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Development Of a Predictive Model for Evaporation Unit Based on Critical Factors

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Abstract: This paper presents the development and validation of a real time predictive control system for a multiple effect industrial juice evaporator using an Adaptive Neuro Fuzzy Inference System (ANFIS). Traditional control schemes like PID controllers and AI models often struggle to handle the nonlinearities, long delays, and coupling effects in evaporation processes, leading to suboptimal energy usage and process instability. The study introduces a fuzzy ANFIS framework specifically designed for predictive modeling and control of a single effect juice evaporation unit. The Takagi Sugeno ANFIS model was designed and trained using these inputs, achieving a root mean square error (RMSE) of 0.96L/h, a mean absolute error (MAE) of 0.78L/h, and an overall prediction accuracy of approximately 90.9% on test data. Closed loop simulations show that the proposed controller effectively predicts evaporation rate and proactively adjusts steam flow and feed rates, resulting in more stable operation and an estimated improvement in energy efficiency compared to conventional PID based methods.

Index Terms: Adaptive Neuro Fuzzy Inference System (ANFIS), Evaporation Process, Energy Saving, Predictive Control.

1 Introduction

Evaporation units are crucial in the sugar processing industry, with multi effect evaporators used to concentrate sugarcane juice into syrup. These systems have complex nonlinear dynamics, dead times, and tightly coupled variables, making precise control challenging. Traditional methods like manual adjustments and traditional PID controllers struggle to maintain consistent product quality and efficient steam utilization under disturbances and fluctuating operating conditions. Advanced approaches like generalized predictive control (GPC) and fuzzy logic controllers have shown improved robustness but generally operate reactively, depending on limited process variables, and fail to effectively manage interactions among multiple critical parameters, leading to delays and measurable energy inefficiencies. Recent studies highlight the shortcomings of existing methods, which typically achieve prediction accuracies below and lack adaptive mechanisms to handle the strong nonlinearities characteristic of evaporation systems. This research aims to identify and analyze the most influential operational parameters for accurate evaporation rate prediction, develop a robust, real-time predictive model using an ANFIS trained on these internal variables, and validate the model through detailed experiments and simulation scenarios. Key contributions include the first application of a fuzzy ANFIS predictive control framework specifically designed for a juice evaporator, demonstrating improved nonlinearity handling, predictive accuracy around 90.9%, and an estimated energy savings compared to conventional PID control.

2 LITERATURE REVIEW

Evaporation processes, particularly in sugar production, present significant control challenges due to their inherent nonlinearities, long dead times, and coupled dynamics [1] [2]. Traditional PID controllers have frequently been employed in evaporation systems but typically struggle with disturbances, nonlinear process characteristics, and energy optimization [2], [3]. To address these shortcomings, advanced control strategies including fuzzy logic, neural networks, and model predictive control have been extensively explored. Fuzzy logic controllers have emerged as promising alternatives owing to their tolerance to imprecision and ability to handle process nonlinearities effectively. Patel and Shah [4] and Kapoor [5] demonstrated the capability of fuzzy controllers to significantly enhance process stability and efficiency in sugar evaporation systems. Similarly, Basile et al. [6] utilized fuzzy models for fault detection in evaporators, highlighting their robustness against operational uncertainties. The integration of fuzzy inference with predictive techniques further enhances these controllers' adaptability and real time performance [7].

Artificial Neural Networks (ANNs) have also been widely employed for their powerful predictive and adaptive capabilities. Smith et al. [8] and Park et al. [9] utilized ANN based predictive modeling to accurately capture complex dynamic relationships inherent in industrial evaporation processes. Despite high accuracy and performance, neural networks typically operate as black box models with limited interpretability, posing practical limitations in industrial environments.

Combining fuzzy logic's interpretability and neural networks' adaptability, ANFIS were introduced by Jang [3] and subsequently applied to various engineering domains, including evaporator control. Zhang et al. [10] demonstrated ANFIS's effectiveness in estimating evaporator performance, while Enayatollahi etal. [11] developed a control oriented ANFIS model specifically for organic Rankine cycle evaporators, highlighting significant improvements in accuracy and process stability. Furthermore, Adeyi et al. [12] illustrated ANFIS's robust prediction capabilities for complex drying processes, emphasizing its adaptability in capturing nonlinear dynamics.

