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FUZZY LOGIC FOR DECISION SUPPORT IN AGRIBUSINESS: FUNDAMENTALS, APPLICATIONS, AND AN ILLUSTRATIVE LIVESTOCK-CONTROL FRAMEWORK

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Abstract

This paper presents an integrative narrative review of the fundamentals and applications of fuzzy logic as a decision-support tool in agribusiness, with emphasis on environmental control and animal welfare in swine production. Proposed by Zadeh (1965), fuzzy logic represents continuous membership degrees between 0 and 1, addressing the imprecision and uncertainty inherent to agricultural production systems. The four operational stages of a fuzzy system — fuzzification, rule base, inference mechanism, and defuzzification — are described within a Mamdani-type architecture using minimum (AND) and maximum (aggregation) operators and centroid defuzzification. Consolidated applications in greenhouse and barn environmental control, precision irrigation, crop recommendation, and animal welfare are discussed, together with a fully specified illustrative Mamdani simulation of thermal control in individual and collective pens for pregnant sows. According to Li et al. (2019), a multivariable fuzzy controller achieved a 19% reduction in energy consumption compared with manual regulation in a confined pig house, together with faster response and higher operational-efficiency output than a proportional controller in the same study. The review indicates that fuzzy logic constitutes an accessible, scalable, and methodologically transparent approach for improving management,

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operational efficiency, and sustainability in agricultural and livestock systems, while requiring local calibration before operational deployment.

Keywords: fuzzy logic; Mamdani inference; decision support; precision agriculture; swine production; animal welfare.

1. Introduction

Brazilian agribusiness stands out as one of the most dynamic and competitive sectors worldwide. However, its growing complexity — shaped by climate variability, animal-welfare requirements, sustainability pressure, and the continuous need for productivity gains — poses challenges that are not always fully addressed by traditional management tools. In this context, fuzzy logic emerges as a relevant approach for supporting decision-making in complex production systems.

Proposed by Lotfi Zadeh in 1965, fuzzy logic was developed to handle the imprecision and uncertainty inherent to the real world. Unlike traditional binary systems, based on rigid "yes-or-no" or "on-or-off" decisions, this approach allows continuous membership degrees between 0 and 1, enabling a more realistic representation of the gradual transitions that characterize biological and environmental phenomena.

In the agribusiness context, this capability translates into practical advantages: fuzzy logic allows the integration of multiple variables into decision processes, incorporates expert empirical knowledge through rules, and adapts to different production conditions. Its applications range from digital agriculture to animal production, such as swine farming, where it contributes to more precise control of environmental conditions in individual and collective pens, favoring animal welfare and productive efficiency (CASTILLO; MELIN, 2024).

Precision agriculture is based on site-specific decision-making that accounts for the spatial and temporal variability of production systems. However, the agricultural environment is characterized by high complexity and uncertainty, since factors such as climate, soil, pests, and diseases interact non-linearly and with frequently imprecise boundaries. Fuzzy logic constitutes an adequate approach for handling these uncertainties, and can be understood as an extension of classical logic that allows the representation of continuous truth degrees in the interval

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between 0 and 1. According to Zadeh (1965), a fuzzy set is defined as a class of objects characterized by a membership function that assigns each element a degree of belonging.

This paper aims to systematize the fundamentals, operation, and main applications of fuzzy logic as a decision-support tool in agribusiness, with emphasis on environmental control for animal welfare in swine production, and to provide a fully specified, reproducible illustrative example of a Mamdani-type fuzzy model.

2. Literature Review

2.1 Fundamentals of fuzzy logic applied to agribusiness

Fuzzy logic is based on the concept of fuzzy sets — sets whose boundaries are imprecise and in which an element may belong partially (ZADEH, 1965; ZANONI et al., 2025). This characteristic makes it particularly suitable for modeling agricultural phenomena, where the boundaries between categories are naturally diffuse.

A typical fuzzy decision-support system for agribusiness includes four fundamental components. The first corresponds to the input variables, which may be sensor-based (temperature, humidity, pH, solar radiation, wind speed) or management-related (animal age, planting density, input cost, labor availability). The second refers to the input fuzzy sets — categories such as “very low”, “low”, “medium”, “high”, and “very high”, each with a membership function (generally triangular, trapezoidal, or Gaussian). The third consists of the rule base, a set of “IF-THEN” propositions capturing specialized knowledge. The fourth involves the output fuzzy sets and the defuzzification process, which converts the fuzzy conclusion into a crisp numerical value, most commonly through the centroid (center-of-gravity) method.

Figure 1 illustrates the structure of a Mamdani-type fuzzy inference system, which is the architecture adopted throughout this review: minimum is used as the AND (conjunction) operator, maximum as the aggregation operator across activated rules, and the centroid method for defuzzification.

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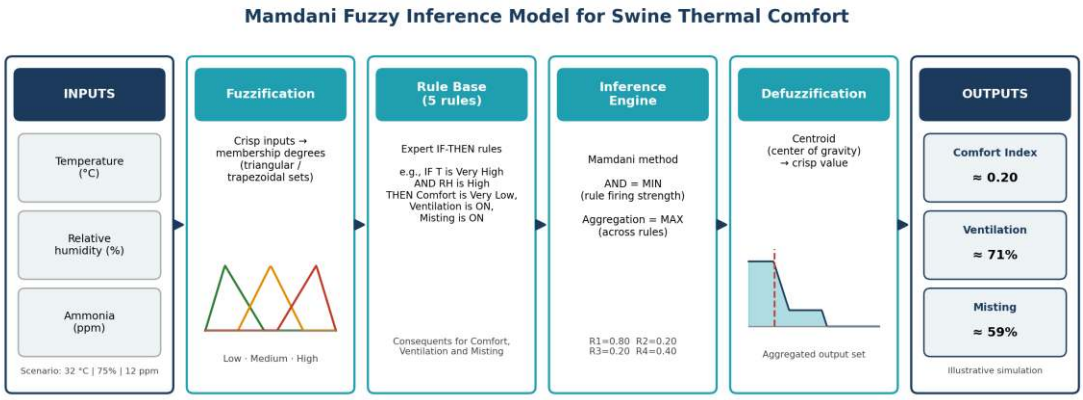


Figure 1 – Mamdani-type fuzzy inference model for swine thermal comfort: from sensor inputs to defuzzified control outputs (values from the illustrative simulation in Section 4.3).
Source: Authors (2026).

