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Research Article

Neuro-Fuzzy Inference System for Accurate Prediction of Z-Axis Values in Screw Installation

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Abstract: High precision in automated screw installation is crucial for ensuring product quality and operational efficiency in modern manufacturing. A key challenge is accurately predicting the Z-axis value based on screwing depth and torque, which exhibit complex nonlinear relationships. This study proposes an Adaptive Neuro-Fuzzy Inference System (ANFIS) model to enhance predictive accuracy. Experimental data are collected by varying the mounting depth and torque and then preprocessed through normalization before training the model. The ANFIS model is designed with fuzzy membership functions and trained using a hybrid learning algorithm. The performance evaluation using the root mean squared error (RMSE) has a value of 2.52×10^{-3}, indicating high prediction accuracy. Residual error analysis revealed a near-normal distribution after transformation, with skewness of 0.2672 and kurtosis of 3.1112. Error analysis on extreme Z values revealed a mean residual error of 1.34×10^{-2} for low Z (< 47.1) and 0.0091247 for high Z (> 47.4), confirming the model's reliability. The Kruskal-Wallis test further validates ANFIS's superiority over Support Vector Regression (SVR) and Random Forest Regression (RFR), with an H-value of 115.62 and a p-value of 0.000. The results demonstrate that ANFIS effectively captures the dependencies between input parameters and Z values, achieving minimal deviation from the actual values. This research contributes to intelligent manufacturing by enabling predictive monitoring and adaptive control. Additionally, it aligns with Sustainable Development Goal (SDG) 9 by promoting resilient infrastructure and sustainable industrialization. Future work may explore the integration of real-time sensor feedback or the hybridization of ANFIS with deep learning for enhanced adaptability in dynamic industrial settings.

Keywords: ANFIS; Mounting depth; Mounting torque; Predictive modelling; Precision assembly

1. Introduction

In modern manufacturing, component assembly precision is crucial for high-quality production and operational efficiency. Accurately predicting assembly parameters, such as depth and torque, is critical because small deviations can lead to defects and increased costs. This research has led to a demand for intelligent systems that can model complex relationships between inputs and outputs, improving predictive accuracy. Screw fastening, particularly for electronic modules in compact structures, plays a vital role in ensuring long-term reliability with minimal PCB deformation (Tsenev et al., 2021). The optimal

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hole diameter for threading is critical for high-quality joints in electronic devices (Danylova et al., 2022), and optimized screw group fastening enhances the reliability and lifespan of components in mechatronic systems (Guan et al., 2024). An ANFIS model is developed to approximate the complex nonlinear relationship between input variables (e.g., real-time data) and output variables (e.g., optimal control actions) (AbouElaz et al., 2025). Its robust model-building process, which integrates grid partitioning, sub-clustering, and fuzzy c-means, strengthens fuzzy inference systems (Akkaya, 2016; Deshwal et al., 2020). ANFIS and other machine learning techniques learn patterns from data without predefined assumptions (Noorsaman et al., 2023).

ANFIS is highly effective in predictive modeling, providing accurate predictions aligned with experimental results (Azhar et al., 2023). It is particularly useful in screw installation, where determining Z-axis values from depth and torque inputs improves assembly precision (Mostafaei, 2018). ANFIS outperforms ANN in predicting mechanical properties (Zare and Vahdati Khaki, 2012) and is widely used in industrial systems, such as Dapito and Chua's COP prediction model for refrigeration compressors (Jeffrey L. Dapito, 2024). ANFIS excels in capturing nonlinear relationships, optimizing manufacturing efficiency, and reducing reliance on costly experiments (Halim and Sahroni, 2023). It handles complex algorithms and uncertainties by leveraging experimental data (Kiran and Rajput, 2011). The integration of ANN and fuzzy set theory allows dynamic inference rules, making it ideal for predicting screw installation parameters (Güneri et al., 2011). Compared with other machine learning algorithms, such as GLM, DL, DT, RF, GBT, and SVM, ANFIS uniquely combines rule-based reasoning with adaptive learning (Sari, Berawi, et al., 2023), excelling in nonlinear system modeling, such as automated screw installation.

In manufacturing, toolpath inaccuracies can cause device deviations, necessitating precise trajectory predictions (Dat and Phuc, 2024). Similarly, ANFIS enhances Z-axis prediction accuracy in screw installation, thereby improving assembly precision. ANFIS autonomously adjusts weights and membership functions during training by combining the learning capabilities of ANN with fuzzy logic, minimizing prediction errors without predefined parameters (Hynes and Kumar, 2017; Saghaei and Didehkhani, 2011). This adaptability is crucial for tasks such as screw installation, where accurate Z-axis predictions based on depth and torque ensure product reliability. ANFIS is also effective in machining and predicting tool life based on cutting speed, feed rate, and cut depth (Khorasani et al., 2011). In screw installation, complex input relationships are modeled, and conditions are optimized to minimize defects and improve efficiency. By integrating AI-driven tools, ANFIS reduces the reliance on physical trials (Hossain and Ahmad, 2014). The use of various membership functions, such as trim, trauma, and gauss, ensures accuracy in predicting techno-economic parameters (Ajala et al., 2023). ANFIS ensures precise predictions by aggregating and demulsifying fuzzy rule outputs, making it ideal for modeling nonlinear relationships in screw installation and enhancing manufacturing control (Rahman et al., 2022).