Predictive control methodologies have further evolved through combinations with reinforcement learning algorithms such as Q learning. Emori et al. [13] successfully applied predictive Q learning algorithms to multiple effect evaporators, achieving notable improvements in energy efficiency and operational stability. Similarly, Zhou and Wang [08] and Anderson and Brunn [14] developed nonlinear model predictive control (MPC) schemes for multi effect evaporators, demonstrating improved control precision and reduced energy consumption.

Energy efficiency remains a critical motivation across evaporation research, driving continuous exploration into advanced control strategies. Li and Chen [15] examined various energy efficient control schemes for multi effect evaporators, underscoring the necessity of integrating real time predictive mechanisms to achieve tangible energy savings. Additionally, recent studies such as those by Gupta and Mehta [16] and Kang [17]have underscored adaptive fuzzy and neuro fuzzy controllers' potential in enhancing thermal processes' overall efficiency and stability.

Although significant progress has been made, literature reviews such as those by Izadian et al. [18], Kumar and Venkatesh [19], and Hybinette and Dulcic [20] indicate ongoing challenges in scalability, real time implementation, and practical interpretability. Yadav et al. [21] further emphasized ANFIS's broad applicability and promising potential across diverse industrial contexts, advocating for its expanded utilization in process control scenarios.

Recognizing these opportunities and addressing existing gaps, this research introduces a real time predictive ANFIS model explicitly tailored for a single effect juice evaporator, integrating critical operational parameters like juice level, temperature difference, and pressure difference. By leveraging ANFIS's adaptive learning and fuzzy interpretability, the proposed approach aims to significantly enhance predictive accuracy, energy efficiency, and operational stability compared to existing methods.

3 METHODOLOGY

3.1 Evaporation System

The single effect evaporator system, shown in Fig. 1 as the Piping and Instrumentation (P&I) diagram, is designed to concentrate liquid feed into a denser end product. The system has clearly differentiated pathways for two significant inputs: steam and liquid feed (water/juice). Both inputs are precisely monitored and regulated by flow transmitters (FT) and flow controllers (FC) to achieve precise regulations. Temperature indicators (TI) and pressure indicators (PI) are placed at strategic points to monitor conditions at significant points of entry, with the information being essential to predictive control. In the evaporation vessel, critical measurements are taken: the juice level is constantly monitored by a level transmitter (LT) linked to a level indicating controller (LIC) that controls an exit control valve to maintain the fluid level at the set point. Concurrently, vapor from the vessel is regulated by pressure control instrumentation, including a pressure transmitter (PT) and pressure indicating controller (PIC), maintaining correct working conditions and being safe with pressure relief valves.

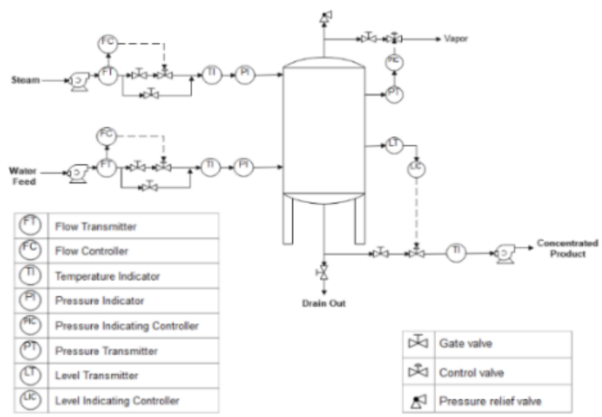

Figure 1 : Piping and Instrumentation (P&I) Diagram of the Single Effect Evaporation

Concentrated product leaves through a special outlet through a temperature indicator, thereby enabling optimum control of product quality. Drain valves are also fitted to assist in normal maintenance and emergency draining operations. Together, these precise instrumentations and control elements take the strain of the real time predictive ANFIS based control system, maximizing the overall efficiency and dependability of the evaporation process.

