Advancing Tilt Angle Control in Friction Stir Welding using Fuzzy Logic

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DOI: https://doi.org/10.51583/IJLTEMAS.2026.150600225

Received: 12 July 2026; Accepted: 17 July 2026; Published: 25 July 2026

ABSTRACT

Friction Stir Welding (FSW) is a solid-state joining technique renowned for its ability to produce high-quality welds in aluminum and other non-ferrous metals. A critical parameter influencing weld integrity is the tool tilt angle, which, if improperly set, can lead to defects such as tunnel voids, surface irregularities, or poor material mixing. This study presents a fuzzy logic-based control system for real-time adjustment of the tool tilt angle during FSW. The proposed system utilizes inputs such as torque, temperature, and plunge depth deviation to infer optimal tilt corrections using a Mamdani-type fuzzy inference system. Triangular membership functions and an expert-defined rule base were implemented in MATLAB to simulate adaptive tilt adjustments. Simulation results showed that for a torque input of 10 Nm, a temperature of 45 °C, and a plunge deviation of 0.5 mm, the system produced a tilt adjustment value of 0.224°, as calculated through centroid defuzzification. Surface plots confirmed that the controller responds smoothly to varying conditions, with tilt adjustments ranging from -0.4° to +0.5° based on combined sensor inputs. The proposed system offers a robust and flexible solution suitable for integration into CNC-based FSW platforms for improved automation and weld quality.

Keywords: Friction Stir Welding, Fuzzy Logic, Tilt Angle, Torque, Temperature, Plunge.

INTRODUCTION

Friction Stir Welding (FSW), developed by The Welding Institute (TWI) in 1991, has emerged as a revolutionary solid-state joining technique, especially for materials such as aluminum and its alloys that are often challenging to weld using traditional fusion-based methods[1]. Unlike conventional welding, FSW does not involve melting of the base materials, resulting in superior mechanical properties, reduced residual stresses, and minimal distortion[2][3].To further advance research of FSW ,Among the various process parameters that govern weld quality in FSW such as tool rotational speed, traverse speed, axial force, and plunge depth the tilt angle of the tool plays a critical role. It influences material flow, heat generation, forging action, and the consolidation of the stirred material[4]. An optimal tilt angle ensures continuous contact between the tool shoulder and the workpiece, promoting effective stirring and reducing surface or subsurface defects.

In conventional FSW operations, the tilt angle is typically set to a fixed value before welding begins and remains unchanged throughout the process. However, this static approach may not be sufficient in practical applications where process conditions vary due to differences in material thickness, joint configuration, thermal gradients, or tool wear[5]. In such cases, a fixed tilt angle can result in inconsistent weld quality, surface irregularities, tunnel voids, or incomplete bonding.

To address this limitation, adaptive control methods are gaining traction in FSW research. Fuzzy Logic Control (FLC), known for its robustness in handling nonlinear, multivariable systems with uncertain or imprecise inputs, presents a compelling solution[6][7]. By mimicking human reasoning and expert decision-making, FLC can

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VI, June 2026

dynamically interpret sensor data such as torque, temperature, and plunge deviation and infer the necessary adjustments to the tilt angle in real time[8].

This study proposes the development and implementation of a fuzzy logic-based control system for real-time tilt angle adjustment during Friction Stir Welding. The goal is to enhance weld consistency, reduce defect formation, and improve process adaptability under varying welding conditions.

LITERATURE REVIEW

Friction Stir Welding (FSW) has gained significant traction in recent decades as a reliable and efficient solid-state joining technique, particularly for aluminum and other low-melting-point materials. Initially developed by The Welding Institute (TWI) in 1991, FSW avoids melting the base materials, thereby reducing defects such as porosity and hot cracking that are common in conventional fusion welding methods[9][10]. Among the several process parameters that influence FSW quality such as rotational speed, travel speed, plunge depth, and tilt angle, the tilt angle plays a critical role in maintaining effective material flow, adequate forging action, and proper consolidation of the weld [4].

