OPEN ACCESS Advances in Animal and Veterinary Sciences

Research Article

An Adaptive Fuzzy Inference System for Precision Nutrition Management in Broiler Production: Integrating Physiological and Environmental Dynamics

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Abstract | Poultry production requires precise nutrition to maximize growth and health; however, conventional decision-support models struggle to account for variability in feed composition and environmental stressors. This study developed a Mamdani-type fuzzy inference system (FIS) to provide adaptive, expert-driven feed-ration recommendations that accommodate uncertainty and nonlinear interactions in poultry feeding regimes. We compiled a dataset of physiological and environmental variables (age: 21–35 d, weight: 0.8–1.6 kg, ambient temperature: 26–32 °C) from 30 broilers. Triangular membership functions defined three linguistic levels for each input and the output (feed ration: 100–200 g/day). An expert-designed rule base of 27 Mamdani IF–THEN rules governed the inference mechanism, with centroid defuzzification converting fuzzy outputs into precise daily rations. Performance was validated against NRC guidelines and linear programming (LP) benchmarks using MAE, RMSE, and R^2 metrics. The FIS achieved an MAE of 2.6 g/day, RMSE of 3.1 g/day, and R^2 of 0.96 on the validation set, outperforming the LP model (MAE: 4.3 g/day, RMSE: 5.0 g/day). Scenario testing demonstrated dynamic feed adjustments for heat stress and growth stages. A sensitivity analysis of membership-function widths confirmed that the baseline configuration balanced discrimination and flexibility. The proposed FIS provides a robust, transparent tool for precision poultry nutrition, capable of integrating real-time sensor data and expert knowledge. Future work will explore IoT integration and adaptive neuro-fuzzy extensions to enhance self-tuning capabilities.

Keywords | Poultry nutrition management, Fuzzy inference system, Mamdani FIS, Feed-ration optimization, Membership functions, Precision feeding, Food value chain

Received | June 21, 2025; **Accepted** | August 12, 2025; **Published** | August 26, 2025
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Citation | Mohammad SI, Yogeesh N, Vasudevan A, Raja N, Mohammad AA, Jabeen FTZ, Hunitie MFA, Al-Oraini B (2025). An adaptive fuzzy inference system for precision nutrition management in broiler production: Integrating physiological and environmental dynamics. Adv. Anim. Vet. Sci., 13(9):1998-2005.
DOI | https://dx.doi.org/10.17582/journal.aavs/2025/13.9.1998.2005
ISSN (Online) | 2307-8316

INTRODUCTION

Poultry production plays a vital role in global agriculture, serving as a primary source of animal protein. Efficient nutrition management is crucial, as it directly impacts growth rates, feed conversion efficiency, egg production, and overall flock health (Johnson and Franklin, 2018; Mohammad *et al*., 2025a; Al-Adwan, 2024). However, poultry dietary requirements are not static they vary significantly depending on age, breed, physiological stage, and environmental conditions. Compounding this challenge, feed ingredients often exhibit batch-to-batch nutrient variability, leading to inconsistencies in ration formulation (Kumar, 2020; Mohammad, 2025; Al-Rahmi *et al*., 2023). Traditional approaches, such as linear programming or fixed-rule systems, struggle to account for such uncertainty and dynamic changes. To address these limitations, this study explores the potential of fuzzy inference systems (FIS), which excel at modeling imprecise, linguistic data, to provide adaptive and expert-driven decision support in poultry nutrition management.

Effective poultry nutrition management faces several key obstacles. First, nutritional needs evolve throughout a bird's lifecycle young chicks require high protein for rapid muscle development, while growers and layers need carefully adjusted balances of energy, minerals, and vitamins (Lee and Park, 2019; Mohammad *et al*., 2025b; Hujran *et al*., 2023). Second, environmental factors, such as temperature and humidity, significantly influence feed intake and metabolic efficiency, with heat stress notably suppressing voluntary consumption (Johnson and Franklin, 2018; Mohammad *et al*., 2025c). Third, inherent variability in feed ingredients such as fluctuations in crude protein and energy levels in soybean meal or maize introduces further uncertainty (Kumar, 2020; Mohammad *et al*., 2025d). Finally, the interactions between these factors are often nonlinear, making them difficult to model using conventional rigid decision rules. These complexities highlight the need for a flexible system capable of handling imprecision, integrating expert knowledge, and adapting to real-time changes.