2.2 Fuzzy logic compared with conventional control strategies

The specialized literature reports advantages of fuzzy control over selected conventional strategies under specific experimental conditions. In environmental control systems for swine facilities, methods based on fixed thresholds (on/off control) have been associated with limited control precision, higher energy consumption, and delayed response, although the magnitude of these limitations depends on system tuning, disturbance structure, and control objectives (LI et al., 2019).

In a direct comparison against a proportional controller conducted by Li et al. (2019) in a confined pig house, the multivariable fuzzy controller responded faster in 90.1% of the analyzed samples and produced a mean actuation-efficiency output 12.7% higher than the proportional system. This should be understood as a result specific to that experimental configuration rather than a general property of fuzzy control. Response speed and precision are nonetheless relevant for mitigating acute heat stress, in which response delays may compromise animal welfare. In addition, whereas the conventional controller in that study relied on a single variable (temperature), the fuzzy evaluation incorporated multiple factors — temperature, relative humidity, and ammonia level — within a single integrated model. Fuzzy-logic implementation is feasible using tools such as MATLAB® (Fuzzy Logic Toolbox), spreadsheets, or low-cost microcontrollers such as Arduino.

Regarding IoT-based smart irrigation, Neugebauer et al. (2023) reported that a fuzzy logic controller reduced water consumption by approximately 12% relative to a conventional clock-

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controlled system when the soil-moisture sensor was optimally positioned, although consumption could increase by up to 20-38% under suboptimal sensor placement or fuzzy-variable configuration — underscoring that calibration quality, not the fuzzy method per se, determines the realized benefit.

2.3 Consolidated applications of fuzzy logic in agribusiness

Decades of research and field application have consolidated fuzzy logic across several domains:

- **Greenhouse and barn environmental control:** fuzzy systems maintain temperature and humidity with documented precision gains over PID and on/off controllers in specific studies; decoupled fuzzy control compensates for temperature and humidity reductions caused by ventilation through the coordinated activation of heaters and humidifiers (LI et al., 2019).
- **Precision irrigation:** fuzzy systems combine soil-moisture sensors, weather forecasts, and historical data to optimize water use (NEUGEBAUER et al., 2023; ZANONI et al., 2025).
- **Crop recommendation:** fuzzy systems suggest suitable crops based on soil parameters such as N, P, K, pH, and organic carbon.
- **Animal welfare:** fuzzy systems integrate temperature, humidity, ammonia, and other variables to coordinate fans, heaters, and humidifiers (GÜNEŞ et al., 2017; DAMASCENO et al., 2017; TRABACHINI et al., 2024).
- **Poultry-house climate control:** hybrid fuzzy-PID architectures have achieved improved temperature, humidity, and CO_2 regulation together with documented energy savings relative to on/off control in experimental prototypes (LAHLOUH et al., 2020).
- **Multicriteria decision-making:** fuzzy logic is widely used as a method for multicriteria decision-making (MCDM), addressing uncertainty across agribusiness domains; this application is methodologically distinct from fuzzy environmental controllers, as it typically ranks discrete alternatives against weighted criteria rather than producing a continuous actuation signal.

2.4 Comparative synthesis of selected studies

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Table 1 summarizes the inputs, outputs, fuzzy architecture, comparator, and principal reported outcome of the main studies discussed in this review, together with their main limitation as reported by the original authors.

Study	Inputs	Outputs	Architecture / Comparator	Key reported outcome	Main limitation
Pandorfi et al. (2007)	Temperature, humidity	Environment classification for sows	Mamdani / descriptive	Characterized productive environment for gestating sows	Descriptive, not a real-time controller
Xie et al. (2017)	Temperature, humidity, air quality	Environmental quality index	Fuzzy comprehensive evaluation / single-factor evaluation	Multi-factor evaluation validated with real data from two commercial swine buildings	Evaluation-only; not coupled to an actuation controller
Cecchin et al. (2016)	Surface temperature, respiratory rate	Thermal-comfort index	Mamdani / none	Fuzzy index for growing-finishing pig comfort	Single production phase; not validated for sows
Günes et al. (2017)	Ammonia, CO2, ventilation rate	Fan speed	Mamdani / on-off	Improved harmful-gas removal via optimized ventilation	Simulation-based; limited field validation
Damasceno et al. (2017)	Temperature, solar heating status	Welfare index for piglets	Fuzzy expert system	Evaluated welfare under solar-heated housing	Species/age-specific (piglets only)
Li et al. (2019)	Temperature, humidity, ammonia	Ventilation, heating, humidification	Mamdani, decoupled / proportional	19% energy reduction; 90.1% faster response; +12.7% efficiency	Findings specific to the studied facility and controller tuning
Lahlouh et al. (2020)	Temperature, humidity, CO2, NH3	Fan/heater/PID gains	Fuzzy-PID (MIMO) / on-off, fuzzy-only	Lower RMSE and 14-43% energy savings vs. on-off/fuzzy-only	Prototype scale; broiler house, not swine
Neugebauer et al. (2023)	Air temperature, soil moisture, time of day	Irrigation intensity	Mamdani / clock-controlled	~12% water saved with optimal sensor depth	Benefit reverses (up to +38% use) if poorly configured
Trabachini et al. (2024)	Multiple environmental variables	Coordinated actuation	Mamdani / conventional automation	Automation improved welfare indicators	Narrative synthesis; heterogeneous source studies
Zhu et al. (2024)	Predicted and current temperature/humidity	Actuator control signal	Hybrid fuzzy + direct control / direct control	Improved accuracy and reduced energy use vs. direct control	Validated for pigsty environment only
Li et al. (2025)	Temperature, humidity, air velocity, CO2, ammonia	Environmental comfort index (radar chart)	AHP-EWM with published membership functions / none	Effectively reflected comfort variation in a real fattening pig house	Weighting-based evaluation; not a real-time actuation controller
Zanoni et al. (2025)	Tensiometer readings, forecasted rainfall/temperature	Irrigation recommendation	Fuzzy decision support / conventional scheduling	Optimized irrigation recommendations for vineyards	Crop- and region-specific (Trentino vineyards)

Table 1 – Comparative synthesis of selected fuzzy-logic studies in agriculture and livestock production.
Source: Authors (2026), based on the cited studies.

