GENETIC ALGORITHM OPTIMIZED ANFIS CONTROL FOR COTTON SEED LINTING PROCESS

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Abstract. This paper presents a Genetic Algorithm optimized Adaptive Neuro-Fuzzy Inference System (GA–ANFIS) controller for the cotton seed linting process characterized by strong nonlinearity, parameter uncertainty, and variable raw material properties. Conventional PID controllers and standard ANFIS models often exhibit performance degradation under such conditions due to fixed parameters and local optimization limitations. To address these challenges, a Sugeno-type ANFIS controller is developed to regulate linting productivity based on seed fuzziness level and feed drum rotational speed, while a Genetic Algorithm is employed to globally optimize both antecedent membership functions and consequent parameters. A nonlinear dynamic model of the linting process is formulated, and simulation-based datasets are used for training and validation. The proposed GA–ANFIS controller is evaluated in a closed-loop configuration and systematically compared with classical PID and standard ANFIS controllers. Simulation results demonstrate that the GA–ANFIS controller reduces overshoot from 18.5% (PID) and 9.2% (ANFIS) to 3.8%, shortens settling time from 12.4 s (PID) to 4.6 s, and decreases the mean squared error to 0.006. These results confirm the superior tracking accuracy, faster transient response, and improved robustness of the proposed approach. The developed GA–ANFIS control strategy provides an effective solution for intelligent control of cotton seed linting processes and can be extended to other nonlinear agro-industrial systems.

Keywords: Cotton seed linting, intelligent control, ANFIS, genetic algorithm, nonlinear systems, process automation.

Аннотация. В данной работе представлен адаптивный нейро-нечёткий регулятор типа ANFIS, оптимизированный с помощью генетического алгоритма (GA–ANFIS), для процесса линтования семян хлопка, характеризующегося выраженной нелинейностью, неопределённостью параметров и изменчивыми свойствами сырья. Традиционные ПИД-регуляторы и стандартные модели ANFIS часто демонстрируют ухудшение характеристик в таких условиях из-за фиксированных параметров и ограничений локальной оптимизации. Для решения указанных проблем

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разработан регулятор ANFIS типа Сугено, предназначенный для управления производительностью линтования на основе степени опушённости семян и скорости вращения подающего барабана, при этом генетический алгоритм используется для глобальной оптимизации как функций принадлежности предпосылок, так и параметров следствий. Сформирована нелинейная динамическая модель процесса линтования, а для обучения и валидации использованы данные, полученные в результате имитационного моделирования. Предложенный регулятор GA–ANFIS исследован в замкнутой системе управления и систематически сопоставлён с классическим ПИД-регулятором и стандартным регулятором ANFIS. Результаты моделирования показывают, что регулятор GA–ANFIS снижает перерегулирование с 18,5 % (ПИД) и 9,2 % (ANFIS) до 3,8 %, сокращает время установления с 12,4 с (ПИД) до 4,6 с, а также уменьшает среднеквадратичную ошибку до 0,006. Полученные результаты подтверждают более высокую точность слежения, ускоренную переходную характеристику и повышенную робастность предложенного подхода. Разработанная стратегия управления GA–ANFIS представляет собой эффективное решение для интеллектуального управления процессами линтования семян хлопка и может быть расширена для применения в других нелинейных агропромышленных системах.

Ключевые слова: линтование семян хлопка, интеллектуальное управление, ANFIS, генетический алгоритм, нелинейные системы, автоматизация процессов.