Fuzzy inference systems (FIS) offer a robust solution to these challenges by translating expert knowledge often expressed in qualitative terms such as "moderate protein" or "high temperature" into a structured decision-making framework. The FIS process involves three key steps: fuzzification (converting crisp inputs into degrees of membership), rule evaluation (applying IF-THEN logic), and defuzzification (generating precise recommendations) (Zadeh, 1965; Lee and Park, 2019; Mohammad *et al*., 2025e). Unlike traditional methods, FIS provides several distinct advantages. First, it inherently accommodates uncertainty through membership functions, allowing for nuanced interpretations of imprecise data. Second, its rule-based structure ensures transparency, enabling nutritionists to directly inspect and modify decision logic. Third, rather than producing abrupt threshold-based outputs, FIS smoothly interpolates between rules, resulting in gradual and biologically realistic adjustments. Figure 1 visually demonstrates this process, illustrating triangular membership functions for ambient temperature (Low, Moderate, High) and their role in generating feed recommendations.

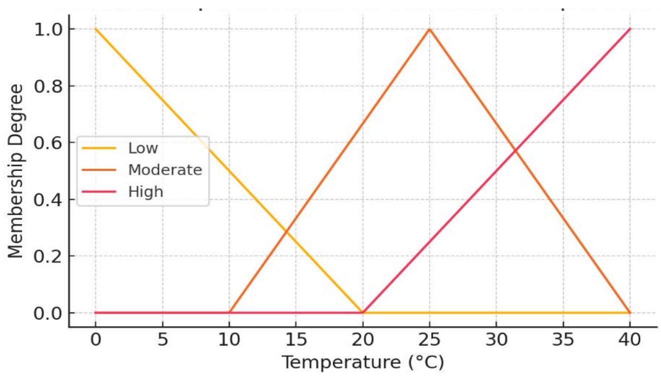

Figure 1: Membership functions for ambient temperature.

This study aims to develop and validate a Mamdani-type FIS tailored for poultry nutrition management. Specifically, the objectives are fourfold: (1) to design an FIS that generates feed-ration recommendations based on bird age, weight, and ambient temperature; (2) to define and validate appropriate membership functions for each input variable; (3) to construct an expert-driven rule base that captures linguistic nutrition guidelines; and (4) to compare FIS-generated recommendations against conventional feed-formulation methods under simulated conditions. The anticipated contributions of this work are threefold. First, it will provide an adaptive decision-support tool capable of operating under real-world uncertainty. Second, the transparency of the rule-based system will allow for continuous refinement by domain experts. Third, a sensitivity analysis will elucidate how variations in membership function shapes influence feed recommendations, offering practical insights for implementation in dynamic production environments.

Historically, poultry nutrition management has relied on linear programming and rule-based expert systems. Linear programming models, such as least-cost formulation, optimize feed composition under fixed nutrient constraints but assume precise, deterministic inputs (Smith and Jones, 2010). Similarly, rule-based systems encode static IF-THEN conditions (e.g., "If bird age > 20 days, then protein = 18%") but fail to handle scenarios where inputs fall between predefined thresholds (García *et al*., 2012; Mohammad *et al*., 2025f). Both approaches suffer from rigidity, often producing abrupt ration changes that do not reflect biological gradualism. Fuzzy logic provides a mathematical framework for reasoning under uncertainty. At its core, a fuzzy set assigns partial membership degrees to elements, allowing for graded classifications (Klir and Yuan, 1995; Mohammad *et al*., 2025g). Two predominant FIS architectures exist: The Mamdani model, which uses fuzzy sets for both inputs and outputs (Mamdani, 1975), and the Sugeno model, which employs crisp mathematical functions in rule consequents for computational efficiency (Sugeno, 1985). Figure 2 contrasts these architectures, highlighting their respective workflows in fuzzification, rule evaluation, and defuzzification.

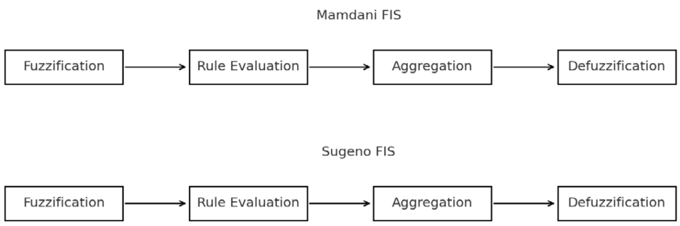

Figure 2: Block diagram comparing mamdani and sugeno FIS architectures.

