

FUZZY LOGIC AND ANFIS IN THE CONTROL OF COTTON PRIMARY PROCESSING OPERATIONS: A REVIEW OF APPLICATIONS, DESIGN CHOICES AND PROSPECTS FOR SEED DELINTING

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Abstract:

Cotton primary processing turns seed cotton into baled lint and planting or crushing seed through drying, cleaning, ginning, lint cleaning and seed delinting. Each stage works on a raw material whose moisture, trash content and fuzz level change from lot to lot, while product quality is usually measured in the laboratory long after the material has passed the machine. Fuzzy logic and adaptive neuro-fuzzy inference systems (ANFIS) are often suggested for such poorly modelled processes, but their use along the cotton processing chain has not been reviewed as a whole. This paper reviews [N] studies published between 1990 and 2026 that apply fuzzy, neuro-fuzzy or ANFIS methods to cotton primary processing or to closely related drying and oilseed operations. The studies were classified by processing stage, task (modelling, classification or control) and level of validation (simulation, laboratory or industrial). Most fuzzy and ANFIS work in the cotton sector deals with fibre grading and quality prediction, whereas closed-loop control is reported mainly for dryers and, rarely, for gin automation. Design choices such as the inference type, the number and shape of membership functions and the source of the rule base are seldom justified. Saw delinting of cottonseed is almost absent from this literature. The review summarises transferable design lessons and proposes a control architecture for saw delinting that

combines an ANFIS quality model, a fuzzy supervisory layer and adaptation to saw wear.

Keywords: fuzzy logic control; ANFIS; cotton ginning; seed cotton drying; cotton grading; cottonseed delinting; process control

1. Introduction

In a cotton gin, seed cotton passes through drying, cleaning, ginning and lint cleaning before the lint is baled. The separated seed then follows its own route, and seed intended for planting or crushing is usually delinted. Gins that run these stages under programmable logic controllers report better throughput, fibre quality and consistency when dryer moisture is held in closed loop and feeder speed is adjusted to the load [1]. In-line moisture meters are now available, and some of them are connected directly to automatic control [2]. Even so, a study at seven industrial gins in Mali needed a dedicated sampling and testing method to detect fibre quality changes at each main stage, and its authors named an online quality monitoring tool as the next step [3].

The seed stream faces similar problems. Mechanical delinting can damage the seed coat when the process is not optimised [4]. Saw linters of the 5LP type are reported to run at about half of their rated capacity because the agitator compacts the seed roll in the working chamber [5], and the interaction between the seed and the saw cylinder is still being described analytically [6]. In both streams the controller faces the same conditions: the input material varies from lot to lot, the key quality index is measured late, the relationships between inputs and quality are nonlinear, and the machine itself changes slowly as working parts wear.

Fuzzy logic was proposed for exactly this kind of process. Fuzzy sets [7] allow an operator's rules to be written in linguistic form, and an early fuzzy controller showed that such rules can run a plant without an analytical model [8]. The Takagi–Sugeno form [9] made fuzzy models easier to identify from data, and ANFIS [10] added a learning procedure that tunes membership functions and rule consequents from measured input–output pairs. Fuzzy control is now widely used in industry [11], and fuzzy methods for product quality control have been reviewed for the food sector, where raw material variability is also high [12].

Existing reviews leave the cotton processing chain largely uncovered. A recent review of deep learning in the cotton industry covers field monitoring and processing but concentrates on neural network methods [13]. A review of artificial neural networks in agricultural drying notes that fuzzy logic has been used for dryer control since the early 1990s, but it does not focus on fuzzy or neuro-fuzzy design [14], and a book on intelligent control in drying treats drying in general rather than cotton [15]. Fuzzy and neuro-fuzzy studies specific to cotton are scattered across gin automation [16], fibre grading [17], [18] and, more recently, seed delinting [19][20][21]. No published review brings these studies together, compares their design choices or asks what they mean for the control of saw delinting.

This paper addresses that gap. Its aim is to map the use of fuzzy logic and ANFIS along the cotton primary processing chain and to draw design lessons for the control of saw delinting. Three research questions guide the review:

RQ1. At which processing stages have fuzzy and ANFIS methods been applied, and for which task: modelling, classification or control?

RQ2. Which design choices were made (inference type, membership functions, rule base source, tuning method), and at what level were the results validated?

RQ3. Which of these experiences can be transferred to saw delinting, and which gaps remain open?