While early FSW processes relied on fixed tilt angles throughout the welding process, researchers have recognized that a static tilt angle can limit weld adaptability and lead to inconsistencies when dealing with varying plate thicknesses, material properties, or joint geometries. Several studies have emphasized that improper tilt angles can result in surface irregularities, tunnel defects, or insufficient material mixing, all of which degrade weld quality[11][12]. Consequently, there is growing interest in real-time control mechanisms capable of adjusting process parameters, including tilt angle, in response to in-process feedback.

Fuzzy logic controllers (FLCs) have emerged as powerful tools in handling the uncertainties and nonlinearities inherent in welding processes. As a rule-based decision-making framework, fuzzy logic mimics human reasoning by transforming vague or imprecise sensor inputs into control actions using linguistic rules[13][14]. Several researchers have applied fuzzy logic to FSW parameter control. For instance, [5] employed fuzzy inference to regulate tool speed based on real-time temperature data, demonstrating improvements in mechanical properties and defect minimization. Similarly, studies by [15] integrated fuzzy systems into robotic FSW platforms to dynamically adjust tool path and force based on resistance feedback.

The integration of torque, temperature, and plunge deviation as inputs into a fuzzy inference system offers a robust method to dynamically control tilt angle. Torque provides insight into the resistance experienced by the tool, often indicating changes in material hardness or improper plunge. Temperature reflects the thermal balance of the process, crucial for maintaining proper softening and flow without overheating. Plunge deviation helps detect variations in plate thickness or tool misalignment critical for maintaining weld consistency. Recent works, such as those by [16], have highlighted the potential of multi-sensor fuzzy-based control systems for achieving adaptive welding quality across different operational scenarios.

Despite the promise of fuzzy logic systems, most implementations still rely on static rule bases defined by experts. There is a growing trend toward enhancing FLCs through hybrid approaches that incorporate machine learning for rule extraction and optimization[17]. Additionally, while dynamic tilt angle control has been discussed conceptually, its practical application, especially in robotic or CNC-based FSW platforms, remains relatively underexplored in the literature.

This study contributes to the body of knowledge by designing and experimentally validating a fuzzy logic-based system for real-time tilt angle correction in FSW. By integrating real-time feedback and a Mamdani-type fuzzy inference structure, the system demonstrates improved adaptability, weld consistency, and quality under varying process conditions.
2.2

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VI, June 2026

Friction Stir Welding for Space Manufacturing

Advancing the missions involving orbital assembly, satellite servicing, lunar base construction, and deep-space exploration will depend on robust joining processes that can fabricate and repair metallic structures with minimal human intervention. Among the available solid-state joining technologies, Friction Stir Welding (FSW) is particularly well suited for in-space manufacturing because it eliminates the need for filler materials, shielding gases, and molten metal, making it highly compatible with vacuum and microgravity environments. A fundamental challenge in deploying FSW in space is maintaining an optimal tool tilt angle throughout the welding process[4].

Advancing tilt angle control is therefore essential to achieving consistent, high-quality welds in space. Emerging technologies such as artificial intelligence, fuzzy logic, machine learning, digital twins, and sensor fusion provide powerful tools for developing adaptive tilt angle control systems. These intelligent approaches enable predictive decision-making, autonomous process optimization, and real-time correction of deviations without human intervention. Consequently, they improve weld quality, minimize defects, enhance structural reliability, and increase the overall efficiency of in-space manufacturing operations [5]. The advancement of adaptive tilt angle control in Friction Stir Welding represents a critical enabling technology for the next generation of autonomous space manufacturing.

METHODOLOGY

System Architecture

The proposed control architecture for tilt angle adjustment in Friction Stir Welding (FSW) integrates a various input parameter, a fuzzy inference system (FIS), and an actuated tilt adjustment mechanism as shown in figure 1. The input parameters are key process variables specifically, torque, temperature, and plunge depth deviation. These inputs are crucial indicators of tool resistance, thermal conditions, and tool alignment, respectively, and are fed into the FIS for intelligent control decisions. The input variables depict the membership value input and output, and fuzzy defines rules formulated by human experts who have good knowledge of the FSW plant.

