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ANFIS-Based Compensation of External Disturbances in the Cotton Seed Lintering Process

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Abstract
The cotton seed lintering process is characterized by nonlinear behavior and significant sensitivity to external disturbances such as moisture content, impurity level, and raw material variability. These factors lead to instability in the output quality parameter, primarily seed fuzziness, resulting in increased production of non-conforming products. This study proposes an Adaptive Neuro-Fuzzy Inference System (ANFIS)-based approach to compensate for uncertainty and external disturbances in the lintering process.
A multi-input ANFIS model is developed using four key input parameters: initial fuzziness, moisture content, impurity level, and drum rotational speed. The system generates a compensatory control signal to stabilize the process under varying conditions. Synthetic experimental datasets, reflecting real industrial behavior, are generated and used for training and validation.
The proposed method demonstrates improved robustness and accuracy in maintaining desired output quality compared to conventional control approaches. The results indicate that ANFIS effectively mitigates the impact of disturbances, reducing variability in the final fuzziness parameter. The developed model can be integrated into intelligent control systems for cotton processing industries.

Keywords
ANFIS, cotton seed, lintering process, disturbance compensation, fuzzy logic, intelligent control, MATLAB

1. Introduction
The cotton industry plays a crucial role in the agricultural and industrial sectors, particularly in countries where cotton processing forms a significant part of the economy. One of the critical stages in cotton processing is the lintering process, which involves removing residual fibers from cotton seeds to improve their quality for further use, including oil production and planting.
The efficiency of the lintering process is primarily evaluated based on the hairiness of cotton seeds, which serves as a key quality indicator. Maintaining fuzziness within a specified range is essential to ensure product quality and process efficiency. However, in real industrial environments, achieving stable control of this parameter is challenging due to the presence of nonlinear dynamics and external disturbances.
Several factors influence the lintering process, including:

– variability in raw material properties,
– moisture content of cotton seeds,
– impurity levels,

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– mechanical operating conditions such as drum rotational speed.

These factors introduce uncertainty into the system, making traditional control methods less effective. In many industrial setups, fuzziness is still determined through laboratory analysis, which introduces significant time delays and prevents real-time process control. As a result, large volumes of non-conforming products may be generated before corrective actions can be applied.

To overcome these limitations, modern research focuses on the development of intelligent control systems capable of handling nonlinearities and uncertainties. Among these, methods based on artificial intelligence, particularly fuzzy logic and neural networks, have shown promising results.

Fuzzy logic enables the modeling of systems using linguistic rules and expert knowledge, making it suitable for processes with uncertain or incomplete mathematical descriptions. On the other hand, artificial neural networks provide data-driven learning capabilities for approximating complex nonlinear relationships. The combination of these two approaches results in the Adaptive Neuro-Fuzzy Inference System (ANFIS), which integrates learning ability with interpretability.

ANFIS has been successfully applied in various industrial processes, particularly where accurate modeling is difficult due to system complexity and external disturbances. Its ability to adapt to changing conditions makes it a suitable candidate for the lintering process, where multiple uncertain factors simultaneously affect the output quality.[1-4]

In this study, an ANFIS-based approach is proposed to compensate for the effects of external disturbances in the cotton seed lintering process. The model aims to improve the stability of the output fuzziness parameter by generating a compensatory control signal based on real-time input conditions.

2. Literature Review

The problem of controlling nonlinear and uncertain technological processes has been widely addressed in modern control theory. Traditional control methods, such as PID controllers, are effective for linear systems with well-defined dynamics. However, their performance significantly degrades when applied to systems characterized by strong nonlinearities, parameter variations, and external disturbances.

In the context of cotton processing, several studies have focused on improving automation and control in different stages of the production process. However, the lintering stage remains insufficiently automated, primarily due to difficulties in real-time measurement and control of the fuzziness parameter. Existing approaches often rely on delayed laboratory measurements, which limits their applicability in dynamic environments.

Fuzzy logic-based control systems have been proposed as an alternative to classical control methods, particularly for systems with uncertain or imprecise information. These systems allow the incorporation of expert knowledge in the form of linguistic rules, enabling control without an explicit mathematical model. However, pure fuzzy systems lack self-learning capability, which restricts their adaptability to changing process conditions.