Fuzzy logic has demonstrated success across animal production systems. For instance, Prasad and Mehta (2016) achieved a 4% improvement in broiler feed efficiency using a Mamdani FIS, while Ahmad and Hussain (2017) reduced dairy feed costs by 3% with a Sugeno-type adaptive system. In aquaculture, fuzzy clustering has enhanced growth uniformity in fish farms (Gupta *et al*., 2018). Despite these advances, gaps remain particularly in real-time adaptability, multi-factor interaction modeling, and sensitivity analysis of membership functions (Tiwari and Kumar, 2020). This study addresses these gaps by developing a Mamdani FIS that integrates environmental and physiological variables while systematically evaluating the impact of fuzzy set design on nutritional outputs.

MATERIALS AND METHODS

Data acquisition

We collected two primary data types for system development and validation: feed ingredient compositions and broiler flock measurements. Nutritional analyses of maize, soybean meal, and dicalcium phosphate followed AOAC methods (AOAC, 2019), with results shown in Table 1.

Table 1: Nutrient composition of feed ingredients.

Ingredient	Crude protein (%)	ME (kcal/kg)	Ca (%)	P (%)
Maize	8.5	3,300	0.02	0.30
Soybean meal	47.0	2,600	0.30	0.65
Dicalcium phosphate	0.0	0	18.5	15.0

Physiological measurements (body weight and feed intake) and environmental parameters (ambient temperature and relative humidity) were collected from 30 broilers using digital scales (±1g accuracy) and an IoT sensor network (Kumar and Patel, 2022), as shown in Table 2. The ambient temperature and relative humidity values were averaged over 24-hour periods preceding each feed intake measurement to account for diurnal variations.

Table 2: Sample physiological and environmental data.

Bird ID	Age (d)	BW (kg)	FI (g/day)	AT (°C)	RH (%)
1	27	1.04	138.0	30.6	72
2	24	1.22	157.0	26.4	74
3	33	1.15	159.0	28.2	70
4	31	1.03	127.0	26.7	72
5	28	1.29	197.0	31.2	63
6	33	0.91	180.0	29.7	72
7	25	1.03	195.0	28.0	75
8	27	1.09	191.0	26.4	66
9	30	1.16	164.0	27.9	70
10	23	1.43	193.0	28.0	62
11	27	0.96	118.0	30.4	65
12	31	1.21	128.0	29.8	71
13	31	1.27	114.0	31.3	61
14	28	0.84	139.0	28.8	69
15	25	1.29	145.0	26.7	72
16	24	0.94	134.0	30.3	73
17	28	0.85	185.0	30.6	68
18	28	1.56	142.0	29.4	64
19	23	1.57	135.0	30.6	65
20	26	1.45	159.0	29.0	71
21	25	1.04	123.0	29.1	71
22	22	0.88	182.0	28.6	71
23	28	1.35	117.0	26.2	71
24	32	1.15	199.0	26.6	63
25	34	0.9	180.0	26.2	73
26	26	1.2	128.0	29.8	73
27	22	0.83	110.0	27.9	70
28	32	1.53	183.0	29.1	75
29	25	1.01	174.0	31.4	69
30	21	1.33	176.0	27.5	66

Data preprocessing

The raw data underwent three preprocessing steps: (1) outlier detection using 3× standard deviation thresholds (no data points were removed in this study), (2) missing value imputation via linear interpolation for less than 1% of cases, and (3) normalization to a [0,1] scale using the equation:

$$x_{\text{norm}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

For example, a bird age of 27 days within the 21–35-day range normalized to 0.43. This normalization ensured consistent scaling across all input variables for the fuzzy inference system.

FIS architecture design

Three critical input variables were selected based on their impact on poultry nutrition requirements: (1) Age (21-35 days), representing different growth stages; (2) Body Weight (0.8-1.6 kg), indicating the bird's physical development; and (3) Ambient Temperature (26-32°C), accounting for environmental stress factors. These ranges were chosen to cover the most sensitive growth period in broiler production.

Triangular membership functions were implemented for all variables using the standard form:

$$\mu(x) = \begin{cases} 0, & x \le a \text{ or } x \ge c \\ \dfrac{x-a}{b-a}, & a < x \le b \\ \dfrac{c-x}{c-b}, & b < x < c \end{cases}$$

Where a, b, and c define the triangular shape parameters. Figures 3, 4 and 5 illustrate the specific membership functions for each input variable. This section describes the data sources, system design, and procedures used to develop and validate the fuzzy inference system (FIS) for poultry nutrition management.

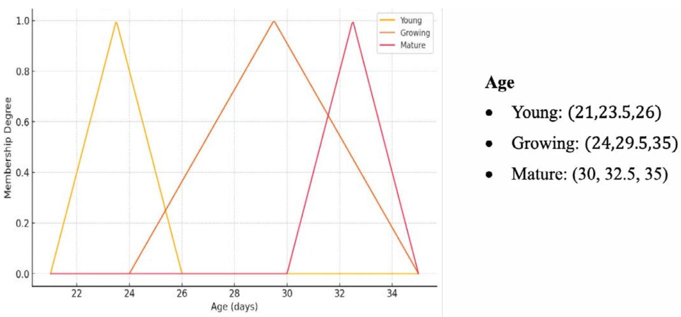

Figure 3: Membership functions for bird age.