3.2 Fuzzy Inference System Design

The fuzzy inference system, designed using the Mamdani fuzzy logic model in MATLAB, interprets these sensor signals to generate real-time tilt angle corrections. The system utilizes a combination of triangular membership functions to fuzzy the input data into linguistic categories such as Low, Medium, and High. For instance, the torque input is classified into three fuzzy sets representing varying levels of resistance encountered by the tool; this helps the controller determine whether increased plunge or tilt is required.

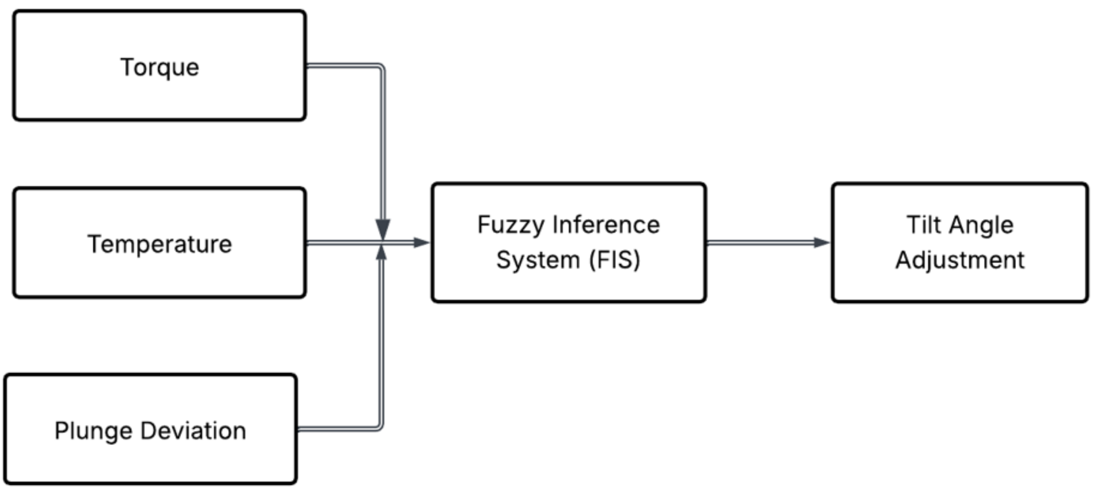


Figure 1: Tilt Angle Control in Friction Stir Welding

Likewise, temperature membership functions play a vital role in managing the thermal dynamics of the welding process. These are also divided into Low, Medium, and High fuzzy sets, with overlapping boundaries to ensure soft transitions between states. This fuzzy categorization enables the system to respond gradually to changes in temperature, preventing abrupt corrections that could destabilize the process. In temperature-sensitive operations like FSW, such gradual adaptation is critical to maintaining consistent material flow, avoiding overheating, and ensuring structural integrity of the weld. Also, the third input, plunge deviation, represents the variation between the actual and desired tool plunge depth. Its membership functions allow the system to recognize whether the deviation is minor or significant, guiding corrective actions accordingly to prevent over-penetration or incomplete joining.

Based on these inputs, the fuzzy logic controller applies a rule base developed from expert knowledge and experimental analysis to infer the appropriate output. The output variable tilt angle adjustment is represented by fuzzy sets such as Decrease, No Change, and Increase. The FIS performs defuzzification using the centroid method to convert the fuzzy output into a crisp tilt correction value. This output is then used to drive an actuated tilt mechanism, which dynamically adjusts the tool orientation during welding. This closed-loop system allows the tool to adapt in real time to changing conditions, thereby reducing defects and improving weld consistency across varying joint configurations and material properties.

Fuzzy logic systems utilize membership functions to model imprecise and gradually changing input variables in a way that supports intelligent and adaptive decision-making. These membership functions define how input values are categorized into linguistic variables such as Low, Medium, High, Increase, or Decrease. For instance, in a process like Friction Stir Welding (FSW) or other precision control applications, various input variables such as torque, temperature, plunge deviation, and tilt angle correction can be fuzzified to enable smooth control actions.

