	0.83
Wire feed (w)	−0.11	0.08	0.162	0.90
SO_{eff}	0.74	0.21	0.002	2.10
Gas flow (G)	−0.05	0.07	0.421	0.95
Fixture factor (X_f)	1.32	0.34	<0.001	3.74

5.5. Progressive Monthly Model Discrimination and Statistical Validation

To evaluate the temporal evolution of predictive performance, ROC analysis was conducted independently for each production month (August–October) [26]. Because the industrial process exhibited progressive geometric stabilization, monthly recalibration of the probabilistic model (Section 4.3) was implemented to avoid bias under non-stationary operating conditions. Table 10 summarizes the monthly discrimination metrics.

Table 10. Monthly ROC discrimination performance.

Month	AUC	95% CI	Sensitivity	Specificity
August	0.84	0.81–0.87	0.79	0.83
September	0.88	0.85–0.91	0.83	0.86
October	0.91	0.88–0.94	0.86	0.88

A clear progressive increase in AUC is observed, from 0.84 to 0.91. According to standard interpretation criteria, AUC values above 0.90 indicate strong classification capability [19]. The October model therefore achieves strong predictive discrimination.

To determine whether the observed improvement was statistically significant, pairwise comparisons were conducted using the DeLong non-parametric test for correlated ROC curves [27].

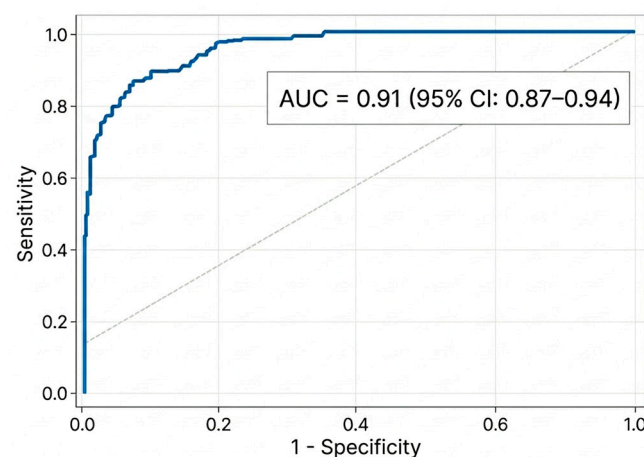
August vs. September: $\Delta AUC = 0.04$, $p = 0.018$

September vs. October: $\Delta AUC = 0.03$, $p = 0.041$

August vs. October: $\Delta AUC = 0.07$, $p < 0.001$

All comparisons show statistical significance ($p < 0.05$), confirming that the improvement in discrimination capability is not attributable to sampling variability.

The final ROC curve corresponding to the stabilized October process is presented in Figure 8.

**Figure 8.** Area Under the Curve (AUC).

5.6. Industrial Validation Through Production Metrics

Production data are summarized in Tables 11–13, while the associated economic impact is shown in Table 14. CW31–CW43 correspond to calendar production weeks (Week 31 to Week 43).

Table 11. Production metrics for August.

Line	CMS					
Month	Aug.					
	CW31	CW32	CW33	CW34	CW35	Accumulated
Availability	87.80%	85.91%	94.35%	103.46%	82.54%	90.81%
Efficiency	99.15%	99.66%	99.51%	98.96%	98.22%	99.10%
Quality	86.46%	84.70%	89.50%	91.05%	87.62%	87.87%
OEE	75.46%	72.97%	84.02%	93.29%	72.15%	79.58%
Parts produced	1729	2057	1115	1618	500	7019
Rework %	14.34%	12.59%	10.49%	9.02%	8.60%	11.58%
Rework Pcs	248	259	117	146	43	813
Downtime (min)	Accumulated					
Production	6	12	0	0	0	18
Maintenance	145	140	194	42	8	529
Control	57	78	0	0	19	154
Mechanical	0	0	0	0	0	0
Robot	415	496	75	98	146	1230
Actual productive time	2908	3489	1858	2648	949	11,852
Total productive time	3531	4215	2127	2788	1122	13,783

Table 12. Production metrics for September.

Line	CMS					
Month	Sept.					
	CW35	CW36	CW37	CW38	CW39	Accumulated
Availability	91.85%	92.20%	98.07%	92.25%	83.71%	91.62%
Efficiency	98.83%	98.79%	99.40%	99.14%	98.96%	99.02%
Quality	89.79%	91.86%	90.60%	93.10%	93.73%	91.82%
OEE	81.81%	83.89%	88.43%	85.18%	77.65%	83.39%
Parts produced	946	1907	865	1593	1442	6753
Rework %	8.99%	7.76%	9.02%	6.97%	4.51%	7.21%
Rework Pcs	85	148	78	111	65	487
Downtime (min)	Accumulated					
Production	10	14	0	0	0	24
Maintenance	35	57	69	184	100	445
Control	18	35	0	7	14	74
Mechanical	0	0	0	0	0	0
Robot	185	312	69	156	388	1110
Actual productive time	1587	3378	1428	2734	2564	11,691
Total productive time	1835	3796	1566	3081	3066	13,344

Table 13. Production metrics for October.