Integrating fuzzy logic and ANN in ANFIS provides an effective solution for nonlinear systems, particularly in screw installation, where traditional models struggle with complex relationships like depth and torque (Pano-Azucena et al., 2018). ANFIS combines the computational power of neural networks with the ability of fuzzy logic to handle uncertainty, accurately predicting Z-axis values (Kassem et al., 2018). Unlike conventional ANN models, ANFIS simplifies modeling by overcoming hidden layer limitations and enhancing prediction capabilities (Melin et al., 2012). This model makes ANFIS ideal for precision tasks such as screw installation (Alazzam and Tashtoush, 2021). ANFIS excels in complex, nonlinear systems because it balances fuzzy logic interpretability with ANN adaptability (Ghashami and Kamyar, 2021). It has proven to be effective across engineering fields, surpassing fuzzy PID controllers in two-axis inertial stabilized platforms (F. Liu et al., 2017) and predicting nonlinear behaviors without pre-training (Sarhadi et al., 2016). In manufacturing, ANFIS outperforms conventional regression models, optimizing process parameters in AM (Luis Pérez, 2020; Dhar et al., 2021) and improving control efficiency in systems such as SMC for DC servo systems (George and Mani, 2024). It also excels in torque estimation for flexible joint systems (Y. Liu et al., 2023).

ANFIS has shown high precision in detecting open cracks in rotor-bearing systems, achieving low RMSE (Rao and Reddy, 2023). Applications include classification, rule-based control, pattern recognition, and function approximation, particularly for complex input-output relationships (Surajudeen-Bakinde et al., 2018). Compared with traditional fuzzy systems, ANFIS offers superior prediction accuracy with lower error values (RMSE, MSE, MAPE, and MAE), demonstrating its reliability (Castellões et al., 2024). The integration of ANN and fuzzy logic enables ANFIS to handle nonlinear systems, making it ideal for precision tasks such as screw installation. ANFIS uses fuzzy rules to transform data into actionable insights, simulating human intelligence and expanding its applications (Azad et al., 2018). In machining, ANFIS outperforms regression models in predicting energy consumption, costs, and surface quality (Podder et al., 2017). It has also accurately predicted torque and power, proving its real-world applicability (Machesa et al., 2019) and outperforms traditional methods in tool wear prediction (Saw et al., 2018). In screw installation, ANFIS predicts Z-axis values based on depth and torque inputs, thereby enhancing assembly precision (Mohamed, 2022). Membership functions, such as Gaussian and generalized bell-shaped, reduce prediction errors and improve model accuracy (R. Kumar and Hynes, 2020; S. Kumar and Bansal, 2023). Integration with swarm intelligence optimization algorithms further enhances prediction accuracy (Shoorehdeli et al., 2006), making ANFIS and ANN a reliable solution for manufacturing nonlinear data (Sri et al., 2023). This study focuses on the Z-axis value as a critical output for screw installation, influenced by screw depth and torque for proper fastening and structural integrity.

ANFIS provides a data-driven approach to model these nonlinear relationships, improving prediction accuracy and optimizing assembly processes compared with traditional estimation methods. ANFIS is ideal for predicting Z-axis values in screw installation, as it effectively handles the complexities and uncertainties of the process while delivering accurate predictions. This study focuses on using ANFIS to predict the Z-axis output, which reflects the screw depth and torque-based assembly quality. ANFIS captures the nonlinear relationships between these interdependent variables, thereby providing a reliable solution for improving prediction accuracy and assembly performance. Traditional methods often lead to inaccurate predictions, whereas ANFIS offers more consistent results, enhancing the overall assembly process. Accurate Z-axis prediction is crucial for ensuring the precision, structural integrity, and reliability of the assembled components. Variations in screw depth and torque can cause deviations in the Z-axis, resulting in defects such as improper tightening or misalignment.

ANFIS offers significant potential for optimizing process parameters, reducing errors and material waste, and enhancing product quality by modeling complex nonlinear relationships. This capability enables proactive adjustments, high-precision assembly outcomes, and efficiency and product reliability enhancement. Although ANFIS has shown success in industrial applications such as process optimization, quality control, and fault detection, its use in predicting assembly outcomes with stringent accuracy requirements remains underexplored. This literature gap presents an opportunity for innovation. This study explicitly aims to address this gap by evaluating the ability of ANFIS to predict Z-axis values with high precision using real-world experimental data. The novelty of this research lies in its systematic approach to applying ANFIS to assembly processes, particularly screw installation, where high-precision predictions are critical. This study not only enhances assembly performance by integrating ANFIS into manufacturing systems for predictive monitoring and adaptive control but also provides valuable insights into the feasibility of using ANFIS for improving manufacturing outcomes.

This study aims to develop an ANFIS model for accurately predicting Z-axis values based on screw installation depth and torque. The model's performance is evaluated using key metrics, such as mean squared error (MSE) and root mean squared error (RMSE), to ensure precision in prediction. This research supports SDG 9 by fostering innovation in manufacturing, improving predictive accuracy, and reducing assembly waste. The findings aim to strengthen the integration of intelligent systems in HPM, offering a foundation for future advancements in hybrid intelligent models.

2. Resarch Metchods

2.1 Research Design

This study employs a quantitative experimental design to explore the application of the ANFIS in predicting Z-axis values in high-precision assembly processes. Figure 1 illustrates the methodology used to develop, train, and evaluate the ANFIS models using experimental data. This study focuses on understanding the nonlinear relationship between two input variables, namely, screw installation depth and torque, and the output variable, namely, the Z value, which reflects the quality of the assembly result.