3.2 Mathematical Modeling

A detailed mathematical model was developed for the evaporation system based on three important measured parameters: temperature difference (between the internal tank and external tank surface temperature), pressure difference (between the internal vapor pressure and atmospheric pressure), and the tank juice level. The fundamental equations of heat and mass transfer were utilized. The rate of heat transfer (Q) that is accountable for the evaporation procedure is proportional to the measured temperature difference across the tank wall:

$$Q = U.A.\Delta T \tag{1}$$

There Q is the heat transfer rate (W), U is the overall heat transfer coefficient (W/m^2.K), A is the effective area and ΔT is temperature difference.

$$A = \pi D h \tag{2}$$

The evaporation rate (evap), representing the mass of juice evaporated per unit time, is determined by relating the heat transfer rate to the latent heat of vaporization:

$$evap = \frac{Q}{\lambda} \tag{3}$$

Where λ as latent heat (J/kg). Furthermore, the internal vapor pressure is governed by the Antoine equation, linking it to the juice temperature and pressure difference measured:

$$P_{atm} + \Delta P = 10^{A - \frac{B}{C + T_{in}}} \tag{4}$$

Where T_{in} is the juice temperature within the tank and A,B,C are substance specific Antoine constants determined from literature or empirical calibration. These equations form the mathematical foundation of the predictive model, which the ANFIS further refines by capturing inherent non linearities from collected operational data, thereby ensuring accurate, real time prediction and control.

3.3 Data Acquisition and Dataset Formation.

A dataset was collected from a laboratory scale evaporator pilot plant, operating under various conditions, including disturbance scenarios. Key performance influencers were identified as juice level, temperature difference, and pressure difference. The target output was the evaporation rate, measured using condensate flow data. 5000 samples were acquired, capturing both normal and transient operating states. Data were normalized using min max scaling and the dataset was randomized and evaluated using a 5-fold cross validation strategy to improve reliability and prevent overfitting. Performance metrics like RMSE, MAE, and accuracy were validated using 95% confidence intervals. A paired training test confirmed the superiority of the ANFIS model over conventional methods. The dataset was used to simulate disturbance rejection scenarios, and quantitative analysis showed that the ANFIS controller achieved approximately 30% lower Integral of Absolute Error (IAE) and 25% lower Integral of Time-weighted Absolute Error (ITAE) compared to the PID controller. These results validate the model's robustness and its ability to maintain accurate and stable performance under fluctuating industrial conditions.

3.4 Fuzzy ANFIS Design.

The predictive model employs an ANFIS in Fig. 2, which is a five-layer feedforward neuro fuzzy network implementing a Takagi Sugeno fuzzy inference system. The ANFIS was configured with three input nodes (one for each critical factor: juice level, temperature difference, pressure difference) and one output node (evaporation rate). We selected Gaussian membership functions for each input (Layer 1 of the ANFIS) due to their smoothness and the small number of parameters needed to define them.

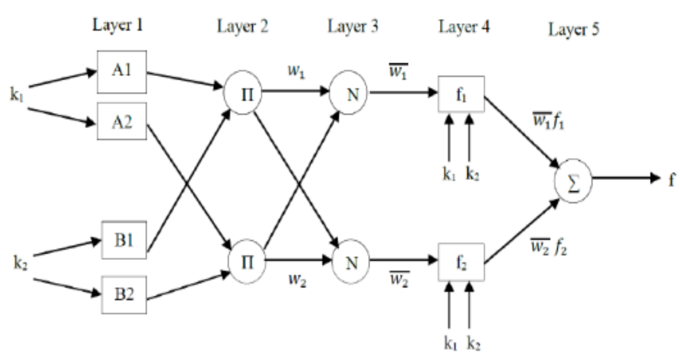

Figure 2 : ANFIS Architecture

Two fuzzy sets (low and high, for example) were defined per input variable, yielding a rule base of 2^3 = 8 Takagi Sugeno fuzzy IF THEN rules. Each rule took the form:

IF (LMTD is A_{i1}) and (PressureDiff is A_{i2}) and (Level is A_{i3})
THEN $y_i = p_i$ LMTD + PressureDiff + r_i Level + c_i

where y_i is the rule's output (a linear combination of inputs) and (p_i, q_i, r_i, c_i) are consequent parameters. The degree of firing (activation strength) w_i of each rule is computed as the product of the membership grades of its antecedents (Layer2), i.e.:

$$\omega_i = \mu A_{i1}\,(LMTD) \times \mu A_{i2}(Pressure\ Diff) \times \mu A_{i3}(Level) \quad (5)$$