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3. Methodology / Materials and Methods

3.1 Literature-search strategy

This study followed an integrative narrative-review design. The literature search was primarily conducted in Google Scholar, which provides the broadest indexing across the multidisciplinary sources cited in this review (agricultural engineering, computer science, and animal science journals); Scopus and Web of Science were consulted opportunistically to confirm bibliographic details (e.g., DOIs, volume/issue numbers) for individual records already identified. The final search was performed on 22 September 2026. Search terms combined "fuzzy logic" with "agribusiness", "precision agriculture", "precision livestock farming", "animal welfare", "environmental control", "swine production", "poultry house", "decision support system", and "Mamdani inference", combined with Boolean operators (e.g., "fuzzy logic" AND "swine" AND "environmental control"). No language restriction excluded Portuguese or Spanish sources; publications with no direct relation to agricultural or livestock decision-making were excluded, as were non-peer-reviewed web pages.

As an indicative measure of the size of the available literature, Google Scholar searches executed by the authors on 22 September 2026 using the strings

"fuzzy logic" AND ("swine" OR "pig") AND ("environmental control" OR "animal welfare"), *"fuzzy logic" AND "precision agriculture" AND "decision support"*, *"fuzzy logic" AND "livestock" AND ("IoT" OR "sensor")*, and *"Mamdani" AND "agriculture"*

each returned results spanning at least ten result pages (i.e., more than 100 potentially relevant records for each combination of terms), confirming that the topic is substantially represented in the indexed literature. Given the breadth and heterogeneity of the topic and the narrative rather than systematic scope of this review, an exhaustive PRISMA-style tally of all retrieved and screened records was not performed. Instead, a purposive selection strategy was adopted, prioritizing (i) the foundational fuzzy-set literature (Zadeh, 1965; Sugeno; Yasukawa, 1993; Ross, 2010), (ii) peer-reviewed studies directly applying fuzzy logic to environmental control in livestock or crop systems, and (iii) recent (2019-2025) peer-reviewed studies reporting quantitative performance comparisons against conventional controllers. Eighteen sources initially met these criteria; three further sources (Xie et al., 2017; Li et al., 2025; Trabachini et

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al., 2025) were subsequently added during revision for closer topical alignment with the swine-housing illustrative example and to reinforce bibliographic recency, bringing the total to twenty-one sources retained for synthesis, of which eleven (52%) were published between 2019 and 2025. This procedure is disclosed as a limitation in Section 5.4 and should be read as an integrative, not systematic, review.

3.2 Specification of the illustrative fuzzy model

To demonstrate, in a fully reproducible manner, how the four operational stages of a fuzzy system apply to swine thermal-comfort control, this study specifies a Mamdani-type fuzzy inference system with the parameters described below. This example is illustrative and hypothetical: it was constructed for pedagogical purposes from plausible parameter values consistent with the ranges reported in the cited literature, and it does not represent original experimental data collected by the authors.

Input variable — Temperature (universe of discourse: 15-40 °C): Low = trapezoidal(15, 15, 18, 22); Medium = triangular(18, 22, 26); High = trapezoidal(22, 25, 28, 33); Very High = trapezoidal(28, 33, 40, 40).

Input variable — Relative Humidity (universe of discourse: 30-100%): Low = trapezoidal(30, 30, 45, 55); Medium = triangular(45, 60, 75); High = trapezoidal(60, 75, 100, 100).

Input variable — Ammonia concentration (universe of discourse: 0-25 ppm): Low = trapezoidal(0, 0, 5, 10); Medium = triangular(5, 10, 15); High = trapezoidal(10, 15, 25, 25).

The general ranges and overlapping-trapezoid/triangle shapes adopted for these three variables are consistent with the membership-function specifications and environmental factor ranges reported for real, instrumented commercial swine buildings by Xie et al. (2017) and, more recently, by Li et al. (2025), who explicitly published membership-function graphs for temperature, relative humidity, and ammonia in fattening pig houses; the exact numerical breakpoints used here remain illustrative and were set independently for pedagogical clarity rather than copied from those studies.

Output variable — Comfort Index (universe of discourse: 0-1): Very Low = trapezoidal(0, 0, 0.15, 0.35); Low = triangular(0.20, 0.40, 0.60); Medium = triangular(0.45, 0.60, 0.75); High = trapezoidal(0.65, 0.85, 1, 1).

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Output variable — Ventilation command (universe of discourse: 0-100%): OFF = triangular(0, 0, 35); LOW = triangular(15, 50, 85); ON = triangular(65, 100, 100).

Output variable — Misting command (universe of discourse: 0-100%): OFF = triangular(0, 0, 30); LOW = triangular(15, 45, 75); ON = triangular(55, 90, 100).

Inference architecture: Mamdani-type; AND operator = minimum; rule-aggregation operator = maximum; defuzzification method = centroid (center of gravity). The reduced illustrative rule base comprises, for each of the three output variables: R1 — IF Temperature is Very High AND Humidity is High THEN Comfort is Very Low, Ventilation is ON, Misting is ON; R2 — IF Temperature is High AND Humidity is High AND Ammonia is Medium THEN Comfort is Low, Ventilation is LOW, Misting is LOW; R3 — IF Temperature is High AND Ammonia is High THEN Comfort is Low, Ventilation is LOW, Misting is OFF; R4 — IF Temperature is Very High AND Ammonia is High THEN Comfort is Very Low, Ventilation is ON, Misting is LOW; R5 — IF Temperature is Medium AND Humidity is Medium THEN Comfort is Medium, Ventilation is LOW, Misting is OFF.