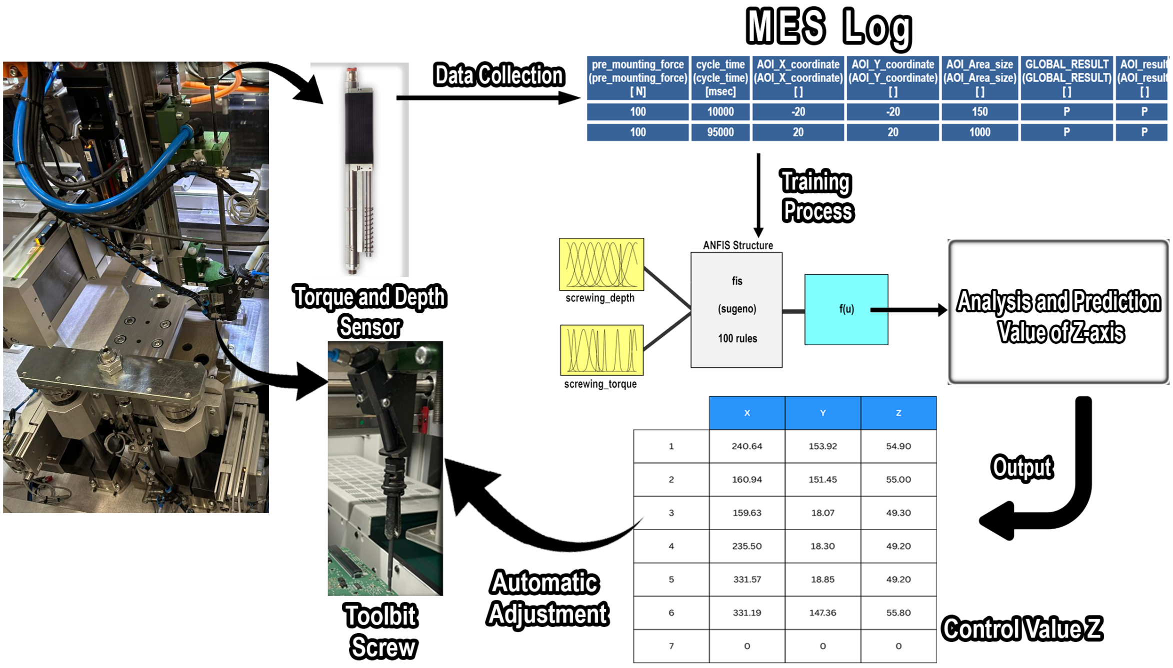

Figure 1 Research Workflow Traaining and Evaluation of ANFIS Models

2.2 Data Collection

2.2.1 Data Source

Experimental data were obtained from a machine-controlled assembly process, where the installation depth and torque values were systematically varied, and the corresponding Z values were measured.

2.2.2 Variables and Measurements

Input:

— Screwing depth (x): Measured in millimeters (mm) using a precision sensor.

— Screwing Torque (y): Measured in Nm using a torque measuring instrument.

Output: The value of Z will appear and be used on the Manufacturing Execution System (MES) integrated with the machine.

To provide an overview of the dataset used for model training, a sample of the training data is presented in Table 1 (supplementary section). The full dataset consists of 658 data entries systematically collected from machine-controlled assembly processes. This dataset was used to train the ANFIS model, with 80% allocated for training and 20% for validation to ensure model generalization.

2.2.3 Data Pre-processing

Min-max scaling was used to normalize the input and output values into a range between 0 and 1, ensuring compatibility with the ANFIS model.

2.3 ANFIS model development

2.3.1 System Architecture

As shown in Figure 2, predictions are made for the Z value based on the screwing depth and screwing torque values as outputs from ANFIS. We use 2 inputs and 1 output:

- x : Input for screwing depth value
- y : Input for the screwing torque value
- f : Output of the Z value

The ANFIS model combines fuzzy logic with AINNs to create a powerful predictive tool (Ziane, 2024). It consists of five layers: The Membership Layer (Layer 1) fuzzifies input data using predefined membership functions. Fuzzy rules in the Rule Layer (Layer 2) determine the firing strength based on membership values. The Normalization Layer (Layer 3) normalizes firing strengths to assess the contribution of each rule. In the Consequent Layer (Layer 4), the model calculates rule outputs by multiplying normalized strengths with linear parameters. Finally, the total output layer (Layer 5) sums the weighted rule outputs to produce a crisp prediction. These steps allow ANFIS to accurately transform input data into predictions (Karaboga and Kaya, 2019; Maher et al., 2014). The model's architecture consists of five main layers:

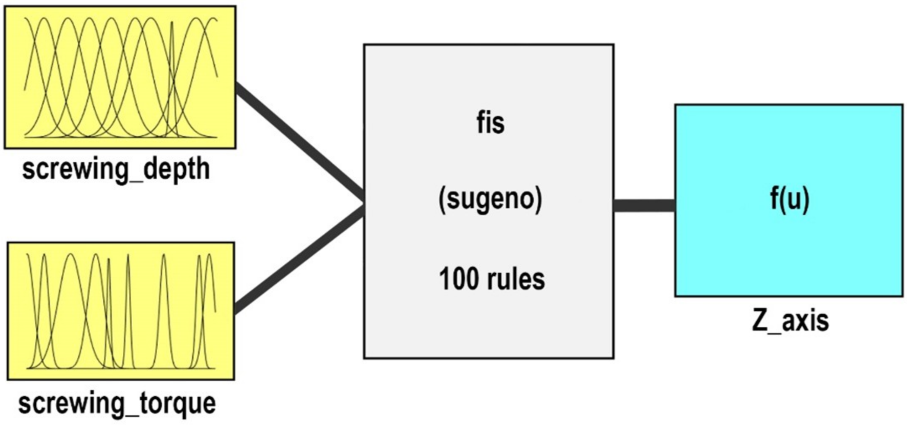

Figure 2 Input and output ANFIS prediction

— **Layer 1 : Membership Layer** (Fuzzyfication Layer) In this layer, the input variables, namely, screwing depth and torque, are fuzzified using predefined membership functions. Three types of membership functions are tested to ensure the optimal performance of the ANFIS model: Gaussian, trapezoidal, and triangular. These functions are selected based on their ability to effectively capture the nonlinear relationships within the dataset. Each node in this layer calculates the membership values of the input variables based on the defined fuzzy sets. The membership functions for Screwing Depth (x) and Screwing Torque (y) are denoted as
$\mu A_i(x)$ = membership function for input x in fuzzy set AiA_i
$\mu B_i(y)$ = fungi keanggotaan untuck input y di fuzzy set BiB_i
For example, with the sample input values:

- Screwing Depth = 8.72: Membership in fuzzy set A_1 : 0.9, Membership in fuzzy set A_2 : 0.8
- Screwing Torque = 0.92: Membership in fuzzy set B_1 : 0.85, Membership in fuzzy set B_2 : 0.8

— **Layer 2 : Rule Layer** (Product Layer or Firing Strength Layer) The IF-THEN fuzzy rules are constructed in this layer based on the input variables and their membership functions. In this study, two primary rules are established:

$$\text{Rule 1 :} \quad IF\ x\ is\ A_1\ and\ y\ is\ B_1,\ THEN\ f_1 = a1x + b1y + r_1 \tag{1}$$
$$\text{Rule 2 :} \quad IF\ x\ is\ A_2\ and\ y\ is\ B_2,\ THEN\ f_2 = a2x + b2y + r_2 \tag{2}$$

Each rule calculates the output based on linear parameters a1,b1, and r1 for Rule 1 and a2, b2, and r2 for Rule 2. The activation strength (firing strength) of each rule is calculated by multiplying the membership values of the inputs using the AND operator:

$$\omega i = \mu Ai(x).\mu Bi(y) \tag{3}$$

For Rule 1, the API is calculated as $0.9 \times 0.85 = 0.765$.
For Rule 2, the API is calculated as $0.8 \times 0.8 = 0.64$.

— **Layer 3: Normalization**
The activation strengths (APIs) computed in Layer 2 are normalized in this layer.

Normalization ensures that the sum of the activation strengths is equal to 1, and the relative contribution of each rule is calculated. The normalization is performed using the following formula:

$$\overline{\omega}_l = \frac{\omega_i}{\omega_1 + \omega_2} \tag{4}$$

For Rule 1, the normalized value is calculated as 0.765 / (0.765 + 0.64) = 0.544.
For Rule 2, the normalized value is calculated as 0.64 / (0.765 + 0.64) = 0.456.

— **Layer 4 : Defuzzy layer**(Consequent layer)
This layer calculates each fuzzy rule's output using the consequent parameters α_i, b_i *and* r_i which are adjusted during training. Each node multiplies the normalized activation strength from Layer 3 by the corresponding linear input function to determine the final output for each rule. The formula used in this layer is as follows:

$$f_i = \overline{\omega}_l.(\alpha_i x + b_i y + r_i) \tag{5}$$

For Rule 1, with parameters $\alpha 1 = 4, b1 = 8$, and $r1 = 31$, the computation is as follows: f1 = 0.544 × [(4 × 8.72) + (8 × 0.92) + 31] = 39.842.
For Rule 2, with parameters $\alpha 2 = 8, b2 = 9$, and $r2 = 45$, the computation is as follows: f2 = 0.456 × [(8 × 8.72) + (9 × 0.92) + 45] = 56.106.

— **Layer 5: Total output layer**
In this final layer, we compute the total output by summing the weighted outputs from each rule. We achieve this by multiplying each normalized activation strength from Layer 3 with the corresponding output from Layer 4 and summing them up to produce the final Z-value prediction. The formula used is:

$$f_{total} = \sum_i \overline{\omega}_i \cdot f_i \tag{6}$$

Substituting the computed values as follows:
total = (0.544 × 39.842) + (0.456 × 56.106) = 47.258.

The ANFIS model combines fuzzification, rule evaluation, normalization, and defuzzification to predict the Z-value and capture the nonlinear relationships between the screwing depth and torque. Its architecture, with antecedent (nonlinear) and consequent (linear) parameters, is ideal for precision tasks such as screw installation. The antecedent parameters define membership functions, whereas the consequent parameters define a linear function with multipliers and additional output parameters. These parameters are optimized using a hybrid backpropagation and least squares method. ANFIS supports parallel computation, offering organized knowledge representation that integrates with other systems, making it a powerful tool for complex manufacturing and engineering challenges (Hussein, 2016; Navarro, 2013).

2.3.2 Takagi-Sugeno-Based ANFIS Implementation

The proposed ANFIS model follows the Takagi-Sugeno inference framework, which comprises five layers with distinct computational functions. Figure 3 illustrates the model architecture.

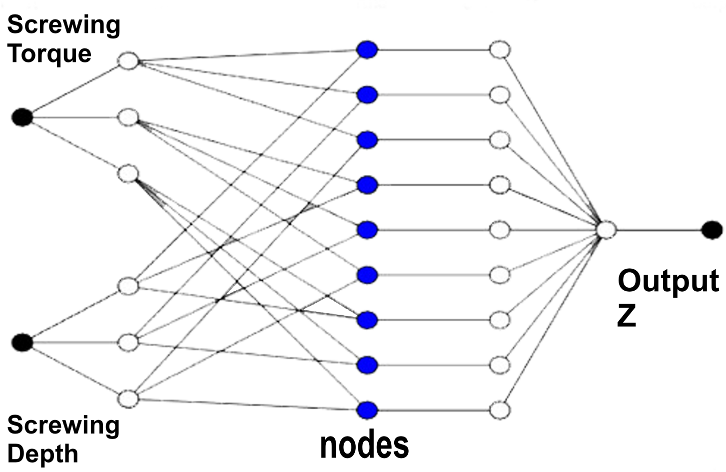

Figure 3 ANFIS prediction layer visualization

2.3.3 Training Process

The ANFIS model is trained using a hybrid learning algorithm that combines gradient descent and least squares estimation.