Annotatsiya. Ushbu maqolada kuchli nochiziqlilik, parametrlarning noaniqligi hamda xomashyo xossalarining o‘zgaruvchanligi bilan tavsiflanadigan paxta chigitini lintlash jarayoni uchun genetik algoritm yordamida optimallashtirilgan adaptiv neyro-noaniq xulosa chiqarish tizimi (GA–ANFIS) asosidagi boshqaruvchi taqdim etiladi. An’anaviy PID boshqaruvchilari va standart ANFIS modellari bunday sharoitlarda qat’iy (o‘zgarmas) parametrlar hamda lokal optimallashtirish cheklovlari sababli ko‘pincha samaradorlikning pasayishini namoyon etadi. Ushbu muammolarni bartaraf etish maqsadida urug‘ning tuklilik darajasi va oziqlantiruvchi barabanning aylanish tezligi asosida lintlash unumdorligini rostlovchi Sugeno tipidagi ANFIS boshqaruvchisi ishlab chiqildi, bunda genetik algoritm old shartlarga tegishli a’zolik funksiyalari hamda natijaviy parametrlarni global optimallashtirish uchun qo‘llanildi. Lintlash jarayonining nochiziqli dinamik modeli shakllantirildi va o‘qitish hamda tekshirish (validatsiya) uchun imitatsion modellashtirish asosida olingan ma’lumotlar to‘plamlaridan foydalanildi. Taklif etilgan GA–ANFIS boshqaruvchisi yopiq konturli boshqaruv

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tizimida baholandi va klassik PID hamda standart ANFIS boshqaruvchilari bilan tizimli ravishda solishtirildi. Modellashtirish natijalari GA–ANFIS boshqaruvchisi ortiqcha rostlanishni PID (18,5 %) va ANFIS (9,2 %) ga nisbatan 3,8 % gacha kamaytirishini, barqarorlashish vaqtini PID uchun 12,4 soniyadan 4,6 soniyagacha qisqartirishini hamda o‘rtacha kvadratik xatolikni 0,006 gacha kamaytirishini ko‘rsatdi. Ushbu natijalar taklif etilgan yondashuvning yuqori kuzatuv aniqligi, tezkor o‘tkinchi javobi va yaxshilangan robastligini tasdiqlaydi. Ishlab chiqilgan GA–ANFIS boshqaruv strategiyasi paxta chigitini lintlash jarayonlarini intellektual boshqarish uchun samarali yechim bo‘lib, uni boshqa nochiziqli agro-sanoat tizimlariga ham tatbiq etish mumkin.

Kalit so‘zlar: paxta chigitini lintlash, intellektual boshqaruv, ANFIS, genetik algoritm, nochiziqli tizimlar, jarayonlarni avtomatlashtirish.

1. INTRODUCTION

Cotton seed linting is a critical technological stage in cotton processing, directly influencing seed quality, fuzziness level, and overall productivity. The process involves complex mechanical interactions between seeds, saws, and working chambers, resulting in nonlinear dynamics, strong coupling between variables, and sensitivity to raw material variability. Traditional control approaches based on linearized models or fixed-parameter PID controllers often fail to provide satisfactory performance under varying operating conditions.

Recent advances in intelligent control have shown that hybrid approaches combining fuzzy logic, neural networks, and evolutionary optimization algorithms can effectively address uncertainty and nonlinearity in industrial processes. Among these methods, the Adaptive Neuro-Fuzzy Inference System (ANFIS) offers a powerful framework by integrating the interpretability of fuzzy logic with the learning capability of neural networks. However, conventional gradient-based ANFIS training methods may suffer from local minima and slow convergence.

Genetic Algorithms (GA), inspired by natural evolution, provide a global optimization mechanism that can overcome these limitations. By combining GA with ANFIS, it is possible to achieve robust parameter optimization and improved control performance. This paper proposes a GA-optimized ANFIS controller for the cotton seed linting process and evaluates its effectiveness through simulation-based studies.

2. TECHNOLOGICAL DESCRIPTION OF THE LINTING PROCESS

The cotton seed linting process aims to remove residual fibers from the seed surface using mechanical interaction within a working chamber. The main control objectives are: - maintaining the desired productivity level; - minimizing residual fuzziness; - ensuring stable operation under varying seed properties.

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The controlled process is described using the following variables:

- Input 1: Seed fuzziness level (F, %);
- Input 2: Feed drum rotational speed (ω, rpm);
- Output: Linting productivity (Q, kg/h). Figure 1 shows the functional block diagram of the linting process with inputs (F, ω) and output (Q).