Torque membership functions classify torque values into fuzzy sets like Low with Triangular MF → $\mu\_low(x) = trimf(x; 0, 0, 10)$, Medium with Triangular MF → $\mu\_medium(x) = trimf(x; 5, 10, 15)$, and High with Triangular MF → $\mu\_high(x) = trimf(x; 10, 20, 20)$, allowing the system to interpret resistance levels encountered during welding. This helps adjust process parameters to maintain weld quality. Similarly, temperature membership functions group readings into overlapping categories, providing a mechanism for gradual thermal control, which is essential in avoiding abrupt shifts that could compromise system stability.

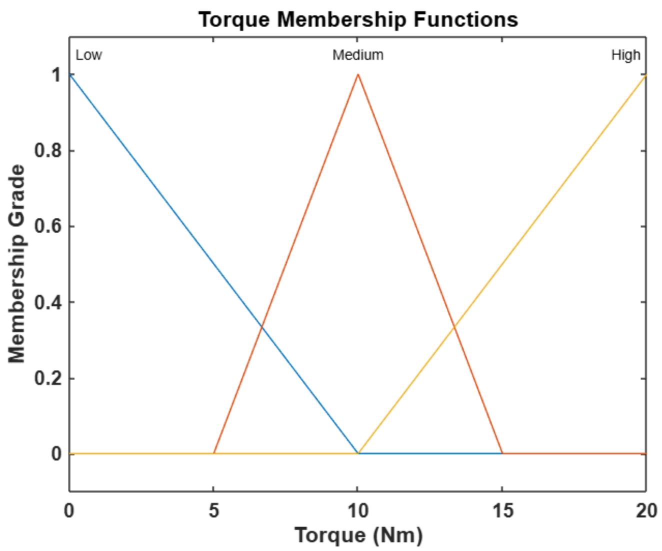


Figure 2: Torque membership functions

Plunge deviation membership functions monitor the variation between actual and desired plunge depth, categorizing deviations as Low, Medium, or High. This classification is particularly useful in precision tasks where maintaining consistent depth is crucial to structural integrity and process success.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VI, June 2026

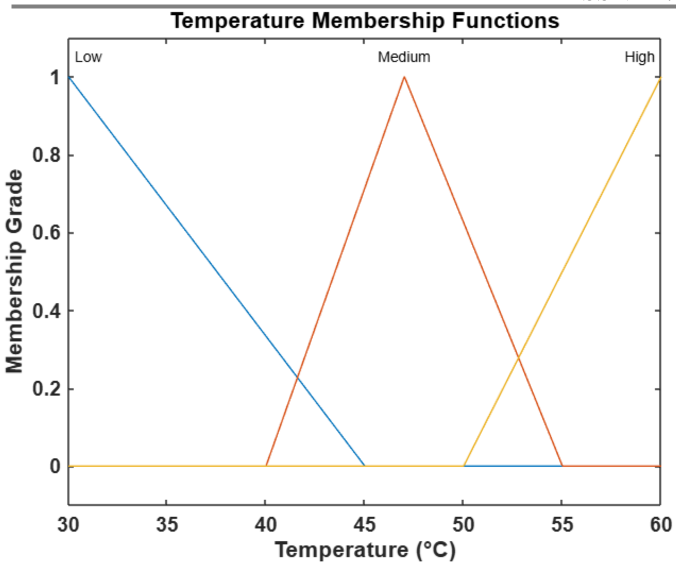


Figure 3: Temperature membership functions

Overall, fuzzy logic membership functions enhance the ability of control systems to handle real-world variability by supporting soft transitions between states. This makes them highly effective in applications such as robotics, smart manufacturing, and digital agriculture, where environmental and operational conditions are often uncertain or continuously shifting.

