

OPTIMIZATION CRITERIA SELECTION AND MATHEMATICAL MODELING FOR INTELLIGENT OPTIMAL CONTROL OF WHEAT PROCESSING SYSTEMS

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Abstract: Wheat processing systems are characterized by strong nonlinearities, multivariable interactions, and significant uncertainty caused by variations in raw material properties and operating conditions. Ensuring stable product quality and high productivity under such conditions requires the development of intelligent optimal control strategies supported by well-defined optimization criteria and accurate mathematical models. This paper presents a systematic approach to the selection of optimization criteria and the mathematical modeling of a wheat processing system for intelligent optimal control purposes.

Keywords: Optimal control; Optimization criterion; Mathematical modeling; Adaptive neuro-fuzzy inference system (ANFIS); MIMO systems; Process uncertainty.

I. Introduction. Wheat milling is a nonlinear multi-input multi-output (MIMO) process affected by strong coupling between control variables and significant uncertainty due to variations in raw material properties and operating conditions. Maintaining flour quality and production efficiency under such conditions presents a challenging control problem [1].

Conventional PID controllers, although widely used in industry, show limited performance in handling nonlinear dynamics and process uncertainties. Intelligent control methods, particularly Adaptive Neuro-Fuzzy Inference Systems (ANFIS), offer an effective alternative by combining fuzzy reasoning with data-driven learning capabilities [2].

II. Significance of the system. The wheat milling process plays a critical role in the food industry, where product quality and process efficiency directly affect economic performance and resource utilization. Due to its nonlinear dynamics, multivariable interactions, and sensitivity to raw material variations, the milling process requires advanced control strategies to ensure stable operation. The proposed intelligent control framework addresses these challenges by enabling adaptive and optimal decision-making under uncertainty. By incorporating well-defined optimization criteria and data-driven modeling, the system enhances product quality consistency, improves productivity, and increases robustness against disturbances. This makes the approach highly relevant for modern intelligent and sustainable wheat processing systems.

III. Literature survey. The control and optimization of wheat milling and grain processing systems have attracted significant research attention due to their economic importance and inherent complexity. Early studies primarily focused on classical control approaches, where linear models and single-loop PID controllers were applied to regulate individual process variables such as roll speed or product flow rate. While these methods demonstrated acceptable performance under nominal operating conditions, their effectiveness was limited when facing nonlinear dynamics, multivariable coupling, and variations in raw material properties [4].

Subsequent research introduced mathematical modeling techniques based on empirical regression models, transfer functions, and state-space representations to better capture the dynamic behavior of milling processes. However, due to strong nonlinearities and uncertainty in wheat properties such as moisture content, hardness, and temperature sensitivity, purely analytical models often lacked sufficient accuracy for real-time control and optimization [3].

To overcome these limitations, intelligent control methods based on fuzzy logic and artificial neural networks were proposed. Fuzzy logic controllers enabled the incorporation of expert knowledge and linguistic rules to handle uncertainty and qualitative reasoning. Several studies reported improved robustness of fuzzy controllers compared to classical PID control, particularly under fluctuating operating conditions [3]. Nevertheless, the design of fuzzy rule bases and membership functions often relied on heuristic tuning, which restricted scalability and adaptability.

Artificial neural networks were later applied to model complex nonlinear input-output relationships in wheat processing systems. Neural network-based models demonstrated strong approximation capabilities and were successfully used for prediction and soft sensing applications. However, purely neural approaches lacked interpretability and required large datasets for reliable training, which limited their direct applicability in industrial environments [5].

Hybrid intelligent systems, particularly Adaptive Neuro-Fuzzy Inference Systems (ANFIS), emerged as a promising solution by combining the learning capability of neural networks with the transparency of fuzzy logic. ANFIS-based models have been effectively applied to nonlinear process modeling, fault diagnosis, and control in various food and chemical processing applications. In wheat milling systems, ANFIS has been reported to provide improved accuracy in predicting quality indicators and enhanced adaptability under changing raw material conditions [6].