The single illustrative scenario adopted consistently throughout this paper (Methods, Results, and figures) represents a collective pen with 8 pregnant sows on a summer day, with air temperature of 32 °C, relative humidity of 75%, and ammonia concentration of 12 ppm — values compatible with critical microclimate conditions reported for swine facilities in the Brazilian Center-West (SANTOS; TINÔCO; COSTA, 2012). The complete fuzzification, rule-firing, aggregation, and defuzzification steps for this scenario are presented in Section 4.3 and Figure 3, allowing independent reproduction in any standard fuzzy-logic toolbox (e.g., MATLAB® Fuzzy Logic Toolbox).

4. Results

4.1 Advantages of fuzzy logic identified in the literature

Beyond its role as an analytical tool, fuzzy logic constitutes a modeling framework — a mathematical structure for representing gradual membership and rule-based reasoning under imprecision — that changes how complex problems are addressed in agricultural and livestock contexts. For farm managers, the advantages of adopting this technology are multiple and strategically relevant (TRABACHINI et al., 2024).

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- **Handling the natural imprecision of the agricultural environment:** in the field, the ideal temperature for a crop does not correspond to a fixed value — it varies with humidity, wind, and the plant's phenological stage. Fuzzy logic incorporates this variability as a structural part of the model, building gradual transitions between reference ranges.
- **Holistic integration of multiple variables:** excessive heat and water deficiency, when combined, produce substantially larger impacts than when considered separately. In swine control systems, fuzzy logic enables variable decoupling, compensating for temperature and humidity reductions caused by ventilation through the coordinated activation of heaters and humidifiers (GÜNEŞ et al., 2017).
- **Gradual and proportional decision-making:** traditional systems operate in a binary ("all-or-nothing") manner, which can generate waste and operational oscillation. Fuzzy logic enables graded actions — e.g., irrigating at 30%, 50%, or 70% according to actual need — resulting in more precise equipment actuation and greater operational stability.
- **Adaptability to different contexts:** the same fuzzy rule base can be reconfigured for different crops, climate conditions, and production systems by adjusting membership functions. It is important to note that this reconfigurability is distinct from autonomous adaptation: a classical rule-based fuzzy controller does not self-adjust unless membership functions or rules are manually recalibrated, or unless adaptive/neuro-fuzzy or machine-learning mechanisms are explicitly implemented.
- **Accessibility and scalability:** implementation can start with simple solutions, such as spreadsheets containing membership functions and a reduced rule set, later evolving to low-cost sensors and microcontrollers.
- **Support for forecast-informed planning:** when combined with external forecasting models, fuzzy decision layers can incorporate historical data and predictions to recommend preventive actions. It should be noted that this predictive capability originates from the forecasting model that supplies the input, and not from the fuzzy inference mechanism itself, which is fundamentally a decision-mapping system rather than a forecasting method. Zanoni et al. (2025) illustrate this integration in irrigation

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systems that combine short-term forecasts and historical field data to generate optimized irrigation recommendations.

4.2 Temperature-related performance reported in the literature

Temperature is one of the most critical variables across virtually all livestock activities. Its effective control requires decisions that go beyond a simple thermometer reading, particularly in animal-production environments where control is multivariable and complex (LI et al., 2019).

In a fuzzy system, temperature is classified into overlapping categories with membership degrees, avoiding the classical problem in which a variation of a few tenths of a degree around a fixed threshold abruptly changes the system's decision. Figure 2 contrasts the two approaches: under a fixed 30 °C threshold (panel a), readings of 29.9 °C and 30.1 °C produce opposite commands, whereas under the fully specified membership functions of this study (panel b; Section 3.2) the same two readings yield nearly identical membership degrees (High = 0.62 and 0.58; Very High = 0.38 and 0.42, respectively). At the scenario temperature of 32 °C, High = 0.20 and Very High = 0.80.

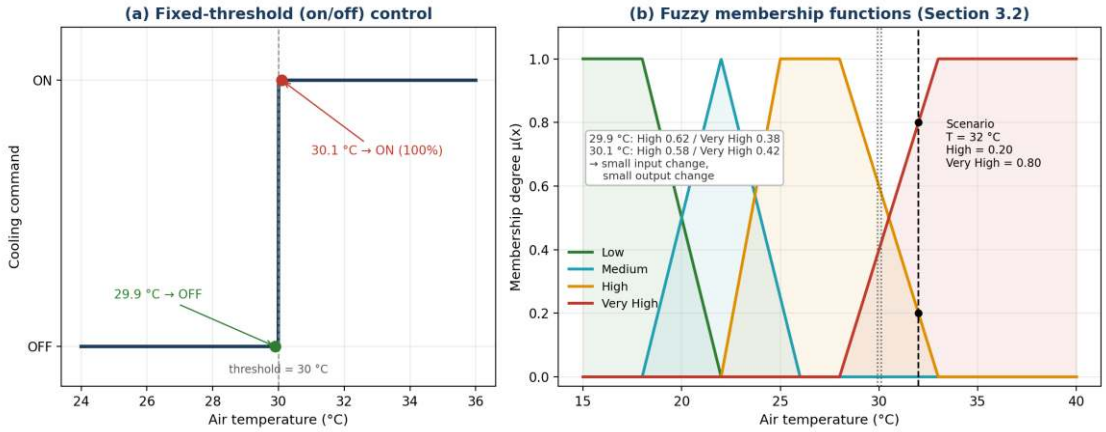


Figure 2 – Temperature classification under (a) fixed-threshold on/off control and (b) the fuzzy membership functions of the illustrative model (universe of discourse: 15-40 °C).
Source: Authors (2026).

