Research Article

Optimizing Native Chicken Layer Diets under Nutrient Uncertainty: A Fuzzy Linear Programming Approach

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Abstract | The high variability in the nutrient composition of local feed ingredients and the lack of well-defined nutrient requirements for native chickens pose major challenges in developing cost-effective and nutritionally balanced diets. This study applied Fuzzy Linear Programming (FLP) to formulate layer diets under nutrient uncertainty by using nutrient ranges rather than fixed values. Near-infrared spectroscopy (NIRS) was used to determine the nutrient composition of corn, rice bran, and fishmeal, while other ingredients were analyzed using proximate analysis for organic components and atomic absorption spectrometry for mineral determination. Feed formulation models were constructed at $\lambda = 0$ and $\lambda = 1$, representing minimum and maximum nutrient requirements, and integrated within an FLP framework. The optimal solution was achieved at $\lambda = 0.33$, yielding a diet with a fuzzy-interpolated crude protein target of approximately 15.66%, expressed as an output range of 15.38–16.36% due to ingredient nutrient uncertainty, and 2670 kcal/kg metabolizable energy (ME). This formulation reduced feed cost by 5.28% compared with the $\lambda = 1$ formulation. Relative to the market price of commercial feed paid by farmers (IDR 7,920/kg), the proposed formulation (IDR 5,436/kg) achieved a 31.37% price reduction at the farmer level, although this comparison should be interpreted with caution because processing, distribution, and profit margin structures differ between commercial and on-farm feed systems. These findings indicate that FLP effectively supports nutritionally adequate and cost-efficient diet formulation under ingredient quality variability, although in vivo validation of the optimized formulation remains necessary.

Keywords | Fuzzy linear programming, Native chickens, Layer diet formulation, Near-infrared spectroscopy, Nutrient uncertainty, Feed cost optimization

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INTRODUCTION

Native chicken production plays a vital role in strengthening rural economies in Indonesia by contributing to household nutrition, food security, and income diversification. Native chickens provide a dependable source of animal protein and serve as a readily marketable asset that supports household financial resilience (Asnawi *et al*., 2023; Hidayat and Asmarasari, 2015). Their development aligns with national strategies to enhance village-level agribusiness and improve community welfare, especially in remote and agricultural regions (Munawaroh *et al*., 2021; Silondae *et al*., 2022).

Despite these benefits, productivity and sustainability of native chicken enterprises are constrained primarily by the high cost of commercial feed. Feed costs typically represent 60–70% of total production expenses and are driven by unstable prices of key imported ingredients, particularly soybean meal, as well as price volatility of major energy sources such as corn (Akhadiarto, 2019; Hidayat and Asmarasari, 2015). This price volatility reduces profitability for smallholder farmers who depend heavily on commercial diets.

Using local feed resources and agricultural by-products is a promising strategy for reducing production costs. Studies have shown that materials such as rice bran, corn, and crop residues can support acceptable performance while lowering feed expenses (Winarti and Wiranti, 2016). However, the nutrient composition of these local feed ingredients exhibits high variability due to differences in cultivation, processing, and storage conditions. This variability creates a major formulation challenge because feed quality becomes inconsistent when fixed nutrient values are used in diet formulation.

In practice, farmers and nutritionists commonly rely on nutrient specifications developed for commercial layer breeds, which differ substantially from native chickens in terms of productivity, feed efficiency, and nutrient utilization (Syafwan *et al*., 2022). When applied as fixed targets, these commercial standards may result in unnecessarily dense diets for native chickens, leading to higher feed costs that do not translate into proportional improvements in egg production. In this study, such standards were therefore used only as reference bounds rather than fixed dietary targets. The lower bound represents a conservative minimum nutritional level that remains physiologically acceptable for native layers, while the upper bound reflects nutritionally adequate levels associated with improved performance reported in the literature. These bounds were then integrated and adjusted through the FLP framework to accommodate nutritional uncertainty.