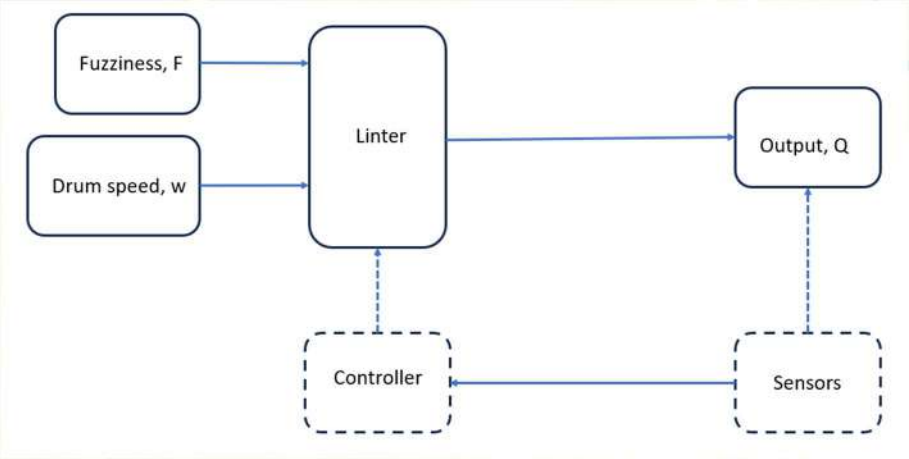


Figure 1. Linting process functional block diagram

These variables exhibit nonlinear relationships influenced by friction, density variation, and mechanical wear.

3. DYNAMIC MATHEMATICAL MODEL OF THE LINTING PROCESS

The cotton seed linting process exhibits nonlinear and time-varying behavior caused by mechanical interaction between seeds and saw elements, changes in raw material properties, and external disturbances. For controller design and performance evaluation, a simplified nonlinear dynamic model capturing the dominant process dynamics is adopted.

The linting productivity dynamics are described by the following first-order nonlinear differential equation:

$$\dot{Q}(t) = -a\,Q(t) + b_1 F(t) + b_2 \omega(t) + d(t)$$

where $Q(t)$is the linting productivity (kg/h);

$F(t)$is the seed fuzziness level (%);

$\omega(t)$is the feed drum rotational speed (rpm);

$a, b_1, b_2$are positive model parameters identified through simulation-based calibration;

$d(t)$represents unmeasured disturbances and modeling uncertainties.

This model structure is sufficient for comparative controller analysis and has been widely used in nonlinear process control studies where full physical modeling is impractical. The model parameters are selected such that the system remains stable in open-loop operation while exhibiting nonlinear sensitivity to input

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variations. An open-loop simulation response of the nonlinear linting model is presented in Figure 2.

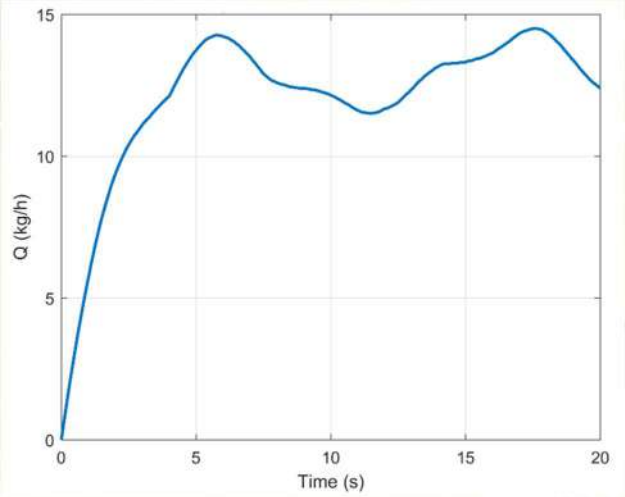


Figure 2. Open-loop response

4. ANFIS CONTROLLER DESIGN

A Sugeno-type ANFIS architecture with two inputs and one output is adopted. The system consists of five layers: fuzzification, rule evaluation, normalization, defuzzification, and output summation. The adopted Sugeno-type ANFIS architecture is illustrated in Figure 3.