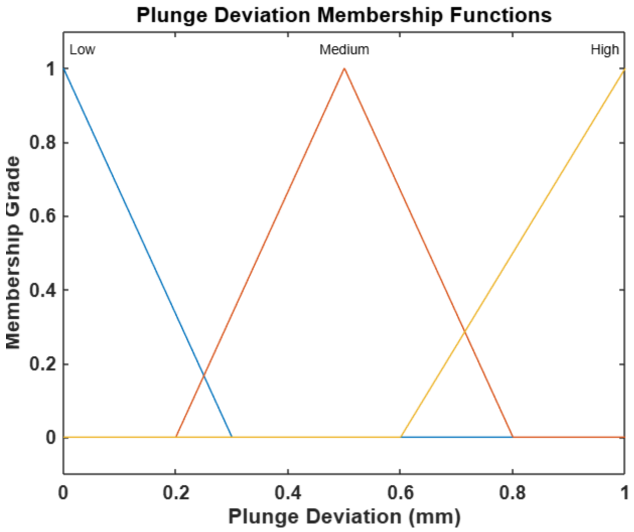
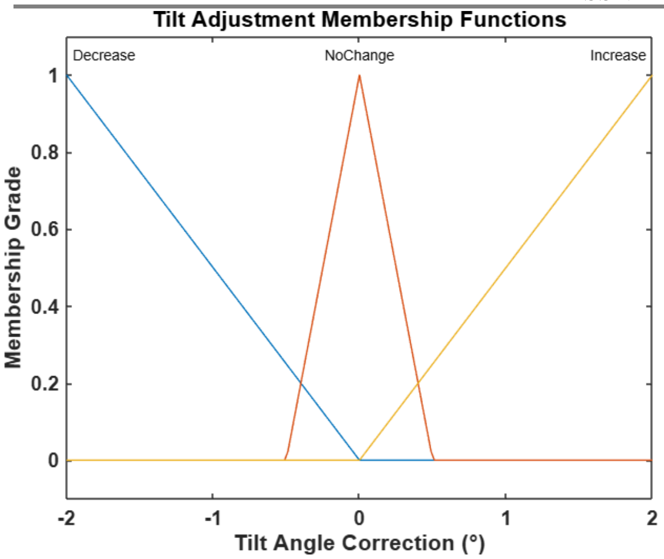


Figure 4: Plunge deviation membership functions

The temperature input variable, measured in degrees Celsius, is critical in processes like Friction Stir Welding, where both high and low temperatures can negatively affect material mixing or cause overheating. To handle this, temperature is fuzzified into three linguistic categories: Low, Medium, and High. The Low temperature membership function is defined as a triangular function with full membership at 30°C that decreases linearly to zero at 45°C. The Medium temperature set peaks at 47°C, with membership gradually increasing from 40°C and tapering off by 55°C. Finally, the High temperature membership function rises starting at 50°C and reaches full membership at 60°C, representing conditions of potential overheating. The overlapping nature of these triangular membership functions allows the control system to interpret temperatures smoothly, enabling gradual and stable adjustments rather than abrupt changes, which is essential for maintaining weld quality and process stability.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VI, June 2026



Finally, tilt adjustment membership functions, as illustrated in the accompanying figure, map tilt angle correction values to fuzzy sets like Decrease, No Change, and Increase. These functions guide the system in correcting the tool's tilt angle gently and accurately, ensuring that optimal orientation is preserved during operation.

Figure 5: Tilt adjustment membership functions

The defuzzification process for this experiment modelling uses a centroid technique method. The Centroid method is used to convert the output fuzzy set into a crisp tilt correction value. This gives a weighted average of the area under the combined output fuzzy set to compute the final tilt angle correction.

$$\textbf{Crisp output} = \frac{\int x.\mu(x)dx}{\int \mu(x)dx} \qquad Eqn\ (1)$$

RESULTS AND DISCUSSION

This section presents the outcomes of the fuzzy inference system simulation and interprets the implications of the findings. The results are visualized using surface plots to demonstrate how the system responds to various combinations of input variables, namely torque, temperature, and plunge deviation in determining the appropriate tilt adjustment.

The discussion aims to provide insights into the logic embedded within the fuzzy controller and how it reflects practical considerations in applications such as friction stir welding.

Simulation Results

The surface plots in figures 6 and 7 illustrate how a fuzzy inference system determines tilt adjustment based on different combinations of input variables specifically, torque, temperature, and plunge deviation. In the figure 6, the relationship between torque and temperature with respect to tilt adjustment is shown. As torque increases from 0 to 20 Nm and temperature remains within a moderate range (approximately 30–40°C), the tilt adjustment value rises significantly.