A key challenge in barn environmental control is the coupling between variables. According to Li et al. (2019) and Günes et al. (2017), forced ventilation reduces temperature but also reduces relative humidity; if airflow is insufficient in volume or unevenly distributed across the facility (e.g., short-circuiting between inlet and outlet, or poorly ventilated dead zones), ammonia —

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continuously generated from manure and urine — may accumulate locally even while overall ventilation is active. Decoupled fuzzy controllers address this problem by compensating for ventilation-induced temperature and humidity reductions through the coordinated activation of heaters and humidifiers, while independently commanding fan speed to address ammonia removal.

Gains documented in the literature with fuzzy-based decisions include: a 19% reduction in energy consumption for a multivariable fuzzy controller compared with manual regulation (LI et al., 2019); improved ammonia removal through fuzzy-calculated optimal fan speeds (GÜNEŞ et al., 2017); reduced temperature and humidity fluctuations relative to reference values, indicating greater microclimate stability (LI et al., 2019); and efficient variable decoupling, maintaining multiple conditions within target ranges even under external disturbances (LI et al., 2019). These findings are specific to the cited experimental configurations and should not be generalized as universal properties of fuzzy control.

4.3 Illustrative Mamdani-model simulation for swine housing

This subsection presents a hypothetical, fully specified simulation — not an empirical result — illustrating how the fuzzy stages described in Section 3.2 apply to a single, consistent scenario: a collective pen with 8 pregnant sows on a summer day, with temperature = 32 °C, relative humidity = 75%, and ammonia = 12 ppm.

Fuzzification (Section 3.2 membership functions): 32 °C → High = 0.20, Very High = 0.80; 75% RH → High = 1.00; 12 ppm NH_3 → Medium = 0.60, High = 0.40.

Rule firing (minimum operator): R1 = min(0.80, 1.00) = 0.80; R2 = min(0.20, 1.00, 0.60) = 0.20; R3 = min(0.20, 0.40) = 0.20; R4 = min(0.80, 0.40) = 0.40; R5 = min(0, 0) = 0 (not activated, since neither Medium-temperature nor Medium-humidity membership is non-zero in this scenario).

Aggregation (maximum operator): the Very Low output set is clipped at max(0.80, 0.40) = 0.80 (from R1 and R4); the Low output set is clipped at max(0.20, 0.20) = 0.20 (from R2 and R3).

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Defuzzification (centroid method): numerically integrating the aggregated output surface, dominated by the Very Low set clipped at 0.80, yields a crisp Comfort Index of approximately 0.20 on a 0-1 scale, where 1 represents maximum comfort. Figure 3 summarizes this complete computational chain graphically, showing each input reading on its membership functions, the evaluation of every rule, and the aggregated output surface with its centroid.

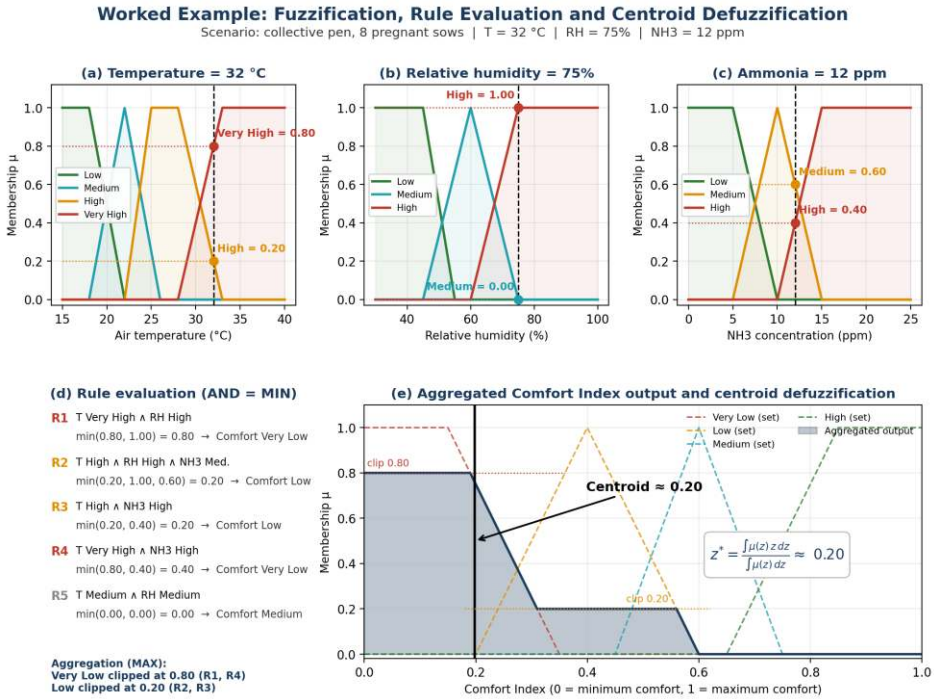


Figure 3 – Worked example of the illustrative model: (a-c) fuzzification of the three inputs, (d) rule evaluation with the minimum operator, and (e) aggregated Comfort Index output with centroid defuzzification (≈ 0.20).
Source: Authors (2026), illustrative simulation.

Beyond the Comfort Index, the same rule firing strengths (R1-R4) drive two actuator-specific outputs defined in Section 3.2: Ventilation command and Misting command. Applying the same minimum/maximum/centroid procedure to their respective consequents (R1, R4 → Ventilation ON; R2, R3 → Ventilation LOW; R1 → Misting ON; R2, R4 → Misting LOW; R3 → Misting OFF) and numerically integrating the aggregated output surfaces yields a crisp Ventilation command of approximately 71% and a crisp Misting command of approximately 59%, as shown in Figure 4.