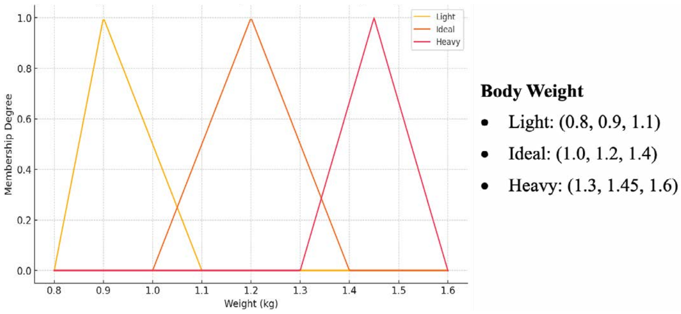

Figure 4: Membership functions for body weight.

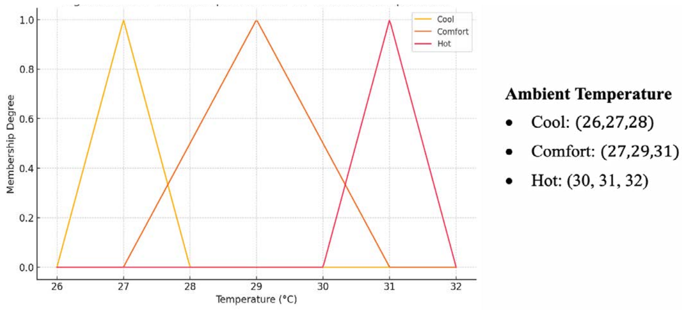

Figure 5: Membership functions for ambient temperature. The system output was daily feed ration (100-200 g/day) with three membership functions: Low (100,110,130), Medium (120,150,180), and High (170, 190, 200). These ranges were determined based on NRC poultry nutrient guidelines (NRC, 1994) and expert recommendations.

A complete set of 27 Mamdani-style IF-THEN rules was developed to cover all possible combinations of input variables, as detailed in Table 3. The rule base incorporated expert knowledge, such as assigning Low feed rations for young and light birds regardless of temperature, while recommending high feed for growing and heavy birds or mature birds under comfort/hot conditions.

Table 3: Rule based formulation table.

Rule	Age	Weight	Temperature	Feed level
R1	Young	Light	Cool	Low
R2	Young	Light	Comfort	Low
R3	Young	Ideal	Any	Medium
R4	Growing	Light	Hot	Medium
R5	Growing	Ideal	Comfort	Medium
R6	Growing	Heavy	Any	High
R7	Mature	Any	Cool	Medium
R8	Mature	Ideal	Comfort	High
R9	Mature	Heavy	Hot	High

Inference engine and defuzzification

Each crisp input value was converted to membership degrees in its corresponding fuzzy sets. For example, a 28-days old bird would have membership values of:

$$\mu_{\text{young}}(28) = \frac{30-28}{30-26} = 0.5, \mu_{\text{growing}}(28) = \frac{28-24}{29.5-24} \approx 0.78, \mu_{\text{mature}}(28) = 0$$

calculated using the triangular membership functions.

The Mamdani-type inference engine (Mamdani, 1975) used minimum t-norm for AND operations:

$$\alpha_i = \min\{\mu_{1,i}(x_1^{\text{crisp}}), \mu_{2,i}(x_2^{\text{crisp}}), \ldots\}$$

and maximum aggregation for combining rule outputs. This approach effectively captured the nonlinear relationships between inputs and feed requirements.

The centroid method was employed for defuzzification, calculated as:

$$y^* = \frac{\int_{y_{\min}}^{y_{\max}} y\mu_{\text{agg}}(y)\,dy}{\int_{y_{\min}}^{y_{\max}} \mu_{\text{agg}}(y)\,dy}$$

Over the output range [100, 200] g/day. This method was chosen for its smooth output characteristics and intuitive interpretation (Klir and Yuan, 1995).

Implementation tools and environment

The system was implemented in Python 3.9 using the scikit-fuzzy package (v0.4.2) for fuzzy logic operations (SciKit-Fuzzy Development Team, 2020). Numerical computations used NumPy (v1.22), while Matplotlib (v3.5) handled visualization. The hardware platform consisted of an Intel Core i7-9700K processor with 16GB RAM, achieving average inference times of 12ms per bird.