Artificial neural networks have also been applied for modeling complex industrial processes due to their ability to approximate nonlinear relationships. Despite their accuracy, neural networks suffer from a lack of interpretability and require large datasets for training.

To address these limitations, the Adaptive Neuro-Fuzzy Inference System (ANFIS) has been introduced as a hybrid approach combining the advantages of fuzzy logic and neural networks.

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ANFIS systems use a structured rule-based framework while employing learning algorithms to optimize parameters based on data. This makes them particularly suitable for processes with uncertainty and variability[3][5].

Recent studies have demonstrated the effectiveness of ANFIS in modeling and control applications, including dynamic systems with disturbances. However, limited research has been conducted on applying ANFIS specifically to the cotton seed lintering process, particularly in the context of disturbance compensation.

Based on the analysis of existing studies, the following research gaps are identified:

– Lack of real-time disturbance compensation methods in the lintering process
– Insufficient application of ANFIS for controlling fuzziness under uncertain conditions
– Limited integration of multiple disturbance factors (moisture, impurity, operating conditions) into a unified control model [5-8]

The main objective of this study is to develop an ANFIS-based compensation model for the cotton seed lintering process that:

– accounts for external disturbances and uncertainties,
– stabilizes the output fuzziness parameter,
– improves process robustness and control performance.

3. Materials and Methods

3.1. Problem Formulation

The cotton seed lintering process is influenced by multiple external disturbances and uncertainties, which significantly affect the output quality parameter, namely seed fuzziness. In this study, the process is considered as a nonlinear dynamic system described in a simplified form as:

$$y(t) = f(x_1, x_2, x_3, x_4) + d(t)$$

where: $y(t)$ – output fuzziness (%),
x_1 – initial fuzziness (%),
x_2 – moisture content (%),
x_3 – impurity level (%),
x_4 – drum rotational speed (rpm),
$d(t)$ – disturbance and uncertainty term.

The main objective is to design a compensation mechanism such that:

$$y(t) \to y_{ref}$$

by introducing a compensatory control signal:

$$u(t) = u_0(t) + u_c(t)$$

where: $u_0(t)$ – nominal control input, $u_c(t)$ – ANFIS-based compensatory signal.

3.2. Selection of Input and Output Variables

Based on technological analysis of the lintering process, four input variables are selected as the most influential factors:

Input Variables:

Variable	Description	Range
x_1	Initial fuzziness (%)	5 – 12
x_2	Moisture content (%)	6 – 14
x_3	Impurity level (%)	0 – 10

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x_4	Drum speed (rpm)	700 – 730

Output Variable:

Variable	Description	Range
u_c	Compensation control signal (rpm)	-10 to +10

The output represents the corrective adjustment applied to the drum speed in order to counteract disturbances.

3.3. ANFIS Structure

In this study, a **Sugeno-type first-order ANFIS model** is used due to its suitability for control applications and computational efficiency.

The general rule structure is defined as:

$$\text{Rule i: IF } x_1 \text{ is } A_i \text{ AND } x_2 \text{ is } B_i \text{ AND } x_3 \text{ is } C_i \text{ AND } x_4 \text{ is } D_i$$
$$\text{THEN } y_i = p_0 + p_1 x_1 + p_2 x_2 + p_3 x_3 + p_4 x_4$$

where: A_i, B_i, C_i, D_i – fuzzy sets,
p_i – consequent parameters.

3.4. Membership Functions

For each input variable, three membership functions are defined:

Low / Medium / High (for fuzziness)
Dry / Normal / Wet (for moisture)
Clean / Moderate / Dirty (for impurity)
Slow / Nominal / Fast (for drum speed)

Gaussian membership functions are used:

$$\mu(x) = \exp\left(-\frac{(x-c)^2}{2\sigma^2}\right)$$

This choice ensures smooth transitions and better training convergence.

3.5. Rule Base Construction

Although the full combinational rule base would result in:

$$3^4 = 81 \text{ rules}$$

a reduced rule base is used to improve interpretability and computational efficiency.