This suggests that the system interprets high torque combined with moderate temperatures as a condition that requires positive tilt correction, likely to reduce tool resistance or enhance process stability in operations such as friction stir welding.

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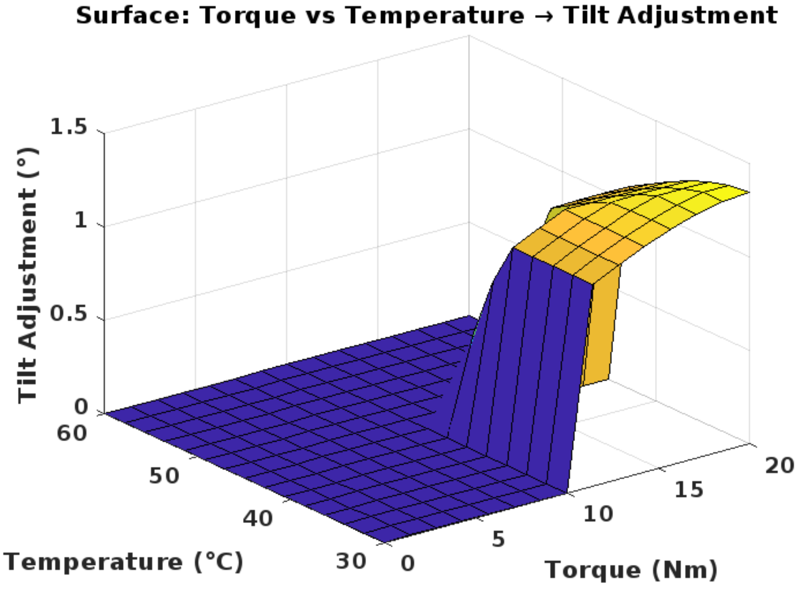

Figure 6:

Surface plot for Torque vs Temperature & Tilt Adjustment

While figure 7 depicts the relationship between plunge deviation and torque with respect to tilt adjustment is visualized. The surface shows that when plunge deviation is high (approaching 1 mm), the tilt adjustment is significantly negative. As the deviation decreases toward zero, the tilt adjustment shifts toward zero or slightly positive values. Interestingly, torque appears to have a less pronounced effect in this scenario, indicating that plunge deviation is the dominant factor influencing tilt correction in this rule set. The system likely responds this way to prevent over-penetration or material distortion by reducing the tool's tilt when excessive plunge is detected.

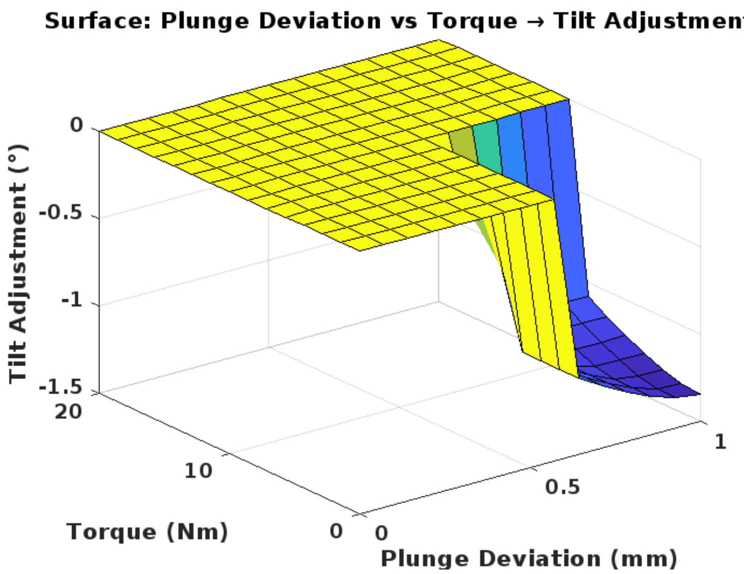

Figure 7: Plunge Deviation vs Torque & Tilt Adjustment

Together, these plots highlight the adaptive nature of the fuzzy logic controller. By integrating multiple sensory inputs and applying rule-based reasoning, the system generates smooth and intelligent tilt adjustments. This approach is particularly useful in real-time control applications where conditions vary continuously, such as welding automation and FSW applications.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue VI, June 2026