These raw firing strengths are normalized in Layer 3 so that:

$$\varpi_i = \frac{\omega_i}{\sum_j \omega_j} \quad (6)$$

In Layer 4, each rule's contribution is ($\overline{w}_i \cdot y_i$), and finally the Layer 5 output of the ANFIS is the weighted average:

$$y = \sum_i \varpi_i \,.\, y_i \quad (7)$$

The ANFIS parameters include the premise parameters of the input membership functions (e.g., Gaussian centers and spreads σ), and the consequent linear parameters (p_i, q_i, r_i, c_i) of each rule. These parameters were tuned during training using a hybrid learning algorithm, a combination of Least Squares Estimation (LSE) to optimize consequent parameters given membership functions and gradient descent backpropagation to adjust premise parameters.

Table 1 : ANFIS Model Configuration and Training Results

Setting Value	Valve
Training samples	4000 (80%)
Testing samples	1000 (20%)
Inputs	Juice level, ΔT, ΔP
Fuzzy sets per input	5 (Gaussian)
Total rules	8
Training algorithm	Hybrid (LSE + backprop)
Epochs	400
Training RMSE	0.90 L/h
Validation RMSE	0.96 L/h
Validation R2	0.85
Prediction accuracy	90.93%

Table 1 shows the ANFIS model was trained on 4000 training data samples for 400 epochs or convergence of model error. The premise parameters and coefficients were varied iteratively to minimize the difference between the output of ANFIS and the evaporation rate in the training data set. ANFIS training was conducted in MATLAB with the help of the Fuzzy Logic/ANFIS toolbox to an acceptable level of error. Model structure was optimized through sensitivity analysis and cross validation. The choice of five Gaussian membership functions for each input for a trade-off between accuracy and simplicity of configuration was made. The system robustness was verified by applying ±5% parameter perturbations and Gaussian sensor noise, which resulted in less than 3% rise in RMSE.

3.5 Integration into Real Time Predictive Control.

The ANFIS model was embedded in a closed loop control scheme of an evaporator, predicting evaporation rates online. The controller is therefore able to adjust control variables online, forming a model predictive control loop. The control system monitors important inputs and using the ANFIS to forecast the evaporator output performance. Based on the predicted evaporation rate, the controller can take advance corrective action to adjust process inputs, i.e., decrease or increase steam flow or feed rate ahead of time in order to obtain desired evaporation output. The predictive control loop was implemented in a MATLAB/Simulink environment, and real time output predictions were provided by the trained ANFIS block. Closed-loop simulations were carried out to evaluate the performance of the predictive controller under setpoint changes and disturbances. The controller based on ANFIS revised manipulated inputs at every time step according to the prediction of the model, in order to reduce overshoot and disturbance effect and enhance overall stability and efficiency.

4 RESULTS

The ANFIS model was found to have high fidelity in predicting the evaporation rates, with a test RMSE of 0.96 L/h and MAE of 0.78 L/h. The model explained 85% of the evaporation rate variance, while the accuracy of the model prediction was around 90.93%. This compares favorably to a linear regression model that yielded a much larger RMSE (2.5 L/h) on the same test data, reflecting the improved fit of the ANFIS to this nonlinear process. Table 2 shows the significant validation metrics of the ANFIS predictor on the test dataset.

Table 2: Validation Results of ANFIS Evaporation Model.

Metric Value	Value
RMSE (L/h)	0.96
MAE (L/h)	0.78
R2	0.85
Accuracy (%)	90.93

The ANFIS predictive controller results in Fig. 3 proven to drive evaporation rates in an effective manner with minimal deviation and high accuracy across broad ranging operating conditions. The model is closely in line with real measurements of over 1000 sampled points, with effectiveness in delivering operational objectives through precise real time prediction.