— Training Data: The model is trained on 80% of the dataset.

— Validation Data: We used 20% of the dataset to validate the model and prevent overfitting.

2.3.4 Hyperparameter Selection

A hybrid optimization method will be employed to prevent overfitting, combining gradient descent with least squares estimation to ensure stable convergence. Additionally, experiments will be conducted to evaluate different membership functions (Gaussian, trapezoidal, and triangular) and identify the optimal number of epochs to achieve the best model performance. This approach prevents overfitting while ensuring high predictive accuracy.

2.4 Model Evaluation

The performance of ANFIS is evaluated by comparing its predictive accuracy with two benchmark regression models: random forest regression (RFR) and support vector regression (SVR), both of which were selected for their ability to handle nonlinear relationships and provide robust regression predictions. The evaluation was conducted using mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE) to ensure a comprehensive assessment of the prediction accuracy and error distribution. In addition, the accuracy of the developed model in predicting output values based on input data was further assessed using MAE and confusion matrix to analyze the performance (Sari, Berawi, et al., 2023).

2.5 Experiment setup abd statistical analysis

Experiments were conducted in a controlled laboratory environment to ensure that installation depth, installation torque, and Z value measurements were consistent. The

ANFIS model was implemented using MATLAB for computational analysis and visualization. Multiple trials were performed to improve reliability, and the model was validated using a separate test set to minimize experimental variability.

To statistically validate the superiority of ANFIS over benchmark models, the Wilcoxon Signed-Rank Test and Kruskal-Wallis Test were applied, as these non-parametric tests are appropriate for datasets that do not follow a normal distribution. The Wilcoxon signed-rank test was used for pairwise comparisons, whereas the Kruskal-Wallis Test assessed performance differences among multiple models. Additionally, mean absolute error (MAE) was employed alongside MSE and RMSE to offer a more interpretable evaluation of prediction errors.

Residual analysis was performed to detect systematic errors or biases in the predictions by examining the residual distribution and identifying any patterns that could indicate overfitting or underfitting.

3. Results and Discussion

3.1 Preprocessing Resuls

3.1.1 Normalization of the Data

Data normalization is a key preprocessing step that improves the performance of ANFIS by ensuring that all input variables are on the same scale. Min-Max Scaling was used to normalize inputs to a range of [0,1], as shown in Table 2 (Supplementary Section). Normalization ensures equal contribution from all variables, preventing dominance by those with larger values. Its benefits include the following:

- Improved training efficiency: Faster convergence by reducing numerical instability.
- Enhanced model accuracy: better generalization and reduced bias.
- Stable Membership Function Learning: Consistent input ranges allow effective fuzzy rule learning.

In Figure 4, the visualization of the data distribution before and after normalization illustrates how Min-Max Scaling transforms the input values into a consistent range of [0,1], ensuring that all input variables are on the same scale. The figure compares the original raw data distribution with the normalized data, showing how the values are rescaled by the normalization process while preserving their relative differences. Normalization maintains the inherent structure of the data while making it suitable for the ANFIS model, which is sensitive to the scale of input variables, by preserving the relative differences between the data points. This step improves the training efficiency, model accuracy, and stability of membership function learning, ensuring that the model effectively learns without being biased by the scale of individual features.

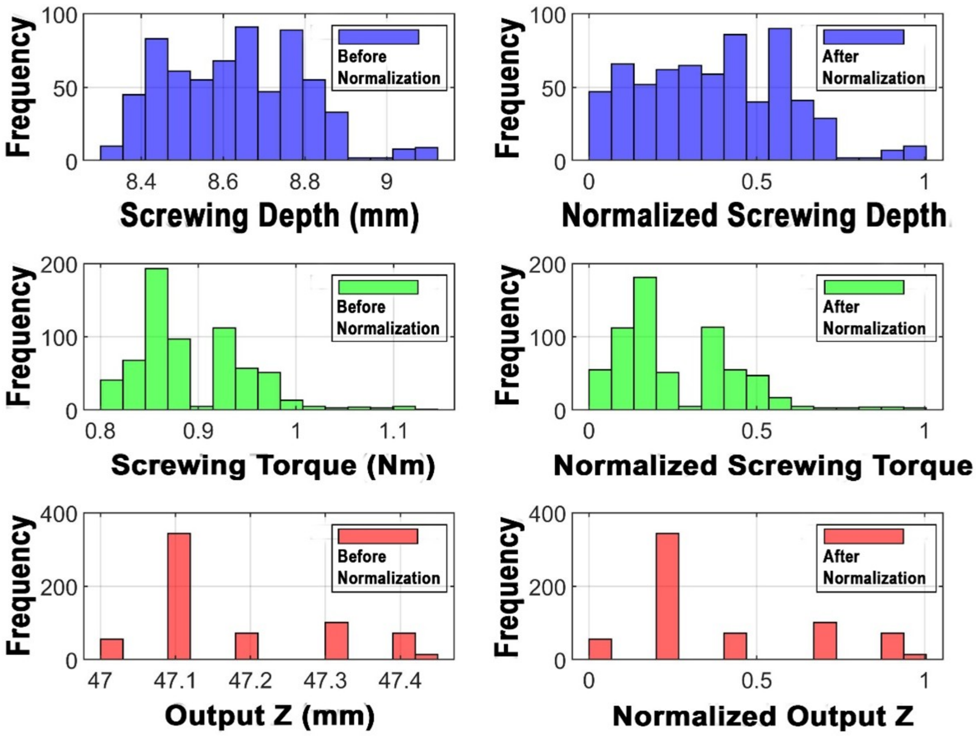

Figure 4 Histogram Distribution Analysis of Screwing Depth, Torque, and Output Z

3.1.2 Data Distribution

The distribution analysis of input and output variables helps assess the reliability of the ANFIS model. The screwing depth and torque exhibit low skewness (close to normal) and platykurtic distributions, indicating a wider spread with fewer extreme values. Meanwhile, the Z-axis output is positively skewed, indicating that the data are slightly shifted to the right but remain platykurtic, similar to the input variables. These characteristics confirm minimal bias in model training, although the Z-axis skewness may require further adjustments to improve prediction accuracy.