Line	CMS				
Month	Oct.				
	CW40	CW41	CW42	CW43	Accumulated
Availability	96.83%	86.18%	94.61%	94.34%	92.99%
Efficiency	98.98%	97.24%	99.78%	99.70%	98.93%
Quality	93.74%	93.47%	96.61%	94.43%	94.56%
OEE	89.84%	78.29%	91.23%	88.68%	87.01%
Parts produced	1643	2129	1943	337	6052
Rework %	6.21%	5.26%	2.93%	5.04%	4.76%
Rework Pcs	102	112	57	17	288
Downtime (min)	Accumulated				
Production	7	26	0	0	33
Maintenance	25	94	104	7	230
Control	4	192	18	0	214
Mechanical	0	3	0	0	3
Robot	121	203	80	49	453
Actual productive time	2891	3896	3403	589	10,779
Total productive time	3048	4414	3605	645	11,712

Table 14. Economic impact of fixture optimization.

Month	Rework Cost (USD)
August	1,500,000
September	890,000
October	432,000

The indicators corresponding to the month of September are presented in Table 12. During this stage, partial improvements were implemented in the geometry of the clamping system, slightly reducing the mechanical variability of the assembly.

Table 12 shows a moderate decrease in rework and downtime compared to the previous month, along with an increase in the OEE of the cell. These results reflect an initial reduction in δ_{tot} and, consequently, in the effective stick-out. From the perspective of the coupled process–fixture model (Section 4.3). This trend is in agreement with previous studies on automated welding, which report that improved process stability—including arc stability through enhanced geometric control leads to reduced welding defects and improved quality [21,23].

The final results, corresponding to the month of October, are presented in Table 13. This period reflects the full implementation of geometric standardization of the fixture and the elimination of the main sources of mechanical variability. As shown in Table 13, the rework percentage decreases to 4.76%, and the OEE reaches 87%, demonstrating a substantial and sustained improvement in productive performance.

From a mathematical perspective, these results correspond to minimal values of δ_{tot} and, therefore, to a reduced fixture influence factor X_f . From an industrial and geometric precision standpoint, reduced geometric variability and improved fixturing consistency have been shown to significantly decrease displacement and geometric errors in welded

assemblies, leading to improved quality and reduced defects in automated welding systems [28]. Indicating that the mechanical contribution of the fixturing system to process variability has been significantly mitigated. Similar improvements in repeatability, defect reduction, and productive performance following geometric standardization and enhanced process stability in welding systems have been reported in the literature, confirming that stabilization of the mechanical state of the system leads to sustained gains in welding quality and efficiency [28,29]. These results confirm the validity of the coupled process–fixture model proposed in Section 4.

Geometric standardization measures included dimensional tolerance control of fixture bases and reinforcement of contact points. These modifications reduced X_f , resulting in decreased porosity and increased OEE, as evidenced in Table 13. Improved arc stability and controlled geometric consistency have been directly correlated with enhanced weld quality and reduced defect formation in automated GMAW systems [29].

The overall economic impact of these improvements is summarized in Table 14, integrating the cumulative effects observed during the three-month evaluation period.

The sustained reduction in rework and cost validates Equation (13):

$$P = f(E_l, X_f)$$

As X_f decreases due to geometric standardization, process stability improves and the probability of porosity formation P is significantly reduced, even under constant nominal welding parameters. These results demonstrate that mechanical fixture control acts as a governing variable within the coupled process–fixture model and has a measurable impact not only on metallurgical quality but also on economic performance. Similar positive correlations between improved fixturing, reduced angular distortion, and lower production cost have been reported in recent welding studies, where optimized welding configurations led to significant reductions in both geometric distortion and welding cost/time compared to conventional methods [30].

6. Conclusions

A coupled thermo-mechanical probabilistic framework for porosity prediction in robotic CMT welding has been developed and validated under industrial operating conditions. The formulation departs from conventional energy-based approaches by explicitly incorporating fixture-induced geometric variability into the effective electrode stick-out SO_{eff} and by defining a dimensionless fixture influence factor X_f . Statistical analysis demonstrated the dominant role of mechanical coupling within the evaluated operating window. The fixture influence factor exhibited the highest standardized effect (OR = 3.74), while a 1 mm increase in effective stick-out doubled porosity probability (OR = 2.10). The final calibrated model achieved strong predictive discrimination (AUC = 0.91; 95% CI: 0.87–0.94).

Industrial implementation confirmed model relevance: geometric stabilization reduced rework from 11.58% to 4.76% and increased OEE from 79.58% to 87%, accompanied by a 71% reduction in rework cost.

These results establish fixture mechanics as a primary control variable in robotic CMT welding and validate the proposed coupled process–fixture framework as a predictive tool for quality optimization under real production conditions.

7. Limitations and Future Work

While the study focused on the Crashbox X246, the proposed framework can be extended to other components, provided δ_{tot} and X_f are defined. Further experiments are required to validate the model across different materials and geometries. Future work

should include validation across different materials and geometries, integration of real-time monitoring systems, and finite element analysis to further enhance predictive capability.

Author Contributions: Conceptualization, P.Y.-C., V.G.-A. and F.J.S.-B.; methodology, P.Y.-C.; software, R.M.d.C.-V. and V.G.-A.; validation, P.Y.-C., F.J.S.-B. and R.M.d.C.-V.; formal analysis, P.Y.-C.; investigation, P.Y.-C.; resources, R.M.d.C.-V.; data curation, P.Y.-C.; writing—original draft preparation, P.Y.-C.; writing—review and editing, P.Y.-C.; visualization, P.Y.-C.; supervision, P.Y.-C.; project administration, P.Y.-C., F.J.S.-B. and R.M.d.C.-V.; funding acquisition, P.Y.-C. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Acknowledgments: The authors are grateful to the Universidad Politécnica de Guanajuato for the support provided for the development of this study.

Conflicts of Interest: The authors declare no conflicts of interest.

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