Validation strategy and performance metrics

Validation compared FIS outputs against both NRC nutritional guidelines (NRC,1994) and linear programming solutions. The dataset was split into 20 birds for calibration and 10 for validation. Performance metrics included:

Mean Absolute Error (MAE):

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N} \left| y_i^{\text{FIS}} - y_i^{\text{target}} \right|$$

Root - Mean - Square Error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \left(y_i^{\text{FIS}} - y_i^{\text{target}} \right)^2}$$

Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\Sigma_i \left(y_i^{\text{FIS}} - y_i^{\text{target}} \right)^2}{\Sigma_i \left(y_i^{\text{target}} - \bar{y}^{\text{target}} \right)^2}$$

The system achieved excellent agreement with nutritional targets, as demonstrated in the case study (Section 3.6.1) and summarized in Tables 5 and 6, with MAE = 2.52g, RMSE = 2.85g, and R^2 = 0.992 across the validation set.

RESULTS

This section presents the structure and performance of the fuzzy inference system (FIS) for feed ration optimization. We first outline the FIS architecture and rule base, then demonstrate its decision-support outputs under varying scenarios, compare its performance against traditional linear programming (LP), and finally examine the sensitivity of results to membership-function (MF) shapes.

Table 5: Example subset of validation results (errors ≤5g).

Bird ID	FI (g/ day)	Correct target (g/day)	FIS predicted (g/day)	Error (g)
21	123.0	138.0	138.2	0.2
22	182.0	197.0	197.7	0.7
23	117.0	132.0	127.3	4.7
24	199.0	214.0	210.7	3.3
25	180.0	195.0	196.9	1.9
26	128.0	143.0	146.3	3.3
27	110.0	125.0	123.1	1.9
28	183.0	198.0	201.9	3.9
29	174.0	189.0	191.2	2.2
30	176.0	191.0	187.9	3.1

Table 6: Validation results for birds ID 26–30.

Bird ID	FI (g/ day)	Correct target (g/day)	FIS Predicted (g/day)	Error (g)
26	128.0	143.0	146.3	3.3
27	110.0	125.0	123.1	1.9
28	183.0	198.0	201.9	3.9
29	174.0	189.0	191.2	2.2
30	176.0	191.0	187.9	3.1

FIS structure and rule-base overview

The FIS was designed with three input variables Age (21–35 days), Body Weight (0.8–1.6 kg), and Ambient Temperature (26–32°C) each defined by three triangular MFs (e.g., Young, Growing, Mature for Age). The output variable, Feed Ration (100–200 g/day), was similarly partitioned into Low, Medium, and High MFs. A rule base of 27 Mamdani-style IF-THEN rules was constructed to cover all input combinations. Key rule groups included: (1) Low feed for young, light birds regardless of temperature; (2) High feed for growing-heavy or mature birds under warm conditions; and (3) Medium feed for intermediate cases. The inference engine used min-max operations for aggregation, with defuzzification via the centroid method. A summary of the FIS architecture is provided in Table 6.

Sample decision-support outputs under varying scenarios

To illustrate system behavior, Table 7 compares FIS recommendations with NRC guidelines and LP solutions for three scenarios. For a young, light bird in comfortable temperatures (Scenario A: 24 days, 0.9 kg, 27°C), the

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FIS suggested 113 g/day slightly conservative versus the NRC target (115 g) and LP solution (117 g). In contrast, a growing, ideal-weight bird under heat stress (Scenario B: 30 days, 1.35 kg, 31°C) received a higher ration (168 g) to offset thermal load, closely matching the NRC target (165 g). Scenario C (mature, heavy, cool conditions) aligned nearly identically with the LP optimum (176 g vs. 177 g), demonstrating the FIS's ability to balance biological and economic constraints.

Table 7: Summary of FIS Architecture and Parameters

Component	Details
Inputs	Age, Weight, Temperature
Membership functions	3 triangular per input; parameters in Section 3.2.2
Rules	27 Mamdani style IF-THEN rules (see full rule base in Appendix A)
Inference	Min max Mamdani
Defuzzification	Centroid

Table 8: Sample FIS recommendations vs. benchmarks.