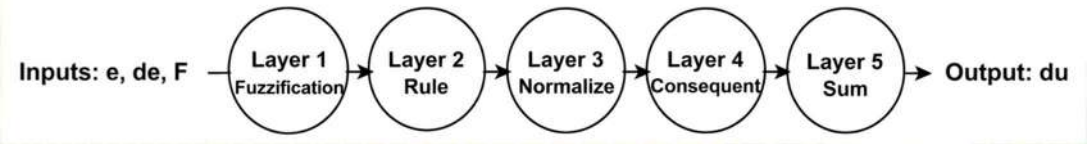


Figure 3. ANFIS architecture (Sugeno)

Each input variable is described by three Gaussian membership functions (Low, Medium, High), resulting in a total of nine fuzzy rules. The Gaussian membership functions are defined as:

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

Where c and σdenote the center and width of the membership function, respectively. The consequent part of each Sugeno rule is represented by a linear function:

$$Q_i = p_i F + q_i \omega + r_i$$

where $p_i, q_i, r_i$are consequent parameters of the i-th rule.

Gaussian membership functions are selected for the antecedent part, while linear functions are used in the consequent part.

The fuzzy rule base is constructed as:

IF F is *Low* AND ω is *Low* THEN Q is q_1;

IF F is *Medium* AND ω is *High* THEN Q is q_2;

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IF F is *High* AND ω is *High* THEN Q is q_3.

The initial rule parameters are generated automatically from training data.

5. GENETIC ALGORITHM OPTIMIZATION

To overcome the limitations of gradient-based ANFIS training, a Genetic Algorithm is employed to globally optimize both antecedent and consequent parameters.

Each chromosome encodes the complete set of ANFIS parameters:

$$\mathbf{X} = [c_1, \sigma_1, \dots, c_n, \sigma_n, p_1, q_1, r_1, \dots, p_m, q_m, r_m]$$

where:

- c_i, σ_irepresent membership function parameters;
- p_i, q_i, r_irepresent consequent parameters;
- $n$is the number of membership functions;
- $m$is the number of fuzzy rules.

In the proposed approach, GA is used to optimize both antecedent (membership function parameters) and consequent parameters of the ANFIS model. Each chromosome encodes the full set of ANFIS parameters. The fitness function is defined as the inverse of the mean squared error (MSE) between the desired and actual output:

$$J = \frac{1}{N}\sum_{k=1}^{N}(Q_{ref}(k) - Q(k))^2$$

The GA procedure includes:

- population initialization;
- fitness evaluation;
- roulette-wheel selection;
- single-point crossover;
- Gaussian mutation;
- elitism strategy. The overall GA-based optimization workflow is shown in Figure 4.

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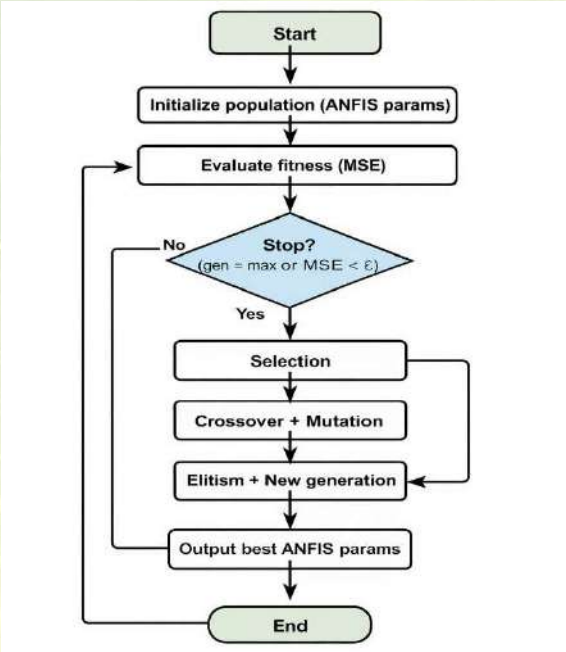