Furthermore, figure 8 displays a Fuzzy Logic Rule Viewer for a system named *TiltAngleAdjustmentFIS*, which likely controls the tilt angle adjustment of a friction stir welding tool based on three input parameters: Torque, Temperature, and Plunge Deviation. The current input values are Torque = 10, Temperature = 45, and Plunge Deviation = 0.5. Each of these inputs is shown with associated membership functions for instance, the third input (Plunge Deviation) shows triangular membership functions in yellow, and the red vertical lines indicate the current crisp input values' positions within these fuzzy sets.

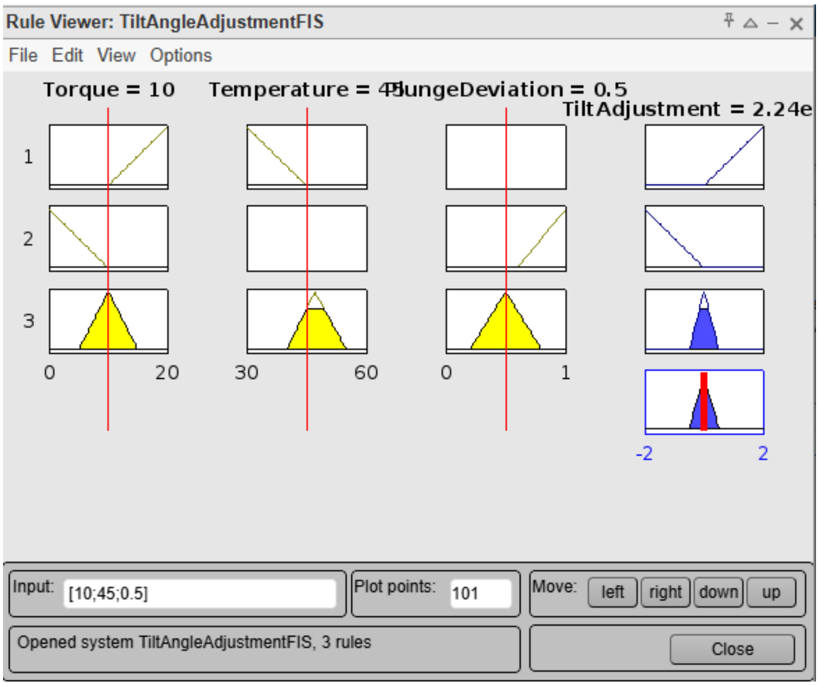

Figure 8: Fuzzy Logic Rule Viewer

The rightmost column represents the output variable, Tilt Adjustment, which is computed based on fuzzy inference rules (three in this case). The overlapping blue and white areas in the output plot reflect the combined output from the activated rules, and the red vertical line represents the final defuzzified value: approximately 2.24e-01 (or 0.224). This value suggests the amount by which the tool's tilt angle should be adjusted in response to the given input conditions, as determined by the fuzzy logic system for smoother or more precise operation during the welding process. The system can be integrated into CNC-based FSW machines or retrofitted into existing setups with minor modifications.

CONCLUSION

This study confirms the feasibility and effectiveness of using a fuzzy logic-based control system for real-time tilt angle adjustment in Friction Stir Welding (FSW). By integrating sensor feedback specifically torque, temperature, and plunge deviation into a Mamdani-type fuzzy inference system, the controller enables dynamic and intelligent tilt corrections that enhance weld consistency, reduce defects, and improve adaptability to varying welding conditions. The results highlight the system's potential for integration into automated or CNC-based FSW platforms, providing a robust and responsive approach to weld quality control. Future work will explore the incorporation of machine learning techniques to optimize the fuzzy rule base and extend the system's capabilities to handle multi-pass welding, dissimilar material joints, and more complex welding geometries.

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