The paper is organised as follows. Section 2 describes the review protocol. Section 3 summarises the

fuzzy and ANFIS concepts used later and reports the reviewed applications stage by stage. Section 4 discusses design lessons and proposes a control architecture for saw delinting. Section 5 concludes.

2. Materials and Methods

2.1. Review design

The study is a structured literature review. Its search and selection steps are reported following the PRISMA 2020 statement [22] where that statement applies to a review without meta-analysis. The unit of analysis is a published study that designs, trains or tests a fuzzy, neuro-fuzzy or ANFIS system for a cotton primary processing operation or for a closely analogous operation.

2.2. Information sources and search

Scopus, Web of Science Core Collection, Google Scholar, CNKI and eLIBRARY.ru were searched, and Lens.org was used for patents. The search covered 1990 to [day month] 2026; 1990 was chosen because fuzzy dryer control appears in the literature from the early 1990s [14]. Foundational works on fuzzy sets and ANFIS [7]–[10] were added by citation tracking. Table 1 lists the search strings.

Table 1. Search strings used in the review

Group	Search string (title, abstract, keywords)
Ginning and cleaning	("cotton gin*" OR "seed cotton" OR "lint clean*") AND (fuzzy OR "neuro-fuzzy" OR ANFIS)
Drying and moisture	("cotton" AND (dry* OR moisture)) AND (fuzzy OR ANFIS)
Grading and quality	("cotton" AND (grad* OR classing OR "fiber quality" OR "fibre quality")) AND (fuzzy OR ANFIS)
Seed processing	(cottonseed OR "cotton seed" OR oilseed) AND (delint* OR linter* OR "oil extraction") AND (fuzzy OR ANFIS)
Russian and Chinese	«линтерование», «нечеткая логика» хлопок; 籽棉 模糊控制; 轧花 模糊

2.3. Eligibility criteria

Studies were included when they (i) appeared as a journal article, conference paper, book chapter, dissertation or patent; (ii) applied fuzzy logic, a neuro-fuzzy network or ANFIS, alone or tuned by a genetic algorithm or particle swarm optimisation; and (iii) addressed seed cotton drying, cleaning, ginning, lint cleaning, fibre grading or cottonseed processing. Drying and oilseed studies outside cotton were included only when they controlled or modelled a comparable variable, such as product moisture or residual content, and were used as analogues.

Studies were excluded when they dealt with crop growth, irrigation or breeding, with weaving or dyeing, or when they named a fuzzy method without describing its structure. Duplicates and papers in languages other than English, Russian, Uzbek or Chinese were also removed.

2.4. Screening and data extraction

Records were screened first by title and abstract and then in full text. For every included study the following items were extracted: processing stage, task, inference type (Mamdani, Takagi–Sugeno or ANFIS), membership function shape and number, source of the rule base (expert or data), tuning method, input and output variables, validation level and performance metric. Items a study did not report were recorded as "not reported" rather than inferred.

2.5. Classification scheme

Each study was placed on three axes: stage (drying, cleaning and ginning, grading, fibre to yarn, seed processing), task (modelling or prediction, classification, control) and validation level. Validation was coded as S (simulation only), L (laboratory or pilot plant) or I (industrial plant). The selection process is summarised in Fig. 1.

Fig. 1. PRISMA-style flow of record selection. [To be drawn after the search: records identified n = ...; after duplicate removal n = ...; screened by title and abstract n = ...; full texts assessed n = ...; studies included n =]

3. Results

3.1. Fuzzy and neuro-fuzzy design choices used in the reviewed studies

The reviewed studies differ mainly in five design choices, summarised in Table 2. The first is the inference type. A Mamdani system [8] has fuzzy sets in both the antecedent and the consequent of each rule, so an operator can read and correct the rule base directly. A Takagi–Sugeno system [9] replaces the consequent with a linear function of the inputs. It is easier to fit to data and gives a smooth output, but its rules are harder to interpret.

ANFIS [10] is a Takagi–Sugeno system written as a five-layer network. Its hybrid learning rule tunes the consequent parameters by least squares and the membership function parameters by gradient descent. Gradient-based tuning can stop in a local minimum, and for this reason many later studies tune ANFIS with genetic algorithms, particle swarm optimisation or other metaheuristics [23]. Genetic algorithms are also used to learn the rule base itself, and in Mamdani systems they can be constrained to keep the rules readable [24].