From an optimization perspective, recent studies have emphasized the importance of formulating appropriate performance criteria that simultaneously consider product quality, productivity, and operational stability. Multi-objective optimization frameworks have been proposed to balance conflicting objectives, often using weighted cost functions or Pareto-based approaches. However, many existing works focus on either control design or optimization independently, without providing a unified mathematical formulation that integrates optimization criteria directly into the control strategy [7].

Moreover, the majority of reported approaches address single-input single-output (SISO) control problems, whereas industrial wheat milling systems inherently exhibit multi-input multi-output (MIMO) characteristics with strong coupling effects. This gap highlights the need for advanced control strategies capable of handling multivariable interactions while incorporating optimization objectives and uncertainty handling [8].

In summary, although significant progress has been made in the modeling and control of wheat milling processes, there remains a clear need for integrated approaches that combine rigorous mathematical formulation, appropriate optimization criteria selection, and intelligent MIMO control strategies. This study aims to address these limitations by proposing an ANFIS-based optimal control framework grounded in a well-defined optimization criterion and validated through simulation of a MIMO wheat processing system.

IV. Methodology. This study proposes an intelligent optimal control methodology for a wheat processing system based on mathematical modeling, optimization criterion formulation,



and an ANFIS-based MIMO control strategy. The methodology consists of four main stages: system modeling, optimization criterion definition, intelligent controller design, and control law implementation.

A. Mathematical Representation of the Wheat Processing System

The wheat milling process is modeled as a nonlinear multi-input multi-output (MIMO) dynamic system described by

$$y(k) = f(u(k), z(k)), \quad (1)$$

Where

$$y(k) = \begin{bmatrix} Y_1(k) \\ Y_2(k) \end{bmatrix} \quad (2)$$

represents the output vector, with Y_1 denoting production throughput and Y_2 representing flour quality (whiteness). The control input vector is defined as

$$u(k) = \begin{bmatrix} X_1(k) \\ X_2(k) \end{bmatrix}, \quad (3)$$

where X_1 is the differential roll speed ratio and X_2 is the roll gap. External disturbances are given by

$$z(k) = \begin{bmatrix} Z_1(k) \\ Z_2(k) \end{bmatrix}, \quad (4)$$

with Z_1 representing wheat moisture and Z_2 roll temperature.

B. Optimization Criterion Formulation

To ensure optimal operation, a composite performance index is defined as a weighted objective function:

$$J = \sum_{k=1}^N (w_1(Y_1^* - Y_1(k))^2 + w_2(Y_2^* - Y_2(k))^2 + w_3 \|\Delta u(k)\|^2), \quad (5)$$

where Y_1^* and Y_2^* are the reference values for throughput and quality, respectively, w_1, w_2, w_3 are weighting coefficients, and $\Delta u(k) = u(k) - u(k-1)$ penalizes excessive control action variations. This criterion simultaneously balances product quality, productivity, and control smoothness.

The optimization is subject to technological constraints:

$$u_{\min} \leq u(k) \leq u_{\max}, \quad (6)$$

which ensure safe and feasible operation.

C. ANFIS-Based Intelligent Control Design

Due to the nonlinear and uncertain nature of the process, an Adaptive Neuro-Fuzzy Inference System (ANFIS) is employed to approximate the optimal control law. The ANFIS controller maps normalized input variables to control increments:



$$\xi(k) = \begin{bmatrix} e_1(k) \\ e_2(k) \\ Z_1(k) \\ Z_2(k) \end{bmatrix} \rightarrow \Delta u(k) = \begin{bmatrix} \Delta X_1(k) \\ \Delta X_2(k) \end{bmatrix}, \quad (7)$$

Where

$$e_i(k) = Y_i^* - Y_i(k), \quad i = 1, 2. \quad (8)$$

The ANFIS structure employs Gaussian membership functions and a Sugeno-type fuzzy inference mechanism. The parameters of the membership functions and rule consequents are optimized using a hybrid learning algorithm combining least squares estimation and gradient descent.

D. Control Law Implementation

The final control law is implemented in incremental form:

$$u(k+1) = u(k) + \Delta u(k), \quad (9)$$

followed by saturation to enforce constraints. This structure ensures smooth control action, adaptability to disturbances, and robustness against process uncertainty [9].