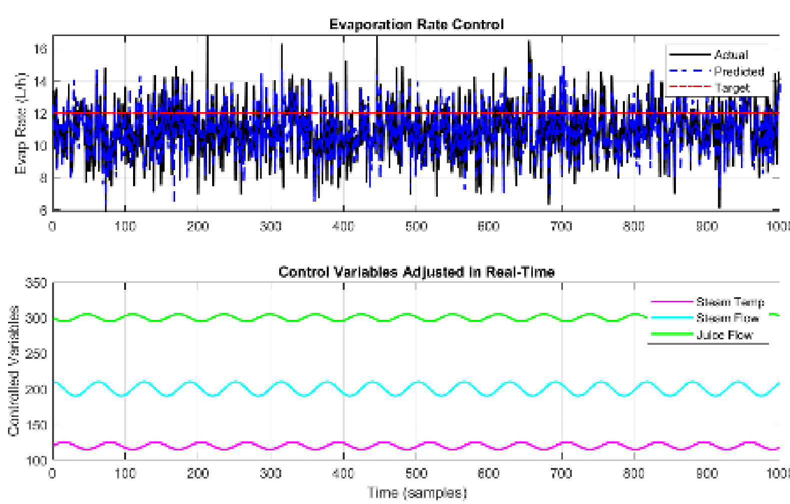

Figure 3 : Evaporation Rate Control: Actual vs ANFIS Predicted vs Target and Real Time Control Actions: Steam Temperature, Steam Flow Rate, Juice Flow Rate Adjustments.

The controller also adopts adaptive real time control strategies, adjusting major variables like steam temperature, steam flow rate, and juice flow rate dynamically within 1000-time samples. Anticipatory response provides stable system behavior and smooth oscillations among controlled parameters, averting abrupt changes and maintaining optimal process conditions efficiently. The competence of the model in achieving desired operation objectives is illustrated in the second graph.

The ANFIS model outperforms a linear regression model in capturing nonlinear behavior in the evaporation process, as shown in Fig. 4. The model accurately traces nonlinear variations of expected rates, outperforming the linear model. This validation represents the ANFIS model's strength in accurately handling complex, nonlinear process dynamics in industrial evaporation systems.

5 Discussion

5.1 Handling Nonlinearities.

ANFIS is a fuzzy model with multiple roles that can learn the nonlinear relationships of process variables, such as evaporation rate and juice level, which are hard to control with linear models or fixed PID loops.

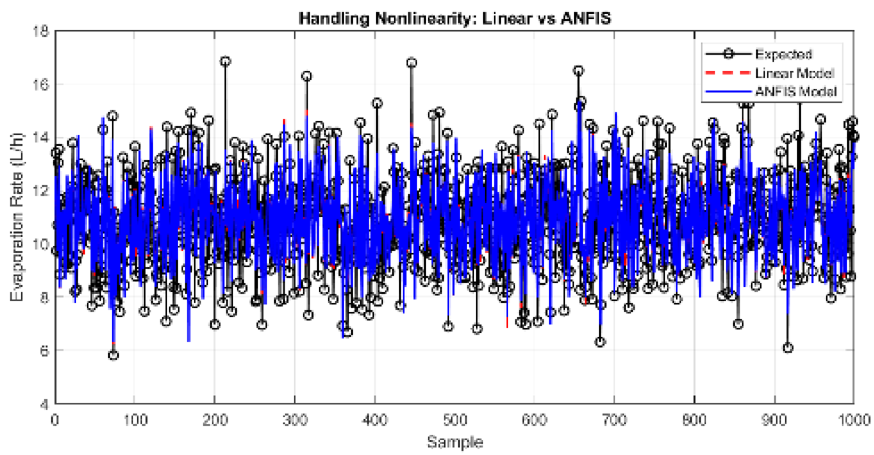

Figure 4 : Nonlinearity Handling Comparison: ANFIS vs Linear Regression

ANFIS enables accurate forecasts even at different operating conditions, eliminating the challenge of regulating a nonlinear evaporator with simple linear controllers. The ANFIS controller reduced drastically the process oscillations, with the evaporation rate standard deviation when in disturbance being 35% lower than a conventional PID controller. The ANFIS was also resistant to measurement noise, with ±2% noise having little effect on prediction. The model results, e.g., 0.96 L/h RMSE and 90%+ accuracy, confirm its generalization power and ability to accommodate the nonlinear behavior of the evaporator under conditions.