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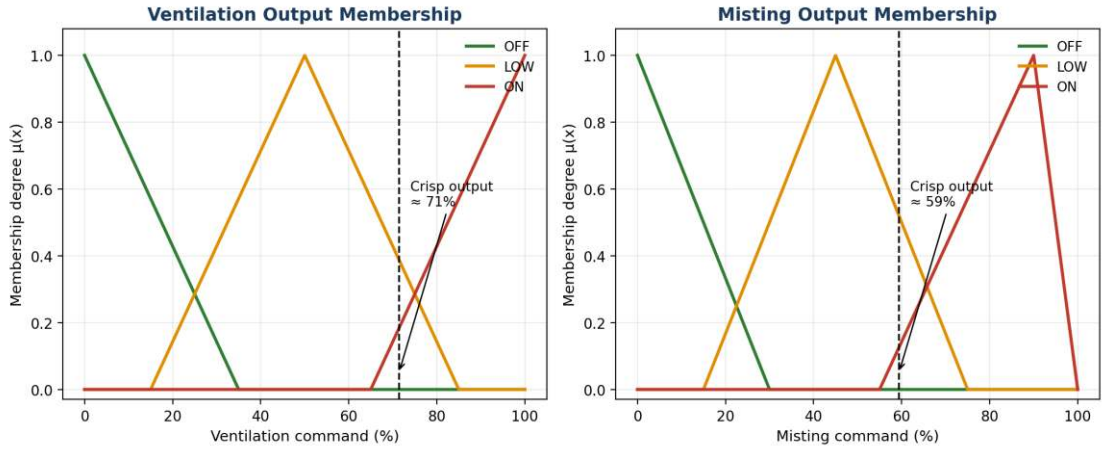


Figure 4 – Membership functions and defuzzified crisp outputs for the Ventilation and Misting actuator commands.
Source: Authors (2026), illustrative simulation.

Based on these critically low comfort and high-actuation outputs, the modeled system would command fans running at approximately 71% of maximum speed and misting operating at approximately 59% duty, as a graded response proportional to the severity of the simulated heat-stress condition, rather than a fixed-threshold response. Figure 5 contrasts the individual and collective housing systems referenced in this scenario, and Figure 6 presents the closed-loop structure of the controller, in which the actuated pen environment is continuously re-measured by the sensors.

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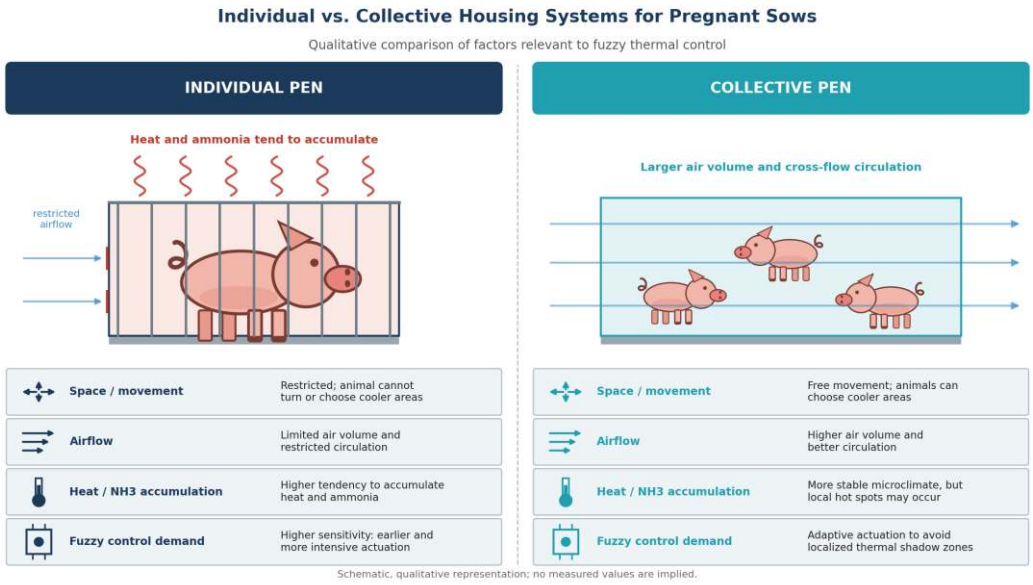


Figure 5 – Qualitative comparison of individual and collective housing systems for pregnant sows regarding space, airflow, heat and ammonia accumulation, and fuzzy control demand (schematic; no measured values implied).
Source: Authors (2026).

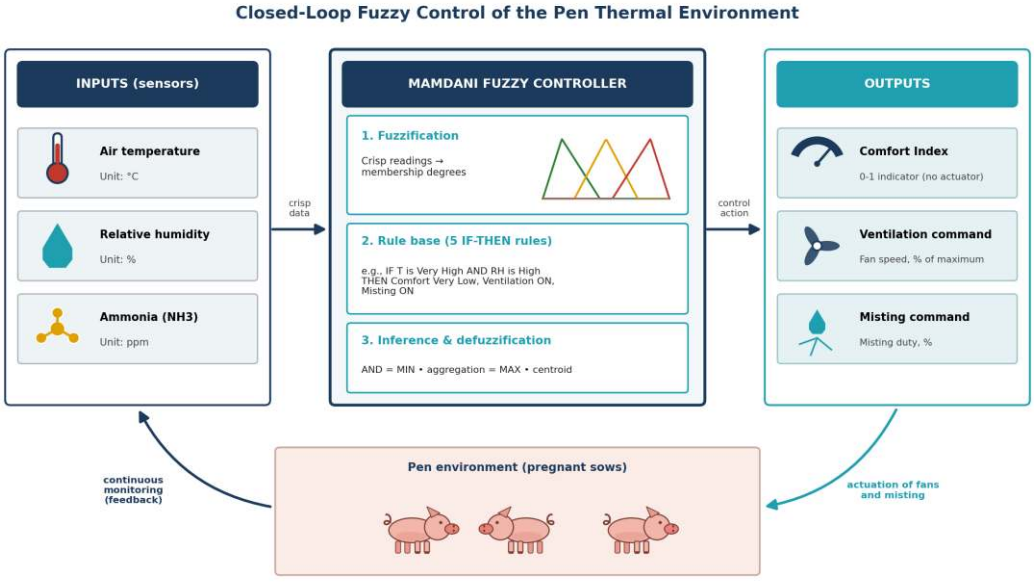


Figure 6 – Closed-loop structure of the illustrative fuzzy controller: sensor inputs, Mamdani inference stages, outputs, and feedback from the pen environment.
Source: Authors (2026).