The second and third choices concern membership functions. Triangular, trapezoidal and Gaussian shapes are the most common, and the number of functions per input sets the size of the rule base. The shape matters in practice. In an ANFIS model of rapeseed oil extraction, trapezoidal functions gave the best fit for three of five outputs and triangular functions for the other two [25]. The fourth choice is the source of the rules: operator knowledge, measured data, or expert rules refined with data. The fifth is how interpretability is judged. Gacto et al. [26] group interpretability measures into those of complexity, such as the number of rules and conditions, and those of semantics, such as the distinguishability of fuzzy sets. Few process studies report either kind.

Table 2. Main design choices in fuzzy and ANFIS systems for process applications

Design choice	Common options	Effect on the model	Ref.
Inference type	Mamdani; Takagi–Sugeno; ANFIS	Mamdani rules are readable; Takagi–Sugeno and ANFIS fit data more closely but are harder to interpret	[8]–[10]
Membership function shape	Triangular; trapezoidal; Gaussian	Changes accuracy; the best shape can differ between outputs of the same process	[25]
Number of functions per input	Two or more per input	With grid partitioning, the number of rules is the product of the numbers of functions per input, so the rule base grows quickly	[10], [26]
Rule base source	Operator knowledge; data; knowledge refined with data	Expert rules work with little data; data-driven rules need representative records	[8], [24]
Tuning method	Hybrid least squares and gradient; genetic algorithm; particle swarm	Metaheuristics reduce the risk of local minima at a higher computing cost	[10], [23], [24]

3.2. Applications by processing stage

Seed cotton drying and moisture control. Among the reviewed studies, drying has the most reports of fuzzy control, although mostly for products other than cotton. In gins, the technical base for closed-loop moisture control already exists: dryer moisture can be held in closed loop under PLC supervision [1], and in-line moisture meters supply the feedback signal [2]. Most fuzzy dryer studies concern grain and food. Liu et al. [27] applied fuzzy control to a mixed-flow grain dryer. Ortíz-Yescas et al. [28] combined a PI controller with a fuzzy component for a drum dryer, using steam pressure and drum speed to control product moisture and temperature, and compared it with classical PI in LabVIEW simulation. Tabares-Martínez et al. [29] built a low-cost fuzzy controller on an Arduino board for a rotary dryer; with a 3.5

kg load of carrot slices the thermal efficiency reached 86%, against 30% and 17% for the smaller loads. In Tashkent, Usmanov et al. [30] tested fuzzy control of a cabinet solar dryer under real climatic conditions. For seed cotton itself, Yunusova [31] simulated a fuzzy regulation system for drying with a trained neural network. Reviews of intelligent drying [14], [15] confirm that fuzzy controllers are well established for dryers but say little about seed cotton.

Cleaning and ginning. Fewer fuzzy studies address the cleaning and ginning machines themselves. Siddaiah et al. [16] treated cotton gin automation as an intelligent-systems problem. [Author: state the method and stage from the full text.] The need for such work is clear from recent industrial data. Togola et al. [3] proposed a sampling and testing method that detects fibre quality changes at the seed cotton cleaning, ginning and lint cleaning stages, and they called for online monitoring of fibre quality during ginning. A review of deep learning in the cotton industry likewise covers processing but reports neural network methods rather than fuzzy control [13].

Fibre grading and classification. Within the cotton sector itself, most of the reviewed fuzzy studies deal with grading. Thakre and Khot [17] proposed a fuzzy logic model for cotton grading. Yuan et al. [18] graded seed cotton from images: yellowness, brightness and impurity features were combined through fuzzy nearness and a neural network, giving about 92% classification accuracy. Machine vision is now the main route for quality grading of saw-ginned cotton [32] and for detecting foreign fibres [33]. In these studies the fuzzy system supports a decision; it does not act on the machine.

Link to yarn quality. Fibre properties set by ginning carry forward into spinning. ANFIS has been used to model cotton yarn properties from fibre and process inputs [34], and neural network methods in yarn manufacturing were reviewed recently [35]. These studies are cited here only to show that a fibre quality model built at the gin has a downstream user.