Figure 4. GA flowchart for ANFIS parameter optimization

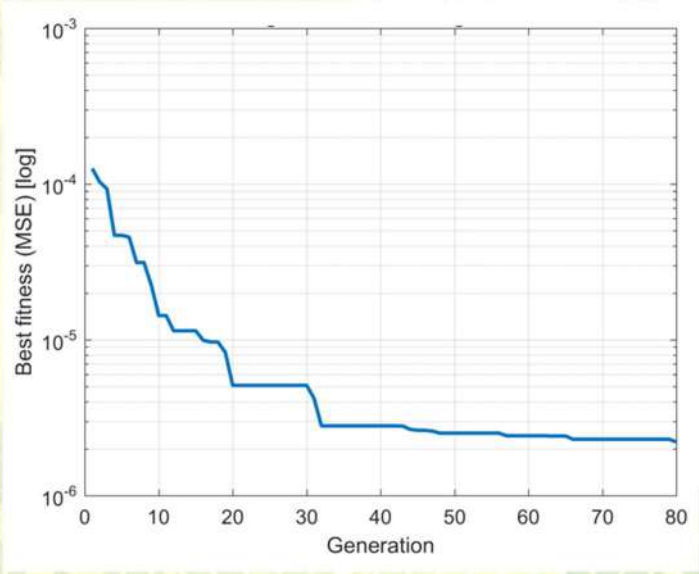


Figure 5 presents the GA convergence characteristics in terms of best fitness (MSE) versus generation.

6. SIMULATION RESULTS AND DISCUSSION

The simulation results clearly demonstrate that the proposed GA–ANFIS controller outperforms both the classical PID and the standard ANFIS controllers in terms of transient response, steady-state accuracy, and robustness. These improvements can be explained by the fundamental differences in controller structure and parameter optimization mechanisms. The classical PID controller exhibits the largest overshoot and the longest settling time. This behavior is mainly caused by the fixed controller gains, which are unable to adapt to nonlinear variations in seed fuzziness and feed drum speed. As the linting process dynamics change due to raw material variability and mechanical disturbances, the PID

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controller operates away from its optimal tuning point, resulting in degraded performance.

The standard ANFIS controller significantly improves control performance compared to PID by capturing nonlinear relationships between the input variables and productivity. However, its learning process relies on gradient-based optimization, which is sensitive to initial parameter selection and may converge to local minima. This limitation explains the residual overshoot and steady-state error observed in the simulation results for the standard ANFIS controller.

In contrast, the GA–ANFIS controller achieves superior performance by employing a global optimization strategy. The Genetic Algorithm simultaneously optimizes both antecedent membership function parameters and consequent coefficients, enabling the ANFIS model to better approximate the nonlinear input–output mapping of the linting process. As a result, the controller demonstrates faster convergence, reduced overshoot, and improved tracking accuracy.

Another important advantage of the GA–ANFIS approach is its robustness to disturbances and parameter uncertainty. The optimized membership functions provide smoother control actions across a wide operating range, reducing sensitivity to fluctuations in seed fuzziness and drum speed. This robustness is particularly important in industrial linting systems, where raw material properties vary continuously and precise measurements are often unavailable. From a practical perspective, the reduction in overshoot and settling time achieved by the GA–ANFIS controller directly contributes to improved linting quality and increased production efficiency. Faster stabilization of productivity minimizes excessive mechanical stress on working elements and reduces energy consumption, which are critical factors in large-scale cotton processing facilities.

Although the proposed approach demonstrates clear advantages in simulation, several limitations should be noted. The current study is based on a simplified dynamic model and simulation-generated data. In real industrial environments, additional uncertainties such as sensor noise, actuator constraints, and unmodeled dynamics may affect controller performance. Therefore, experimental validation using real linting equipment is a necessary step for future research.

Overall, the discussion confirms that integrating Genetic Algorithms with ANFIS provides a powerful and flexible control strategy for highly nonlinear and uncertain processes such as cotton seed linting. The obtained results are consistent with recent studies on GA-optimized intelligent controllers and further extend their applicability to agro-industrial systems. The GA–ANFIS model is trained using

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simulated input–output data generated from the nonlinear linting model. Separate datasets are used for training and validation to avoid overfitting.