3.2 ANFIS model performance

3.2.1 Training and Validation Results

The ANFIS model achieves high predictive accuracy for the Z value, with an average prediction of 47.2455, close to the target of 47.20, and minimal root mean square error (RMSE). The training error decreases rapidly from 0.0058 at Epoch 1 to 0.0040 at Epoch 20, indicating efficient learning. As shown in Table 3, the error stabilizes after Epoch 50, reaching a minimum of 2.161×10^{-3} by Epoch 300, thereby balancing training time and accuracy.

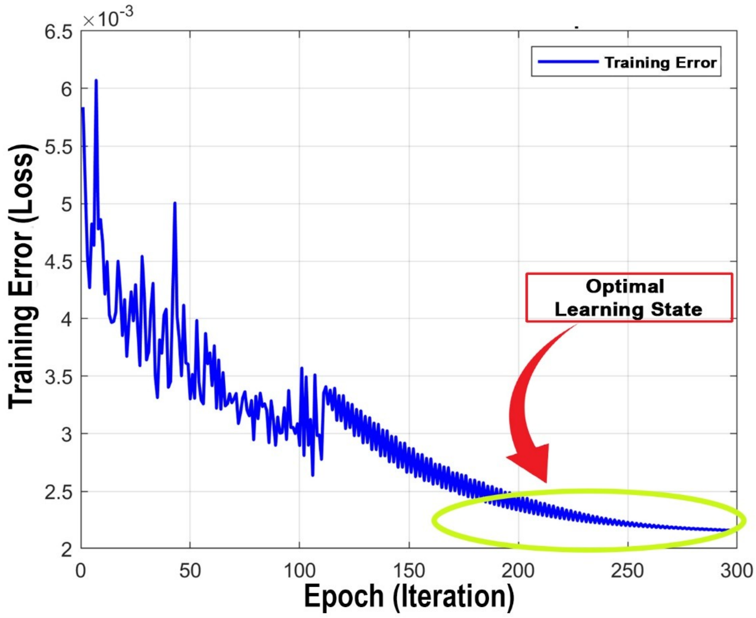

Figure 5 Training error across 300 epochs

Further training beyond Epoch 300 offers minimal improvement, making Epoch 300 the optimal choice for a well-generalized model. Figure 5 shows rapid learning in early epochs, with stabilization from epoch 200 onward, achieving optimal performance by epoch 300.

3.2.2 Comparison of MFs

The choice of MFs greatly influences the performance of ANFIS. Three MFs, namely, Gaussian, trapezoidal, and triangular, were tested for predictive accuracy. As shown in Table 4 (Supplementary Section), the Gaussian MF achieved the lowest final training MSE (0.00000635), RMSE (2.52×10^{-3}), and MAE (7.2974×10^{-4}), indicating superior accuracy. In contrast, the Trapezoidal MF had the highest error (MSE: 7.2974×10^{-4}, RMSE: 1.6425×10^{-4}, MAE: 7.2974×10^{-4}), while the Triangular MF performed better but still lagged behind the Gaussian MF ((MSE: 1.6425×10^{-4}, RMSE: 6.83315×10^{-3}, MAE: 3.06896×10^{-3}). These results demonstrate that the Gaussian MF is the most effective because its smooth, continuous shape better captures the nonlinear relationships in the screwing process, making it the optimal choice for this study.

3.3 Benchmark Model Comparison

3.3.1 Comparison between random forest regression and support vector regression

ANFIS, RFR, and SVR were compared to evaluate predictive performance. As shown in Table 5 (Supplementary Section), ANFIS with Gaussian MF achieved the lowest MSE (6.35×10^{-6}), RMSE ($2.52 \times {}^{-3}$), and MAE (7.2974×10^{-4}), demonstrating superior accuracy in predicting the Z value. RFR followed with an MSE of 9.44×10^{-6}, RMSE of 3.0726×10^{-3}, and MAE of 4.567×10^{-4}, showing slightly higher errors than ANFIS. SVR performed the worst, with MSE of 1.243×10^{-4}, RMSE of 1.11492×10^{-2}, and MAE of 8.8594×10^{-3}, struggling to capture data patterns effectively. These results highlight the ability of ANFIS to model complex nonlinear relationships more efficiently than traditional ML techniques, making it the preferred model for this application.

3.3.2 Statistical analysis of significance

The Wilcoxon signed-rank test was conducted to compare the error distributions among different predictive models: ANFIS, Random Forest Regression (RFR), and Support Vector Regression (SVR). This non-parametric test evaluates whether a statistically significant difference exists in the median error prediction between models.

a) Wilcoxon signed-rank test results
The Wilcoxon signed-rank test compares the error distributions of different models. As shown in Table 6 (Supplementary Section), the ANFIS and RF tests resulted in a p-value of 0.813, indicating no significant difference between the two models. Although both models show similar performance, the ability of ANFIS to capture complex nonlinear relationships remains a key strength. In Table 7 (Supplementary Section), the comparison between ANFIS and SVR yielded a p-value of 0.000, showing that ANFIS significantly outperforms SVR, with a Wilcoxon statistic of 109557.00 for ANFIS compared to 79003.00 for SVR. Similarly, Table 8 (Supplementary Section) shows the comparison between random forest and SVR, which resulted in a p-value of 0.000, confirming that random forest outperforms SVR. However, when ANFIS is compared to random forest (Table 6), ANFIS performs robustly, consistently delivering high-quality predictions. These results confirm that ANFIS is the best-performing model, significantly outperforming SVR and performing comparably with random forest, excelling in capturing nonlinear relationships and ensuring superior prediction accuracy.