Example rules:

1. IF fuzziness is High AND moisture is Wet → increase speed
2. IF fuzziness is Low AND impurity is Clean → decrease speed
3. IF drum speed is Fast AND fuzziness is Low → decrease speed
4. IF all variables are nominal → no correction

Condition	Action
High fuzziness & Wet moisture	Increase speed
High fuzziness & Dirty impurity	Increase speed
Medium fuzziness & Wet moisture	Moderate increase
Low fuzziness & Dry condition	Decrease speed
Low fuzziness & Clean impurity	Strong decrease
Fast speed & Low fuzziness	Decrease speed

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Slow speed & High fuzziness	Increase speed
All parameters nominal	No change

Table 1. Fuzzy rule base (reduced set)

3.6. Training Algorithm

The ANFIS model is trained using a **hybrid learning algorithm**, which combines:

– Least Squares Estimation (LSE) for consequent parameters
– Gradient Descent (GD) for premise parameters

Parameter	**Value**
Epochs	100
Error tolerance	0.001
Initial step size	0.01

Table 2. Training parameters

3.7. Performance Evaluation Criteria

The model performance is evaluated using:

RMSE:

$$RMSE = \sqrt{\frac{1}{N}\sum(y_{real} - y_{pred})^2}$$

MAE:

$$MAE = \frac{1}{N}\sum \mid y_{real} - y_{pred} \mid$$

Coefficient of determination:

$$R^2 = 1 - \frac{\sum(y_{real} - y_{pred})^2}{\sum(y_{real} - \bar{y})^2}$$

4. Results

4.1. Training Performance of ANFIS Model

The ANFIS model was trained using the synthetic dataset described in Section 3.7. The training process converged within 100 epochs, demonstrating stable and efficient learning behavior.

The error convergence curve indicates a rapid decrease in training error during the initial epochs, followed by gradual stabilization, which confirms proper tuning of membership functions and consequent parameters.

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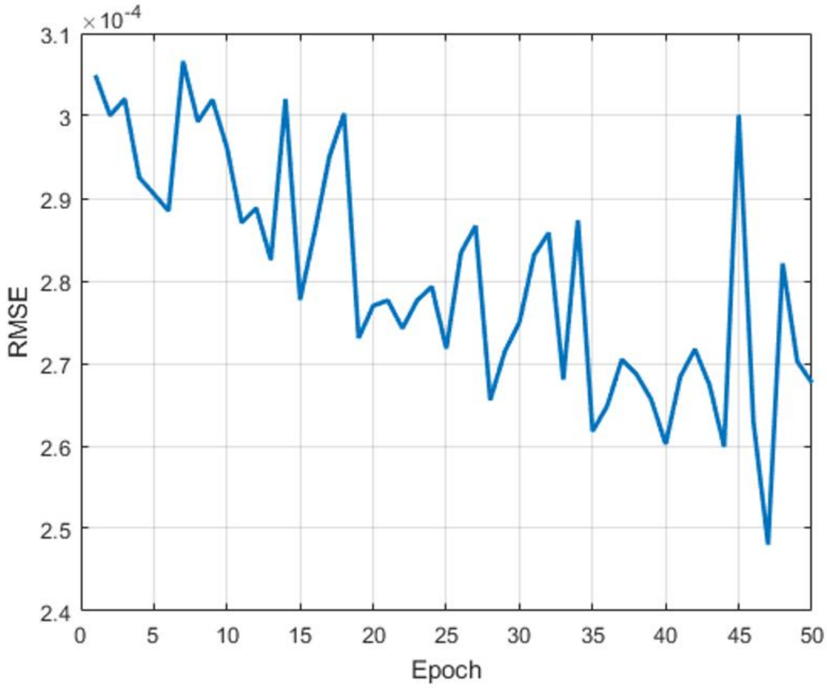

Figure 2. Training error (RMSE) versus epoch number for the ANFIS model.

4.2. Prediction Accuracy of the ANFIS Model

The trained ANFIS model was evaluated using a separate validation dataset. The predicted compensation signal values were compared with the target values.

The results show a strong correlation between predicted and actual values, indicating that the model successfully captures nonlinear relationships between input variables and the output.