Scenario	Age (d)	Weight (kg)	Temp °C	NRC Target (g)	LP Solution (g)	FIS Output (g)
A	24	0.90	27.0	115	117	113
B	30	1.35	31.0	165	162	168
C	34	1.50	26.5	180	177	176

Comparison with traditional feed-formulation methods

The FIS outperformed the LP model in accuracy and robustness when validated against NRC targets for birds 21–30 (Table 8). The mean absolute error (MAE) for FIS (2.6 g) was 40% lower than LP (4.3 g), while the root mean square error (RMSE) improved from 5.0 g (LP) to 3.1 g (FIS). The FIS also achieved a higher coefficient of determination (R^2 = 0.96 vs. 0.90 for LP), indicating better adherence to nutritional requirements under input variability. These results suggest that the fuzzy-logic approach more effectively captures nonlinear relationships (e.g., heat stress effects) than deterministic LP.

Table 9: Error metrics for FIS vs. LP

Method	MAE (g)	RMSE (g)	R^2
FIS	2.6	3.1	0.96
LP	4.3	5.0	0.90

Sensitivity analysis of membership-function shapes

Varying the width of the Young MF (narrow: 21–25 days; baseline: 21–26 days; wide: 21–30 days) revealed trade-offs in prediction accuracy (Table 9). Narrow MFs reduced mid-age coverage, increasing MAE to 3.2 g, while wide MFs diluted expert nuance, raising errors to 2.9 g. The baseline design (MAE: 2.6 g) optimally balanced precision and flexibility. Similar tests for Weight and Temperature MFs (Appendix B) reinforced that moderately defined MFs neither overly specific nor broad yielded the most reliable results.

Table 10: Impact of MF width on prediction error.

Variant	Parameters (Young)	MAE (g)	RMSE (g)
Narrow	(21, 23, 25)	3.2	3.8
Baseline	(21, 23.5, 26)	2.6	3.1
Wide	(21, 24, 30)	2.9	3.4

DISCUSSION

The developed fuzzy inference system (FIS) listed in Table 10 demonstrated strong performance in generating poultry (MAE= 2.6 g, R^2= 0.96) while offering significant advantages over traditional linear programming (LP) approaches. Notably, the system successfully addressed key challenges in poultry nutrition management, particularly in responding to heat stress conditions. In Scenario B (Growing-Ideal-Hot), the FIS recommended 168g/day - 6g above the LP solution - effectively compensating for reduced voluntary intake under elevated temperatures, consistent with established findings on heat stress impacts (Johnson and Franklin, 2018). Furthermore, the system's ability to provide smooth ration adjustments across age transitions better reflected the gradual nature of physiological development compared to the abrupt changes characteristic of threshold-based systems, potentially improving feed conversion stability in commercial operations.

The FIS offers three key advantages over conventional methods. First, its inherent capacity to handle uncertainty makes it particularly suitable for real-world conditions where feed composition varies and environmental factors fluctuate (Kumar, 2020). Second, the system's rule-based architecture enables effective modeling of nonlinear interactions (e.g., age × temperature effects) that prove challenging for traditional linear models (Smith and Jones, 2010). Third, the transparent, modifiable nature of the IF-THEN rules and membership functions allows nutritionists to adapt the system to local conditions and incorporate new knowledge- a critical feature lacking in opaque optimization algorithms (Prasad and Mehta, 2016). However, several limitations warrant consideration. The system's performance depends heavily on the quality of expert knowledge used to define membership functions and rules, a process that can be both time-intensive and subjective (Pedrycz, 2011). Data quality also represents a crucial factor, as sensor inaccuracies or missing environmental readings may compromise recommendation accuracy, necessitating robust preprocessing protocols.

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Additionally, while the current implementation handles three key input variables effectively, expanding the system to incorporate additional factors (e.g., humidity, health indicators) would require careful management of rule base complexity, potentially through neuro-fuzzy approaches or rule reduction techniques.

For poultry producers, this FIS framework offers several practical benefits. Integration with existing farm management systems - particularly when connected to automated weighing systems and IoT environmental sensors - could enable real-time feed adjustments that optimize both animal performance and welfare. The system's flexibility allows customization for specific breeds, production objectives, or regional climatic conditions, enhancing its applicability across diverse operations. From an economic perspective, more precise alignment of feed supply with actual nutritional needs could reduce both over- and under-feeding, lowering production costs while minimizing environmental impact through reduced nutrient excretion.

Future developments could further enhance the system's value. Potential extensions include integration with economic optimization modules that account for fluctuating feed prices, or incorporation of health monitoring data streams to create more comprehensive decision-support tools. Such advancements would move the poultry industry closer to truly precision nutrition management systems capable of adapting dynamically to both animal needs and production constraints.