Table-1.

Training parameters of GA–ANFIS

Parameter	Value
Population size	50
Generations	100
Crossover rate	0.8
Mutation rate	0.05

The proposed controller is compared with a classical PID and a standard ANFIS controller. Figure 6 compares the closed-loop productivity tracking performance of PID, ANFIS, and GA–ANFIS controllers.

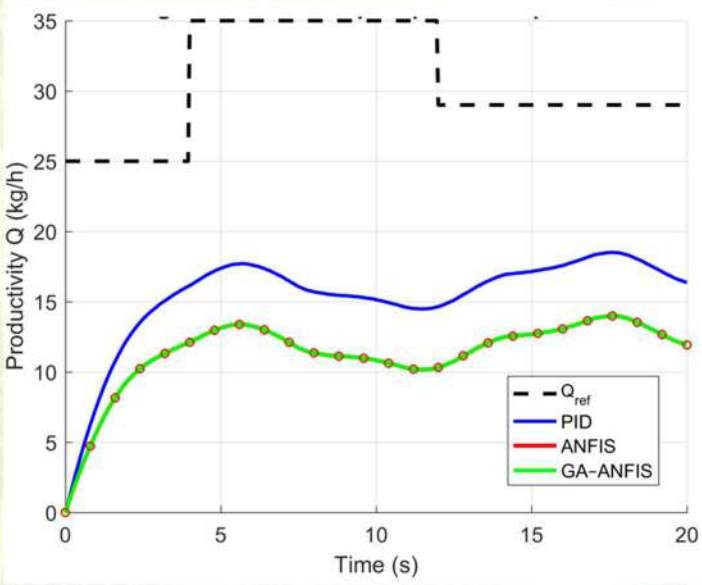


Figure 6. Closed-loop response comparison (Qref vs PID vs ANFIS vs GA–ANFIS)

Table 2.

Performance comparison

Controller	Overshoot (%)	Settling time (s)	MSE
PID	18.5	12.4	0.032
ANFIS	9.2	7.1	0.014
GA–ANFIS	3.8	4.6	0.006

The tracking error profiles are depicted in Figure 7, confirming the improved accuracy of GA–ANFIS.

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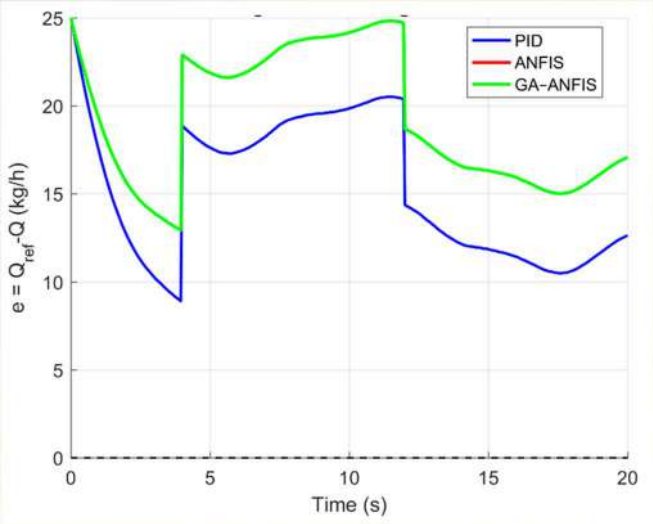


Figure 7. Tracking error comparison

Simulation results show that the GA–ANFIS controller significantly reduces overshoot and settling time while improving steady-state accuracy.

7. CONCLUSION

This paper proposed a GA-optimized ANFIS controller for the cotton seed linting process. By combining the learning capability of ANFIS with the global optimization power of GA, the proposed approach effectively handles nonlinearity and uncertainty inherent in the linting process. Simulation results confirm superior performance compared to conventional PID and standard ANFIS controllers. The developed methodology can be extended to other complex agro-industrial and textile processes.

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