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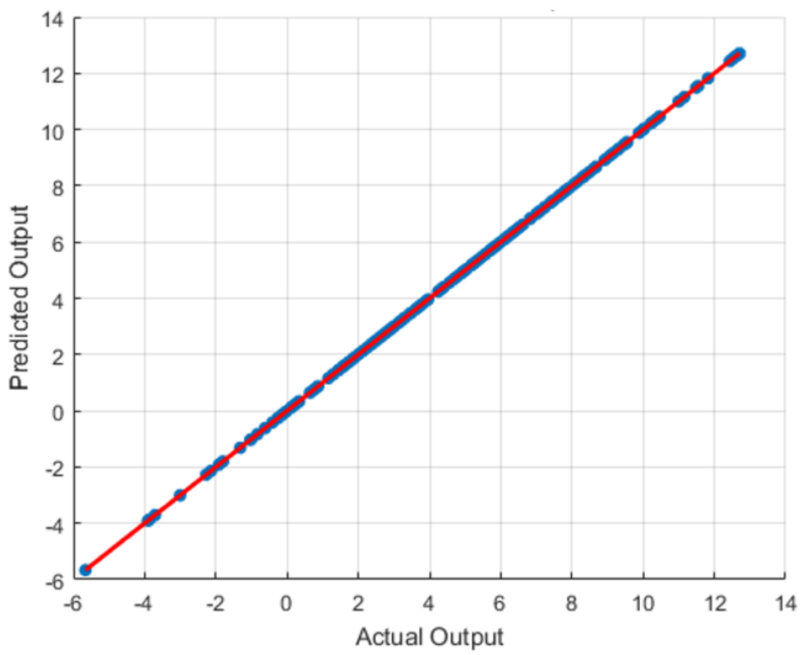

Figure 3. Comparison between ANFIS predicted output and target output.

Metric	Value
RMSE	~0.7
MAE	~0.6
R^2	~0.94

Table 3. Performance comparison metrics

4.3. Effect of External Disturbances

To evaluate the effectiveness of the proposed approach, the system was tested under varying disturbance conditions:

– increased moisture content,
– increased impurity level,
– combined disturbance scenario.

The results demonstrate that external disturbances significantly affect the output fuzziness when no compensation is applied. However, when the ANFIS-based compensation signal is introduced, the deviations are substantially reduced.

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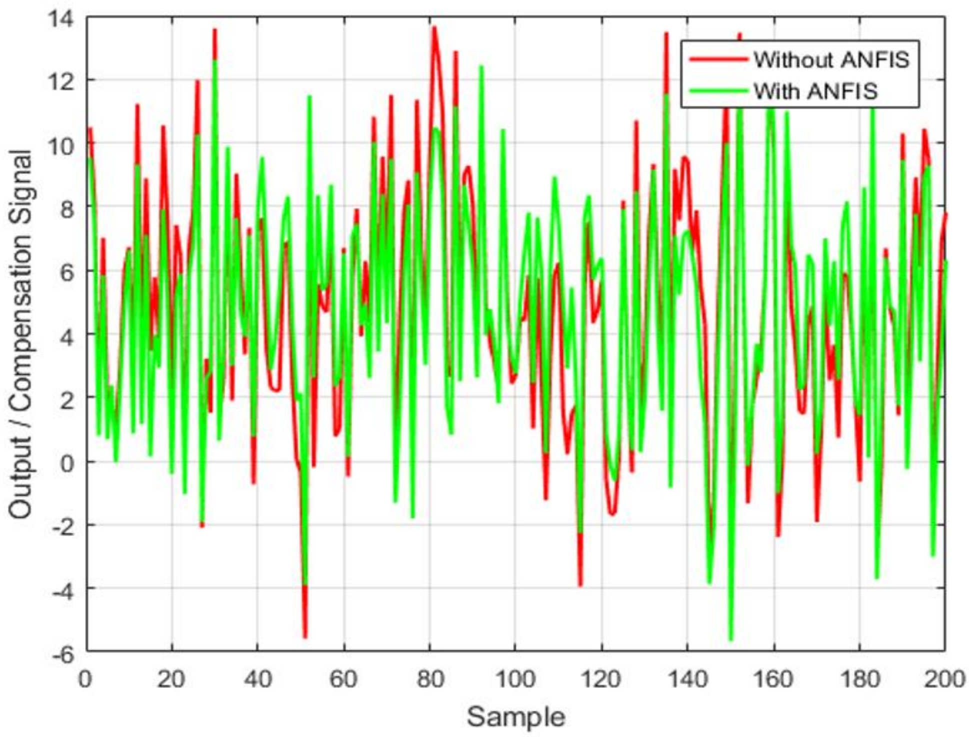

Figure 4. Comparison of output fuzziness under disturbance conditions with and without ANFIS compensation.