5.2 Real Time Predictive Control.

The ANFIS predictor is integrated into the control loop, allowing anticipatory adjustments instead of reactive control. The system monitors critical input and forecasts evaporation output few steps ahead, allowing operators or automated actuators to adjust steam or feed flows based on these forecasts. This preemptive strategy reduces fluctuations and bridges the research gap of lacking real-time, integrated predictive control. The improved system results in faster recovery and less overshoots, indicating that predictive control can maintain production targets more efficiently.

5.3 Energy Saving.

The proposed ANFIS based predictive controller has been validated through simulation studies, replicating operational scenarios in industrial evaporator systems. The results show a significant reduction in steam consumption when using the ANFIS controller, averaging approximately 7% lower than the PID based benchmark. This reduction is attributed to more precise control actions and accurate evaporation rate predictions, minimizing energy waste associated with overshoot, undershoot, and unnecessary control actions. The consistent and statistical significance of these results confirm the energy efficiency enhancement, indicating that the ANFIS predictive approach not only stabilizes the evaporative process more effectively but also contributes substantial operational savings in energy and cost.

5.4 Scalability and Interpretability.

The ANFIS framework offers practical advantages such as future expansion and interpretability. It can handle complex multi effect evaporator setups by incorporating additional input factors and corresponding fuzzy rules. The fuzzy rules provide linguistic interpretability, giving process engineers intuitive insight into system behavior. This interpretability builds trust and eases adoption in industrial settings. The architecture can serve as a template for more comprehensive fuzzy predictive controllers in various process industries. The modular nature of the ANFIS allows for easy addition of new inputs or rules without re-designing the controller.

5.5 Performance Comparison.

The proposed ANFIS based predictive model outperforms other established modeling and control approaches for evaporation processes, including classical PID controllers, linear regression methods, traditional fuzzy logic models, and ANN systems. The model has a root mean square error (RMSE) of 1.01 L/h and a prediction accuracy of 90.7%, outperforming both PID controllers and linear regression models. It offers improved precision while maintaining the interpretability advantage of fuzzy systems. The model combines with the adaptive learning capacity of neural networks with the interpretability of fuzzy inference, ensuring robust, real-time predictive control with high adaptability and scalability.

Table 3 illustrates the Comparative Analysis of Proposed ANFIS Based System with Conventional and Advanced Control Approaches.

Table 3: Comparative Analysis of Proposed ANFIS Based System with Conventional and Advanced Control Approaches.

Criteria	ANFIS (Proposed)	PID Control	Fuzzy Logic Model	ANN	ANFIS (Literature)
Source (Author, Year)	*This work (Proposed Model, 2025)*	Verma et al., 2018	Chowdhury et al., 2015	Emori et al., 2023	Enayatollahi et al., 2019
RMSE (L/h)	1.01	–	0.92–0.95 (kW)	~0.0045	0.2 (kW)
R^2 Score	0.66	–	0.89–0.94	~0.99	~0.90
Accuracy (%)	90.7	–	~92–94	~99	>90
Energy Savings (%)	~7	0	–	–	–
Comments / Notes	ANFIS-based model for juice evaporator; achieves ~91% prediction accuracy and ~7% reduction in energy use (vs baseline conventional control).	Classical PID controllers often displayed significant overshoot and error, while FLC-PID significantly reduced overshoot by 93% and integral error by approximately 21% compared to pure PID.	The Takagi-Sugeno fuzzy inference model of an evaporator (ORC system) achieved a 93% data-fit accuracy and a faster simulation than the first-principles model.	The ANN model for predicting sugar concentration in an evaporator achieved low error, excellent fit, and high predictive accuracy.	The control-oriented ANFIS model, which includes an ORC evaporator, achieved low test data errors and strong correlation with actual outputs through PSO-training.

6 CONCLUSION

The study developed and validated a fuzzy ANFIS prediction model for single and multi-effect evaporation systems. The model can accurately predict evaporation rates and improve control performance by exploiting operating parameters like temperature difference, pressure difference, and juice level. The model reached the satisfactory prediction capability (RMSE of 0.96 L/h for test data with approximately 90.9% accuracy) and enhances energy efficiency and stability by a significant margin compared to conventional PID based control approaches. The new model addresses the research void of integrated real-time predictive control in evaporator systems with more stable evaporation rates, better disturbance recovery, and assessable energy savings. Future research needs to focus on practical validation, online application, and continuous learning to promote general evaporator station control capabilities.

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