In individual pens, the smaller area and more restricted ventilation make the environment more susceptible to heat and ammonia accumulation, requiring higher control sensitivity; the simulated controller would therefore actuate fans and misting earlier and more intensively than

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in the collective-pen scenario, to compensate for the individual system's inherent disadvantages. In collective pens, larger air volume and better circulation tend to produce a more stable microclimate, although the presence of multiple animals introduces behavioral variables, such as competition for cooler areas, which an adaptive fuzzy rule base can in principle accommodate by adjusting actuation parameters to avoid localized “thermal shadow zones”. Figure 7 places the controller within a broader set of thermal-mitigation strategies: of these, forced ventilation and misting are the actuators commanded by the illustrative model, whereas radiation blocking (roof insulation) and routine management are complementary structural and management measures outside the controller.

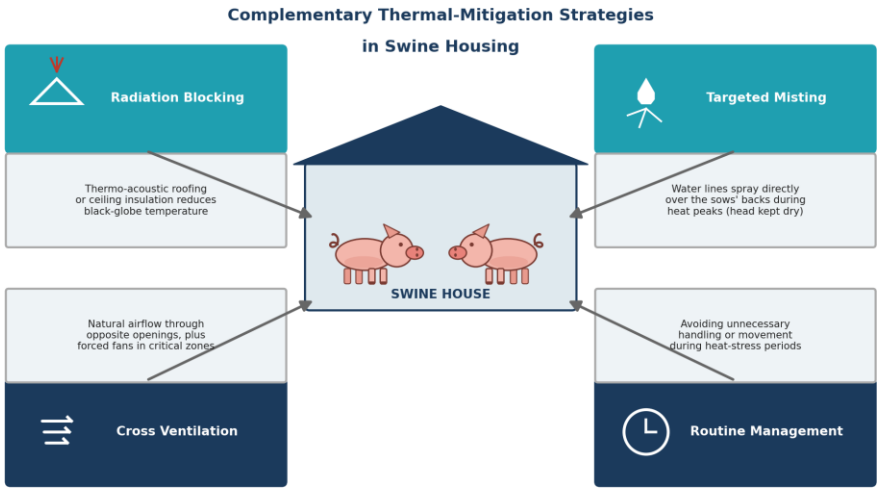


Figure 7 – Complementary thermal-mitigation strategies in swine housing; ventilation and misting correspond to the outputs of the illustrative fuzzy controller, whereas radiation blocking and routine management are structural and management measures.
Source: Authors (2026).

4.4 Control surface of the illustrative model

To show how the illustrative controller behaves beyond the single scenario, the Ventilation command was computed with the same Mamdani procedure over the full temperature (15-40 °C) and relative-humidity (30-100%) universes, with ammonia fixed at the scenario value of 12 ppm (Figure 8). Where rules are active, the command increases gradually from 50% to approximately 88% as temperature rises, without the abrupt switching of a fixed threshold; the scenario point (32 °C, 75%) reproduces the value of approximately 71% reported in Section 4.3. At this ammonia level, humidity has a comparatively smaller effect, because rules R3 and R4 are activated by temperature and ammonia regardless of humidity.

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The surface also exposes a structural property of the reduced five-rule base: in approximately 22% of the evaluated input space (mainly temperatures below 18-22 °C), no rule is activated and the Mamdani output is undefined. This region is shown hatched in Figure 8 rather than being assigned an arbitrary value. It confirms that the illustrative rule base is sufficient to demonstrate the inference mechanism but not to control a real facility, which would require a complete rule base covering all combinations of linguistic terms (see Section 5.4).

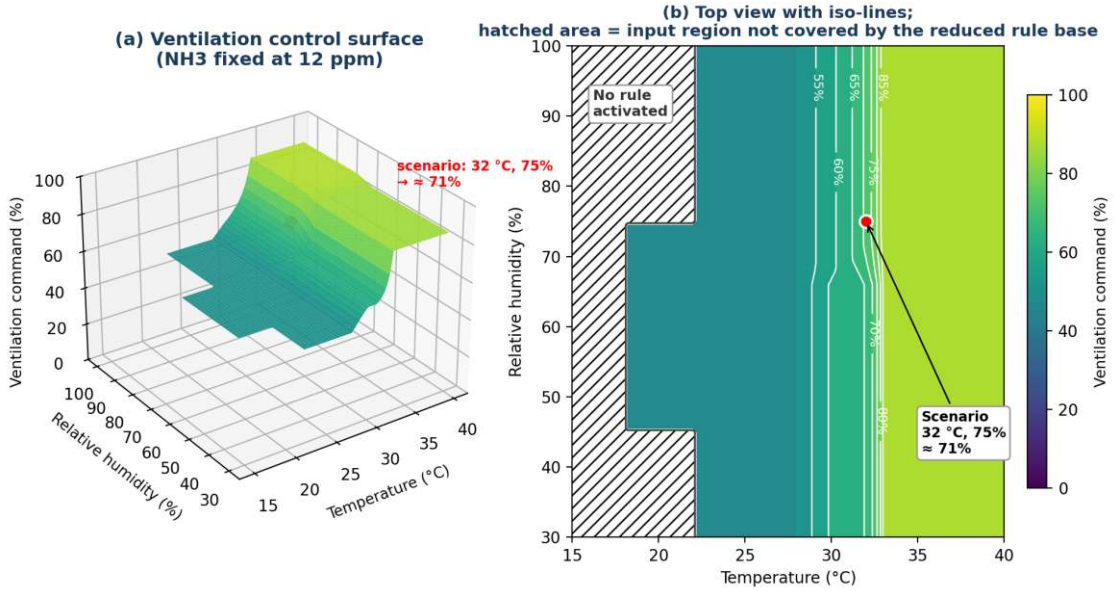


Figure 8 – Ventilation control surface of the illustrative Mamdani model as a function of temperature and relative humidity (ammonia fixed at 12 ppm): (a) three-dimensional surface; (b) top view with iso-lines. The hatched area indicates input combinations for which no rule of the reduced rule base is activated.
Source: Authors (2026), computed from the model specified in Section 3.2.