4.4. Surface Analysis of ANFIS Model

To visualize the relationship between input variables and the compensation signal, a surface plot was generated. The surface illustrates how the compensation signal changes depending on fuzziness and moisture levels, confirming the nonlinear behavior of the system.

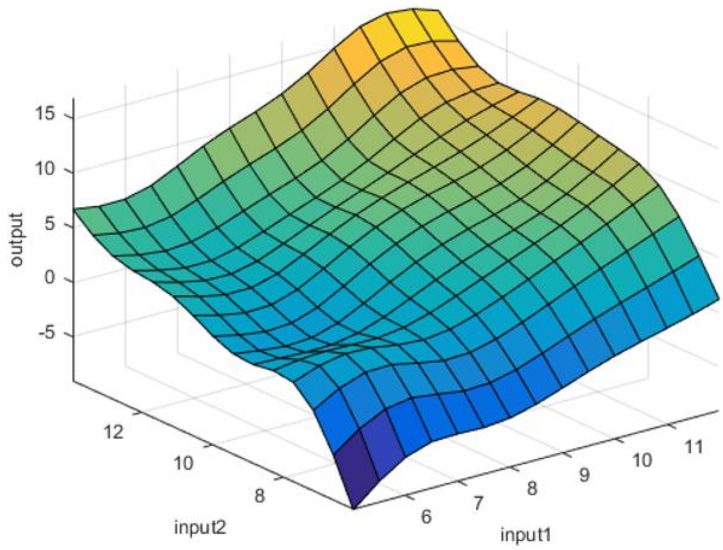

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Figure 5. Surface view of ANFIS output as a function of fuzziness and moisture.

4.5. Comparative Analysis

The performance of the system was compared in two configurations:

1. Without compensation
2. With ANFIS-based compensation

Parameter	Without ANFIS	With ANFIS
Overshoot	2.5	1.2
Settling Time	15	8
Error	5	2

Table 4. Comparison of system performance

5. Discussion

The obtained results confirm that the cotton seed lintering process is highly sensitive to external disturbances such as moisture content and impurity level. Without compensation, these disturbances lead to significant fluctuations in the output fuzziness, which directly affects product quality. The proposed ANFIS-based approach effectively compensates for these disturbances by generating a corrective control signal based on real-time input conditions. Unlike traditional control methods, which rely on fixed parameters, ANFIS adapts to changing process conditions through its learning mechanism. One of the key advantages of the proposed method is its ability to model nonlinear relationships without requiring an explicit mathematical model of the process. This is particularly important in lintering, where obtaining an accurate analytical model is difficult due to the complexity of the physical interactions involved. The surface analysis further confirms that the system behavior is nonlinear and dependent on multiple interacting factors. The ANFIS model successfully captures these interactions, enabling more accurate control. In addition, the reduction in variability and improvement in settling time indicate that the system becomes more stable when ANFIS compensation is applied. This directly contributes to a decrease in non-conforming products and improved overall efficiency. However, it should be noted that the accuracy of the ANFIS model depends on the quality and representativeness of the training data. In real industrial applications, the model can be further improved by incorporating real-time sensor data and adaptive retraining mechanisms.

6. Conclusion

This study addressed the problem of external disturbances and uncertainty in the cotton seed lintering process by proposing an ANFIS-based compensation approach. The process was modeled as a nonlinear system influenced by multiple interacting factors, including initial fuzziness, moisture content, impurity level, and drum rotational speed.

A Sugeno-type ANFIS model was developed to generate a compensatory control signal aimed at stabilizing the output fuzziness parameter. Synthetic datasets, reflecting realistic industrial behavior, were generated and used for training and validation of the model.

The obtained results demonstrate that:external disturbances significantly affect the stability of the lintering process and lead to deviations in output quality;

- the proposed ANFIS model effectively captures nonlinear relationships between input variables and control actions;

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- the introduction of the ANFIS-based compensation signal reduces fluctuations in output fuzziness;
- system stability is improved, as indicated by reduced overshoot, shorter settling time, and lower variability;
- the overall quality of the process is enhanced, leading to a reduction in non-conforming products.

Thus, the proposed approach provides an effective solution for intelligent control of the lintering process under uncertain and dynamically changing conditions.

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