Cottonseed processing and delinting. Delinting methods are chemical, physical (mechanical or thermal) or biological, and mechanical delinting can damage the seed if it is not optimised [4]. For 5LP saw linters, the main reported limits are compaction of the seed roll by the agitator, which keeps the machine at about half of its rated capacity [5], and the seed–saw interaction in the working chamber [6]. Seed quality after delinting is now measured by image analysis: seed breakage online by a Light-YOLO network with 96.1% detection accuracy and 86.7% online sorting accuracy on acid-delinted seed [36], and residual lint and seedling traits by phenotyping images [37]. In the closely related oilseed sector, ANFIS predicted the quality of rapeseed oil and meal from seed temperature and moisture after cooking [25]. Control of saw delinting itself has been studied with an experimental-statistical model that includes time drift [38] and with a linear state-space model that treats the plant as stationary [39]. Fuzzy and ANFIS methods for this process appear only in recent work by the present authors' group: an optical converter of seed pubescence for in-line measurement [21], GA-optimised ANFIS control of the linting process [19] and ANFIS-based compensation of external disturbances [20].

Table 3 places the studies on the three axes of Section 2.5.

Table 3. Reviewed studies by processing stage, task, method and validation level (S simulation, L laboratory or pilot, I industrial)

Ref.	Stage	Task	Method	Validation
[27]	Drying (grain)	Control	Fuzzy controller	[check]
[28]	Drying (drum)	Control	Hybrid PI–fuzzy	S
[29]	Drying (rotary)	Control	Fuzzy, Arduino	L
[30]	Drying (solar cabinet)	Control	Fuzzy controller	[check]
[31]	Drying (seed cotton)	Control	Fuzzy with neural network	S
[16]	Ginning	Automation	[check]	[check]
[17]	Grading	Classification	Fuzzy model	[check]

Ref.	Stage	Task	Method	Validation
[18]	Grading (seed cotton)	Classification	Fuzzy pattern recognition with neural network	L
[34]	Fibre to yarn	Prediction	ANFIS	[check]
[25]	Oilseed (rapeseed)	Prediction	ANFIS	[check]
[19]	Seed delinting	Control	GA-optimised ANFIS	[check]
[20]	Seed delinting	Disturbance compensation	ANFIS	[check]

Studies identified by the systematic search (Section 2) will be added to this table.

4. Discussion

4.1. Where fuzzy methods are used and how they are designed (RQ1, RQ2)

The reviewed studies show an uneven picture. In the cotton sector, fuzzy and ANFIS methods are used mostly for grading and for predicting quality [17], [18], [34]. They act as decision tools that classify a sample or estimate a property, not as controllers that move an actuator. Closed-loop fuzzy control is reported mainly for dryers [27]–[30], and most of those dryers handle grain or food rather than seed cotton. For gin machinery, the documented practice is conventional PLC control [1], and fuzzy work on the machines themselves is rare [16]. Seed delinting appears only in the work of the present authors' group [19]–[21].

Validation is a second weakness. Several control studies stop at simulation [28], [31], and few report tests on an industrial machine. Design choices are also seldom argued. Studies rarely explain why a given number or shape of membership functions was chosen, although the rapeseed example shows that the shape alone can change which model fits best [25]. We found no cotton study that reports an interpretability measure of the kind collected by Gacto et al. [26].

4.2. Lessons for saw delinting (RQ3)

Saw delinting shares the main difficulties of the other stages, and Table 4 links each difficulty to a remedy found in the reviewed literature.

Table 4. Control difficulties in cotton processing, remedies from the reviewed studies and their relevance to saw delinting

Difficulty	Remedy reported in the literature	Relevance to saw delinting	Ref.
Quality measured late in the laboratory	In-line sensing; data-driven soft sensor	Residual lint estimated from in-line signals instead of a standard laboratory test	[2], [21], [40]
Variable raw material	Closed-loop moisture control; fuzzy supervision of set points	Initial fuzz and seed moisture treated as measured disturbances	[1], [11]
Nonlinear input–quality relationships	ANFIS models tuned by hybrid learning or metaheuristics	Nonlinear map from saw speed and seed feed to residual lint	[10], [19], [23]
Slow change of the machine	Models that include time drift	Saw wear treated as a slow drift instead of assuming a stationary plant	[38], [39]
Operators must trust the controller	Readable Mamdani rules; interpretability measures	Rule base that shift operators can read and check	[8], [26]
Few representative data	Expert rules refined later with data	Start from operator rules, then tune them with plant records	[8], [24]

Two points deserve emphasis. First, closed-loop moisture control in gins depends on in-line moisture meters [1], [2]; a quality loop can be no better than its measurement. For saw delinting, this means an in-line residual lint signal [21]. Without it, an ANFIS model can serve only as a soft sensor [40]. Second, the stationary plant assumption used in earlier control work [39] conflicts with the experimental evidence of time drift [38]. A delinting controller therefore needs a slow adaptation path in addition to the fast

quality loop.