5. Discussion

5.1 Interpretation of findings

The results discussed above indicate that a central advantage of fuzzy logic lies in its capacity to detect environmental stress from the simultaneous combination of factors, to compensate for spatial variability in the production environment, to promote proportional and gradual control actions, to support operational management, and to contribute to preventing critical situations and continuously improving animal welfare.

The illustrative simulation in Section 4.3 demonstrates how a Mamdani fuzzy model integrates multiple environmental inputs into a control decision proportional to the severity of the

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simulated condition, in contrast to fixed-threshold approaches. This example should be interpreted strictly as a hypothetical demonstration of the computational method, not as empirical validation: it was constructed from plausible parameter values for pedagogical purposes and has not been tested against measured animal or facility data. The quantitative performance figures cited in Section 4.2 (19% energy reduction, 90.1% faster response, 12.7% higher efficiency output) refer specifically to the experimental controller and facility reported by Li et al. (2019) and should not be read as general properties of fuzzy control, or extrapolated to the illustrative simulation presented in this study.

5.2 Conceptual clarifications

Three conceptual distinctions merit emphasis. First, fuzzy inference is fundamentally a decision-mapping mechanism; predictive capability, when present in fuzzy-based systems, typically originates from an auxiliary forecasting layer (e.g., time-series or machine-learning models) rather than from the fuzzy inference engine itself. Second, the reconfigurability of a fuzzy rule base — its capacity to be manually adjusted to different crops or production systems — should not be confused with autonomous adaptation, which requires adaptive or neuro-fuzzy mechanisms not implemented in the classical Mamdani architecture described here. Third, fuzzy environmental control and fuzzy multicriteria decision-making (MCDM) are methodologically distinct applications of the same mathematical foundation: the former produces continuous actuation signals from sensor inputs, while the latter typically ranks discrete alternatives against weighted criteria.

5.3 Practical implications

From a practical standpoint, the possibility of implementation across different technological levels — from spreadsheets to low-cost microcontrollers — broadens the technology's reach to producers with varying degrees of capitalization, which is particularly relevant in the heterogeneous context of Brazilian agribusiness. The comparative synthesis in Table 1 shows that reported benefits (energy savings, faster response, improved regulation precision) are consistently facility- and configuration-specific, reinforcing that local calibration of membership functions and rule bases — rather than the adoption of fuzzy logic per se — is the primary determinant of realized performance.

5.4 Limitations

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This review has three main limitations. First, as an integrative narrative review rather than a systematic review, it did not apply an exhaustive PRISMA-style protocol for tallying retrieved and excluded records; source selection followed the purposive criteria described in Section 3.1, which may introduce selection bias relative to a fully systematic search. In this respect, a recent systematic review by Trabachini et al. (2025), which analyzed 75 articles on precision livestock farming in swine production, independently identified the lack of standardized welfare and environmental metrics as a persistent obstacle in this research area — a limitation consistent with the heterogeneous outcome metrics observed across the studies synthesized in Table 1 of the present review. Second, the illustrative numerical simulation presented in Section 4.3 is hypothetical and has not undergone experimental calibration or field validation; moreover, as the control surface in Section 4.4 shows, its reduced five-rule base leaves approximately 22% of the input space without any activated rule, so a complete rule base would be required for operational use; its rule base and membership functions must be recalibrated using site-specific data — including animal genetics, local edaphoclimatic conditions, and available infrastructure — before any operational deployment, and the simulated control policy should not be directly implemented in a real facility without such calibration. Third, despite the bibliographic update carried out for this revision (raising 2019-2025 coverage to 50% of the reference list), several cited quantitative results derive from a limited number of primary studies and specific facility configurations, and broader replication across production contexts remains warranted. Future studies could explore validated fuzzy rule bases for different Brazilian biomes and the integration of fuzzy inference with machine-learning methods for automatic membership-function tuning over time.

6. Conclusion

Fuzzy logic has become a relevant approach for decision-making in modern agriculture, particularly in scenarios marked by environmental variability and uncertainty, such as those related to animal thermal comfort. Compared with traditional methods, such as on/off controls and proportional systems, this approach offers greater flexibility in representing complex phenomena, allowing gradual transitions between states and a modeling structure closer to real production conditions — while its comparative advantages, as discussed in Section 5, remain dependent on system-specific tuning rather than being universal.

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Among its main contributions is the capacity to handle imprecise information and integrate multiple environmental variables — such as temperature, humidity, gas concentration, and thermal radiation — within a single decision system. In addition, the rule-based structure allows the incorporation of expert knowledge and the reconfiguration of the system for different production contexts, including climatic, genetic, and management variations, provided that reconfiguration is understood as a manual, expert-guided process rather than automatic adaptation.

Another important aspect concerns its practical applicability: fuzzy logic can be implemented at different technological levels, from simple spreadsheets to automated systems with sensors and microcontrollers. Evidence from the reviewed literature indicates that its use can contribute to improved environmental control, with positive effects on animal welfare and production-system efficiency, provided that membership functions and rule bases are locally calibrated and validated before operational deployment.

Fuzzy logic therefore constitutes a methodologically transparent and scalable alternative for decision support in agricultural and livestock systems, particularly when used in a manner complementary to other technologies and adjusted to the specific conditions of each production system. Its application is likely to expand as the sector advances toward more integrated, data-driven, and hybrid decision-support models.

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