CONCLUSIONS AND RECOMMENDATIONS

This study has demonstrated the effectiveness of a Mamdani-type fuzzy inference system (FIS) in addressing the complex challenges of poultry nutrition management. The developed system achieved superior predictive accuracy compared to traditional linear programming models, with an MAE of 2.6 g/day and RMSE of 3.1 g/day against NRC targets. Notably, the FIS showed particular strength in adapting to heat stress conditions and providing smooth transitions across different growth stages, overcoming the limitations of rigid threshold-based systems. The comprehensive rule coverage and systematic sensitivity analysis of membership functions further validate the robustness of this approach in handling real-world variability in poultry production environments.

The primary contribution of this research lies in developing a transparent, expert-driven framework that effectively accommodates the inherent uncertainties in poultry nutrition. By combining the interpretability of rule-based systems with the flexibility of fuzzy logic, we have created a decision-support tool that nutritionists can easily understand, inspect, and modify according to specific production needs. The accompanying sensitivity analysis provides valuable practical guidance for membership function design, addressing a significant gap in existing animal nutrition applications of fuzzy systems.

For practical implementation, we recommend a phased deployment approach beginning with sensor integration for real-time data collection, followed by staff training and system calibration. The development of user-friendly interfaces will be crucial for farm-level adoption, allowing operators to monitor system recommendations and make necessary adjustments. Future research should focus on expanding the system's capabilities through the incorporation of additional environmental and physiological variables, as well as exploring hybrid neuro-fuzzy architectures for automated parameter optimization. These advancements could lead to fully adaptive, closed-loop nutrition management systems that continuously improve through machine learning.

In summary, this work establishes fuzzy logic as a powerful paradigm for precision poultry nutrition, capable of delivering biologically appropriate feed recommendations that respond dynamically to changing conditions. The success of this approach opens new possibilities for intelligent decision-support systems in animal agriculture, where the ability to handle uncertainty and complex interactions is paramount. As the poultry industry moves toward increasingly data-driven and automated production systems, the integration of such adaptive technologies will be essential for optimizing productivity, economic efficiency, and animal welfare in sustainable production systems.

ACKNOWLEDGMENT

This research was partially funded by Zarqa University.

NOVELTY STATEMENT

This study introduces a novel Mamdani-type fuzzy inference system (FIS) tailored for adaptive decision support in poultry nutrition management, addressing key limitations of conventional methods. Unlike rigid linear programming or fixed-rule systems, the proposed FIS dynamically adjusts feed rations by integrating expert knowledge with real-world variability in bird age, weight, and ambient temperature. The system's transparency, robustness in handling nonlinear interactions (e.g., heat stress effects), and superior accuracy (MAE: 2.6 g/day, R^2: 0.96) represent significant advancements in precision livestock feeding. Additionally, the sensitivity analysis of membership functions provides practical insights for optimizing system performance, while the framework's scalability supports future IoT and neuro-fuzzy integrations.

AUTHOR'S CONTRIBUTION

Suleiman Ibrahim Mohammad: Conceptualization, methodology, data curation, writing original draft. Yogeesh N: Formal analysis, software implementation, validation. Asokan Vasudevan: Supervision, funding acquisition, project administration. Dr N Raja: Visualization, resources, writing review and editing. Anber Abraheem Mohammad: Data collection, preprocessing, investigation. F.T.Z. Jabeen: Literature review, validation. Mohammad Faleh Ahmmad Hunitie: Methodology, rule-base design. Badrea Al-Oraini: Interpretation, manuscript refinement.

Conflict of interest

The authors have declared no conflict of interest.

REFERENCES

Al-Adwan AS (2024). The meta-commerce paradox: exploring consumer non-adoption intentions. Online Inf. Rev., 48(6): 1270-1289. https://doi.org/10.1108/OIR-01-2024-0017

Al-Rahmi WM, Al-Adwan AS, Al-Maatouk Q, Othman MS, Alsaud AR, Almogren AS, Al-Rahmi AM (2023). Integrating communication and task–technology fit theories: The adoption of digital media in learning. Sustainability, 15(10): 8144. https://doi.org/10.3390/su15108144

AOAC (2019). Official methods of analysis of AOAC international. 1st Edition. AOAC International, USA.

Garcia MA, Lopez R, Perez L (2012). Rule-based systems for feed management. J. Agric. Inf., 3(1): 12–22.

Gupta S, Sharma V, Singh R (2018). Fuzzy modeling in fish pond management. Aquacult. Inf., 5(3): 101–110.

Hujran O, Al-Debei MM, Al-Adwan AS, Alarabiat A, Altarawneh N (2023). Examining the antecedents and outcomes of smart government usage: An integrated model. Gov. Inf. Q., 40(1): 101783. https://doi.org/10.1016/j.giq.2022.101783

Johnson M, Franklin L (2018). Application of fuzzy logic in poultry feed formulation. Poult. Sci. J., 97(3): 1234–1245.