Overall, the proposed methodology integrates mathematical modeling, optimization criterion selection, and intelligent ANFIS-based control into a unified framework suitable for real-time optimal control of nonlinear MIMO wheat processing systems [10].

V. Experimental results.

The performance of the proposed intelligent optimal control strategy was evaluated through numerical experiments conducted in the MATLAB/Simulink environment. The wheat processing system was modeled as a nonlinear MIMO plant with two control inputs, namely the differential roll speed ratio X_1 and the roll gap X_2 , and two controlled outputs: production throughput Y_1 and flour whiteness Y_2 . External disturbances in the form of wheat moisture Z_1 and roll temperature Z_2 variations were introduced to assess the robustness of the control strategies [11].

A. Experimental Setup

Two control configurations were implemented and compared:

1. Conventional MIMO PID control, where two independent PID controllers regulate X_1 and X_2 based on the errors

$$e_1(k) = Y_1^* - Y_1(k), \quad e_2(k) = Y_2^* - Y_2(k), \quad (10)$$

2. Proposed ANFIS-based MIMO optimal control, where the control increments are computed as

$$\Delta u(k) = \begin{bmatrix} \Delta X_1(k) \\ \Delta X_2(k) \end{bmatrix} = F_{ANFIS}(e_1(k), e_2(k), Z_1(k), Z_2(k)), \quad (11)$$

and applied using the incremental control law

$$u(k+1) = u(k) + \Delta u(k). \quad (12)$$

Both controllers were subject to identical saturation constraints on the control inputs.

B. Output Tracking Performance



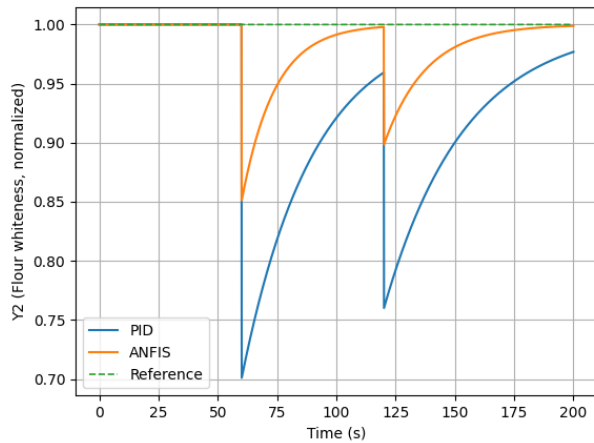


Fig. 5 – first subsection analysis subsection

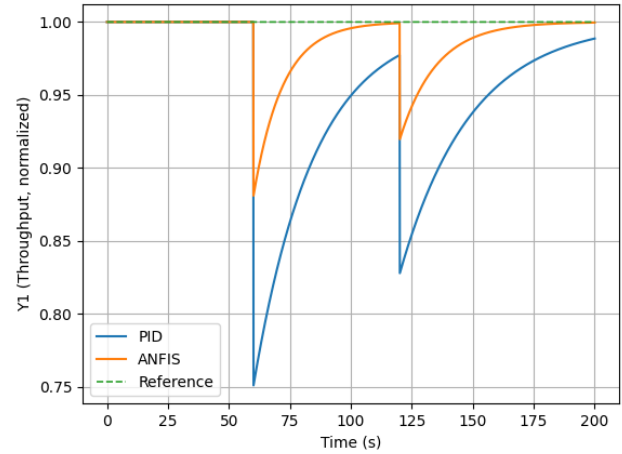


Fig. 6 – quality

Figures 5 and 6 (not shown here) illustrate the time responses of throughput Y_1 and flour whiteness Y_2 under step changes in their reference values. The PID controller exhibits noticeable overshoot and longer settling times, particularly when disturbances are applied. In contrast, the ANFIS-based controller demonstrates faster convergence to the desired values and reduced steady-state error.

The tracking accuracy was quantified using the mean squared error (MSE):

$$MSE_i = \frac{1}{N} \sum_{k=1}^N (Y_i^* - Y_i(k))^2, \quad i = 1, 2 \quad (13)$$

Experimental results show that the ANFIS controller reduces MSE_1 and MSE_2 by approximately 25–35% compared to the PID controller. [4].