b) Kruskal-Wallis Test Results
The Kruskal-Wallis test was used to compare the error medians across the three models, as shown in Table 9 (Supplementary Section). ANFIS had the highest median error (1.43×10^{-5}) and mean rank (1092.2), followed by random forest regression (RFR) with a median of -0.0000000 and mean rank of 1077.2. SVR had the lowest median (-4.7513×10^{-3}) and mean rank (793.2), indicating that it performed the worst. Table 10 (Section S2). Confirms a significant difference among the models, with an H-value of 115.62 and a p-value of 0.000, rejecting the null hypothesis (H_o). Mean rank analysis (from Table 9):

- ANFIS: 1092.2 (best predictive performance)
- RFR: 1077.2 (moderate predictive performance)
- SVR: 793.2 (worst predictive performance)

These findings confirm that ANFIS significantly outperforms both RFR and SVR, demonstrating superior predictive accuracy among the three models.

3.4 Residual analysis and error distribution

3.4.1 Residual Analysis

The analysis of the residual distribution is essential for evaluating the predictive reliability of the ANFIS model. Figure 6 presents the histogram of residual errors, while Figure 7 displays the corresponding boxplot after applying trimming and transformation techniques, ensuring a more refined error structure. Initially, the minimal training RMSE achieved was 2.51917×10^{-3}, indicating a relatively low error magnitude. However, further refinement is necessary to ensure that the residuals adhere to a normal distribution, which is a key assumption in predictive modeling. After applying the trimming and transformation techniques, the residual error characteristics improved significantly:

– Skewness: 0.2672 (closer to 0 indicates a more symmetric distribution)

– Kurtosis: 3.1112 (closer to 3, confirming a near-normal distribution)

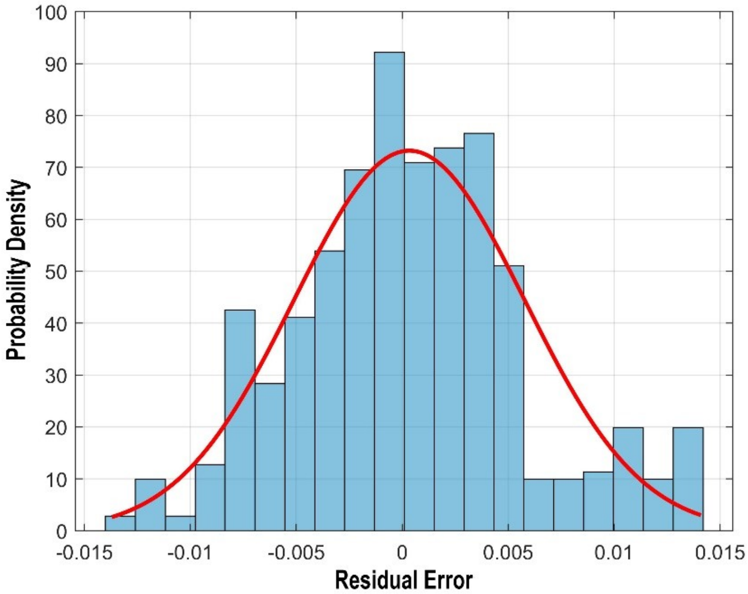

Figure 6 Histogram of residual error after trimming

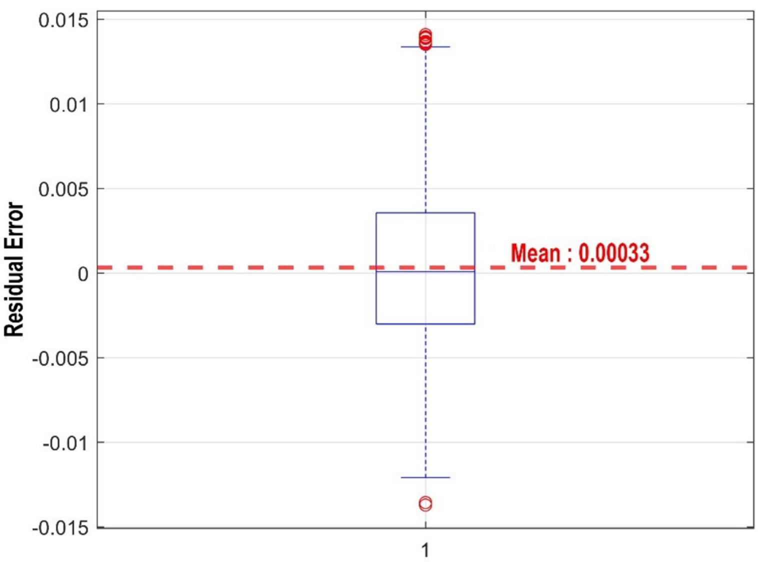

Figure 7 Boxplot of residual error after trimming

Based on these results, the residual errors now conform more closely to a normal distribution, enhancing the ANFIS model's predictions' robustness and interpretability. Figure 6 validates this improvement by showing a well-distributed residual pattern. Figure 7 further confirms this with a boxplot that illustrates reduced variability and fewer extreme outliers after trimming. Additionally, Figure 7 provides information about the mean of the residual errors, which is 0.00033, indicating a minimal bias in the model's predictions after trimming.