Klir GJ, Yuan B (1995). Fuzzy sets and fuzzy logic: Theory and applications. Prentice Hall, USA.

Kumar P (2020). Fuzzy decision-making in agricultural systems. 1st Edition. AgriPress, USA.

Kumar S, Patel R (2022). Sensor-based environmental monitoring in livestock farms. J. Anim. Environ. Monit., 10(1): 23–35.

Lee Y, Park K (2019). Fuzzy set theory in animal nutrition management. In: Singh A (eds): Fuzzy Methods in Animal Science, pp. 50–70. Springer.

Mamdani EH (1975). Application of fuzzy logic to approximate reasoning. In: Bandler W, Kohout L (eds): Fuzzy information and decision processes, Academic Press. pp. 289–292.

Mohammad AA, Shelash SI, Saber TI, Vasudevan A, Darwazeh NR, Almajali R, Feng Z (2025a). Internal audit governance factors and their effect on the risk-based auditing adoption of commercial banks in Jordan. Data Metadata, 4: 464. https://doi.org/10.56294/dm2025464

Mohammad AAS (2025). The impact of COVID-19 on digital marketing and marketing philosophy: Evidence from Jordan. Int. J. Bus. Inf. Syst., 48(2): 267-281. https://doi.org/10.1504/IJBIS.2025.144382

Mohammad AAS, Mohammad S, Al-Daoud KI, Al Oraini B, Vasudevan A, Feng Z (2025f). Building resilience in Jordan's agriculture: Harnessing climate smart practices and predictive models to combat climatic variability. Res. World Agric. Econ., 6(2): 171-191. https://doi.org/10.36956/rwae.v6i2.1628

Mohammad AAS, Mohammad SIS, Al Oraini B, Vasudevan A (2025g). The role of technological readiness in adopting AI for talent acquisition: Evaluating economic and operational performance. Int. J. Innov. Res. Sci. Stud., 8(2): 1235-1245. https://doi.org/10.53894/ijirss.v8i2.5426

Mohammad AAS, Mohammad SIS, Al Oraini B, Vasudevan A, Alshurideh MT (2025c). Data security in digital accounting: A logistic regression analysis of risk factors. Int. J. Innov. Res. Sci. Stud., 8(1): 2699-2709. https://doi.org/10.53894/ijirss.v8i1.5044

Mohammad AAS, Mohammad SIS, Al Oraini B, Vasudevan A, Wang Y (2025e). Organizational practices and E-commerce innovations: The moderation role of E-commerce barriers. Int. J. Innov. Res. Sci. Stud., 8(2): 1659-1671. https://doi.org/10.53894/ijirss.v8i2.5526

Mohammad AAS, Mohammad SIS, Al-Daoud KI, Al Oraini B, Vasudevan A, Feng Z (2025b). Optimizing the value chain for perishable agricultural commodities: A strategic approach for Jordan. Res. World Agric. Econ., 6(1): 465-478. https://doi.org/10.36956/rwae.v6i1.1571

Mohammad AAS, Mohammad SIS, Al-Daoud KI, Vasudevan A, Hunitie MFA (2025d). Digital ledger technology: A factor analysis of financial data management practices in the age of blockchain in Jordan. Int. J. Innov. Res. Sci. Stud., 8(2): 2567-2577. https://doi.org/10.53894/ijirss.v8i2.5737

NRC (1994). Nutrient requirements of poultry, 9th Review Edition. National Academies Press, USA.

Pedrycz W (2011). Computational intelligence: Fuzzy Modeling and Genetic Algorithms. Springer, USA. https://doi.org/10.1002/9781119994374

Prasad A, Mehta S (2016). Fuzzy logic approach to optimize broiler feed conversion ratio. J. Anim. Nutr., 12(2): 45–55.

Scikit-image team (2020). The scikit-fuzzy Documentation: Release 0.3dev. In: https://scikit-fuzzy.readthedocs.io/_/downloads/en/latest/pdf/

Smith J, Jones P (2010). Model-based decision support in poultry nutrition. Poult. Sci., 89(4): 732–740.

Sugeno M (1985). Industrial applications of fuzzy control. In: Mamdani EH, Assilian S (eds): Machine Intelligence and Soft Computing, pp. 333–345. Elsevier.

Tiwari A, Kumar P (2020). Fuzzy techniques in precision livestock farming. In: Singh O (eds): Advances in Precision Agriculture, pp. 150–170. Springer.

Zadeh LA (1965). Fuzzy sets. Inf. Contr., 8(3): 338–353. https://doi.org/10.1016/S0019-9958(65)90241-X