4.3. Proposed control architecture

These lessons lead to the architecture in Fig. 2. Measured signals (residual lint, seed flow, saw cylinder speed and drive current) feed an ANFIS quality model. A fuzzy supervisory layer compares the predicted or measured residual lint with its set point and adjusts saw speed and seed feed. A slow loop retunes the model as the saws wear. Operator rules provide the initial rule base and remain readable after tuning. The architecture is a proposal drawn from the reviewed literature; its performance has to be shown on an industrial linter.

A fast quality loop and a slow wear loop for saw delinting

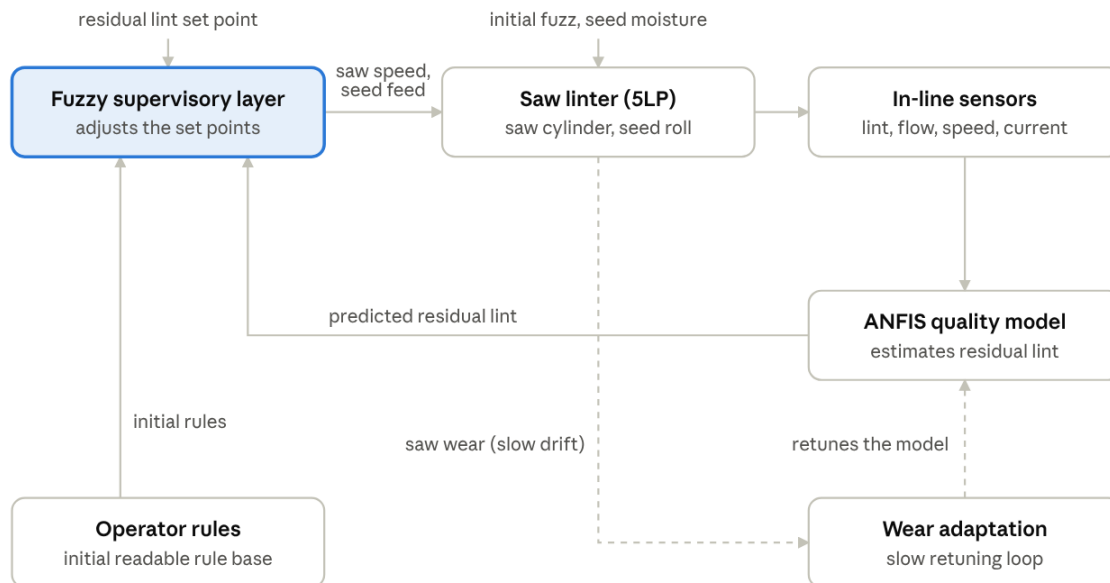


Fig. 2. Proposed control architecture for saw delinting. Solid arrows form the fast quality loop; dashed arrows form the slow loop that retunes the ANFIS model as the saws wear.

4.4. Limitations of the review

The review is limited to the sources and languages listed in Section 2. Much of the cotton processing literature from Central Asia and China is published in national journals without DOIs or in languages not covered, and some studies may have been missed. Several included studies give too little detail for full data extraction, and those items are marked as not reported rather than inferred.

5. Conclusion

This review mapped the use of fuzzy logic and ANFIS along the cotton primary processing chain. Three conclusions follow.

Fuzzy and ANFIS methods in the cotton sector serve mainly fibre grading and quality prediction. Closed-loop fuzzy control is reported mostly for dryers, few studies were validated on industrial machines, and saw delinting is almost absent from the literature (RQ1).

The inference type, the number and shape of membership functions and the source of the rule base are seldom justified, and interpretability is rarely, if ever, measured (RQ2).

For saw delinting, the transferable lessons are to close the loop on an in-line quality signal, to treat raw material properties as measured disturbances, and to add a slow adaptation path for saw wear (RQ3).

Future work should test the proposed architecture on an industrial 5LP linter, report design choices

together with interpretability measures, and publish open process data so that controllers for cotton processing can be compared on the same records.

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