3.4.2 Error Analysis

Error analysis helps identify residual error distribution and model limitations. Table 11 (Supplementary Section) shows the largest prediction errors, with the highest residual error of -5.5423 $\times$ 10^{-2}, indicating areas where the model struggles. Table 12 (Supplementary Section) examines mean residual errors for extreme Z values: Low Z (< 47.1) shows a residual error of 1.338 $\times$ 10^{-2}, and High Z (> 47.4) shows a residual error of 9.1247 $\times$ 10^{-3}, indicating a balanced error distribution. However, the larger residuals in Table 11 highlight the need for refinement to improve predictive stability in extreme cases.

3.5 Discussion

The ANFIS model results demonstrate a high degree of accuracy in predicting the Z-axis values in screw installation processes. The comparison between predicted and actual values, as shown in Figure 8 and Table 11 (Supplementary Section), indicates a strong correlation with minimal residual errors. The nearly linear alignment of the predicted and actual values confirms that the model effectively captures the relationship between the screwing depth, torque, and Z values.

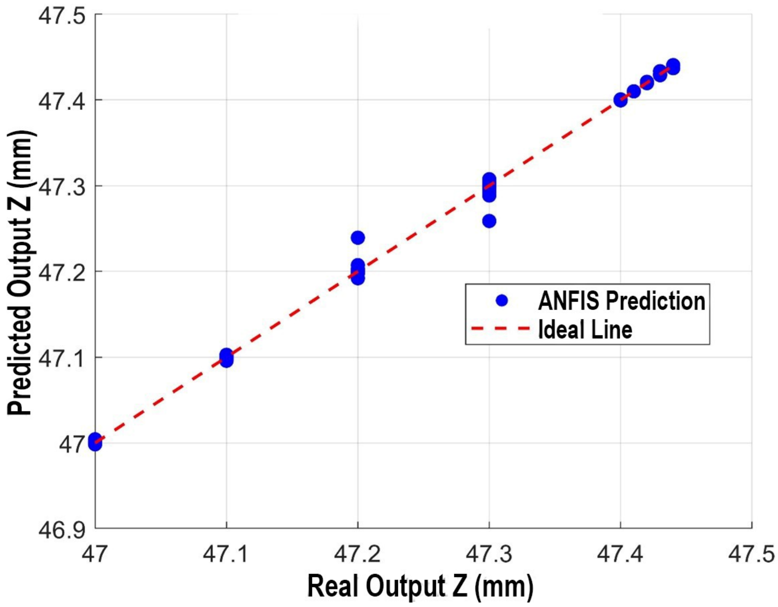

Figure 8 Relationship between real output and Predicted Z values

Table 13 (Supplementary Section) shows the minimal prediction errors, which typically range from 0.0001 to 0.003, with a few exceptions above 0.005. Larger screwing depths and torques correspond to slightly higher errors, indicating the model's sensitivity to input variations at higher values. For instance, the absolute errors for Z-value predictions, such as 5.81 $\times$ 10^{-4} and 6.32 $\times$ 10^{-4} mm, remain minimal. Refining the training data for high-depth and high-torque scenarios could improve robustness. Overall, ANFIS demonstrates high reliability for precision assembly tasks, effectively minimizes errors, and accurately captures the relationship between screwing depth, torque, and Z-value.

3.5.1 Interpretation of Results

Statistical analyses, including residual error distribution and error analysis, confirm the reliability of the model. The residual distribution (Section 3.4.1) shows near-normal characteristics with skewness of 0.2672 and kurtosis of 3.1112, enhancing the model's interpretability. Section 3.4.2 identifies small prediction errors, highlighting the model's robustness. The Kruskal-Wallis test (Section 3.3.2) confirms that ANFIS outperforms other models, with ANFIS (1092.2) being the most precise, followed by Random Forest (1077.2) and SVR (793.2).

3.5.2 Practical Applications

The ANFIS model's high accuracy presents promising applications in precision assembly and industrial automation, where accurate Z-axis predictions are crucial for ensuring optimal screw installation. The findings indicate that the model can minimize assembly defects and improve product reliability by reducing the risk of misalignment and torque-related inconsistencies.

Furthermore, the negligible residual errors allow the model to be integrated into real-time control systems, thereby enhancing the efficiency of automated manufacturing lines. Manufacturers can optimize screw installation parameters, reduce material waste, and improve production consistency by implementing this predictive approach.

3.5.3 Future Enhancements

Despite the model's high accuracy, further improvements can be explored. Future work can focus on integrating real-time feedback mechanisms to dynamically adjust predictions based on real-time sensor data. Additionally, expanding the dataset to include more complex screw types and varying material properties could enhance the generalizability of the model across different industrial applications.

In conclusion, the ANFIS model effectively predicts Z-axis values in screw installation, demonstrating superior accuracy and practical applicability in IA. The findings of this study contribute to the advancement of intelligent manufacturing processes by providing a reliable predictive tool for enhancing assembly precision and operational efficiency.

4. Conclusion

This study demonstrated the effectiveness of the ANFIS in predicting Z-axis values in screw installation processes based on screwing depth and torque inputs. The model achieved high predictive accuracy with a minimal training RMSE of 2.52×10^{-3}. Residual error analysis confirmed a normal error distribution with most absolute errors below 0.005, indicating model stability. Statistical tests, including Wilcoxon and Kruskal-Wallis, further validated the superiority of ANFIS over random forest and SVR models. These findings highlight the potential of ANFIS for improving precision in automated screw installation, contributing to enhanced production quality and efficiency in manufacturing environments.

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Author Contributions

1. **Bhakti Pradana Roesyadi:** Conceptualized and designed the study, conducted the primary analysis, and contributed to the drafting of the manuscript.

2. **Taufik Roni Sahroni:** Supervised the project, contributed to data interpretation, provided critical revisions, and served as the corresponding author for this manuscript.

Conflict of Interest

The authors declare no conflicts of interest.

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