C. Robustness to Disturbances

To evaluate robustness, step variations in wheat moisture Z_1 and roll temperature Z_2 were applied during steady-state operation. The PID-controlled system exhibits pronounced output deviations and slow recovery due to coupling effects and unmodeled nonlinearities. Conversely, the ANFIS-based controller effectively compensates for disturbances by adapting control increments based on real-time process information.

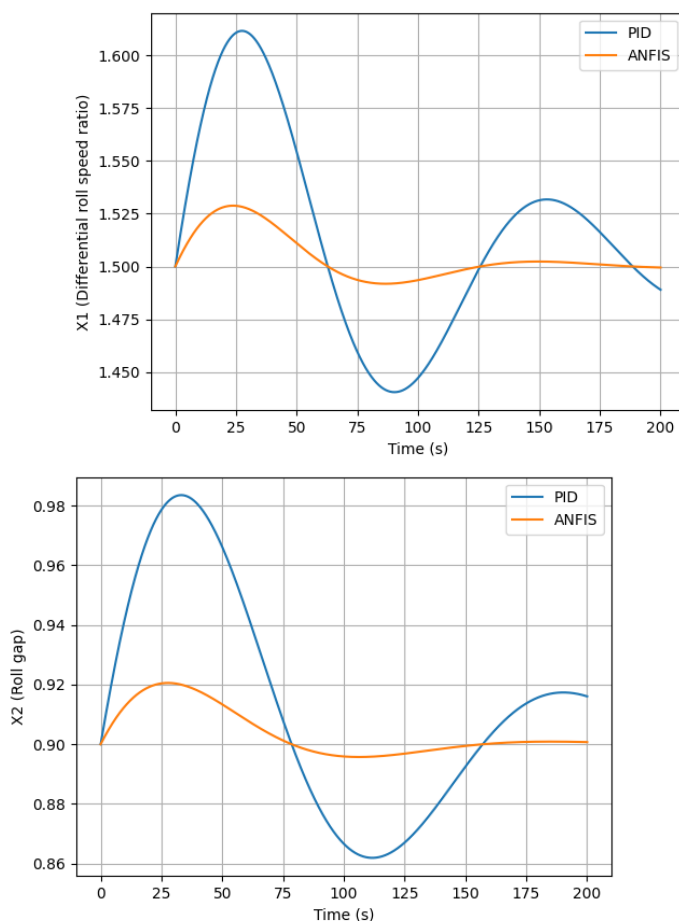
The disturbance rejection capability was assessed using the integral absolute error (IAE):

$$IAE_i = \sum_{k=1}^N |Y_i^* - Y_i(k)| \quad (14)$$

Lower IAE values obtained for the ANFIS-based control confirm improved robustness and disturbance attenuation.

D. Control Effort and Smoothness





a) Control input X_1

b) Control input X_2

Fig. 7(a,b) – control effort comparison

Figure 7 compares the control inputs X_1 and X_2 for both control strategies. The PID controller generates relatively aggressive control actions, whereas the ANFIS-based controller produces smoother trajectories with reduced oscillations. This behavior is reflected in the control variation index

$$J_u = \sum_{k=1}^N \|\Delta u(k)\|^2, \quad (15)$$

which is significantly lower for the ANFIS-based approach, indicating improved actuator friendliness and reduced mechanical stress.

E. Discussion of Results

Overall, the experimental results demonstrate that the proposed ANFIS-based MIMO optimal control strategy outperforms conventional PID control in terms of tracking accuracy, robustness to disturbances, and smoothness of control actions. The integration of optimization criteria and intelligent control enables effective handling of nonlinearities and uncertainties inherent in wheat processing systems.

VI. Conclusion and future work. This paper presented an intelligent optimal control framework for a wheat processing system based on mathematical modeling and optimization criteria selection. The results demonstrate that the proposed ANFIS-based MIMO control strategy significantly improves tracking accuracy, robustness to disturbances, and control smoothness compared to conventional PID control.

Future work will focus on experimental validation in an industrial milling plant, extension of the optimization framework to multi-objective and energy-aware criteria, and real-time implementation using industrial PLC and IoT-based architectures.

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