These challenges highlight a clear need for formulation models capable of accommodating uncertainty, thereby addressing a critical methodological limitation of conventional deterministic approaches. Most previous studies employ deterministic linear programming, which assumes precise nutrient values and therefore does not reflect real-world conditions characterized by variability in ingredient composition. There is limited research on formulation approaches that explicitly address nutrient variability in native chickens.

The present study introduces the application of Fuzzy Linear Programming to formulate diets for native laying chickens under nutrient uncertainty. This approach integrates fuzzy logic with classical linear programming, allowing nutrient constraints to be expressed as intervals rather than fixed points (Adrizal *et al*., 2025; Cadenas *et al*., 2004). This provides a novel and more flexible framework for achieving least-cost formulations that remain robust despite fluctuating nutrient profiles in local feed ingredients. To our knowledge, this is a first attempt to apply FLP specifically for native chicken diets within the context of small-scale feed production in Indonesia, offering both methodological and practical contributions to rural poultry development.

MATERIALS AND METHODS

Materials

The feed ingredients used in this study were sourced from West Sumatra, Indonesia. The feed ingredients included corn, rice bran, fishmeal, coconut meal, soybean meal, cabbage waste, oyster shell, limestone and mineral supplements. The nutrient content of feed ingredients was determined using NIRS for corn, rice bran, and fishmeal (Adrizal and Andasuryani, 2023). However, for coconut meal, soybean meal, cabbage waste, proximate analysis was used to measure crude protein, crude fat, and crude fiber. Calcium and phosphorus were analyzed using the atomic absorption spectrometry. ME data are quoted from Leeson and Summers (2008) except for cabbage waste quoted from Mahgoub *et al*. (2018). Accordingly, nutrient values for corn, rice bran, and fish meal are expressed as predicted nutrient values ± standard error of prediction (SEP), whereas all other ingredients are represented by single deterministic values, as summarized in Table 1.

This study integrates nutrient uncertainty into diet formulation using an FLP approach based on NIRS-predicted and conventionally analysed feed ingredient data. The model development involves the construction of lower- and upper-bound linear programming formulations that are subsequently integrated into a fuzzy optimization framework. The overall experimental design and optimization workflow are illustrated in Figure 1.

Within this framework, nutrient and metabolizable energy (ME) requirements were categorized into two groups based on fuzzy membership values (λ). A membership value of zero ($\lambda = 0$) indicates a lower-bound nutritional scenario, approaching or slightly below the required standards, while a value of $\lambda = 1$ represents the upper-bound nutritional scenario. The nutritional requirements corresponding to these two extreme values are presented in Table 2. Because definitive requirement standards for crude protein and crude fat in native laying chickens are not available, published recommendations vary across studies.

Table 1: Nutritional content, ME and feed ingredient price.

Variable	Feed ingredients	Nutritional content (%)					ME	Price (IDR/Kg)
		Crude protein	Crude fat	Crude fiber	Ca	P		
X_1	Corn	6.62 ± 0.24[1)]	3.50 ± 0.16[1)]	3.50 ± 0.11[1)]	0.86 ± 0.21[1)]	0.25 ± 0.06[1)]	3313[2)]	6500
X_2	Rice bran	8.30 ± 0.06[1)]	9.35 ± 0.18[1)]	14.30 ± 0.18[1)]	0.09 ± 0.02[1)]	1.26 ± 0.21[1)]	1900[2)]	2500
X_3	Fish meal	49.47 ± 3.59[1)]	8.55 ± 0.12[1)]	0.25 ± 0.05[1)]	4.19 ± 0.69[1)]	2.37 ± 0.33[1)]	2750[2)]	6000
X_4	Soybean meal	41.06 [3)]	5.33[3)]	4.35 [3)]	0.35[3)]	0.33[3)]	2540[2)]	10000
X_5	Coconut meal	24.34[3)]	13.00[3)]	8.00[3)]	0.38[3)]	0.38[3)]	2200[2)]	4400
X_6	Cabbage Waste	17.23[3)]	12.39[3)]	5.07[3)]	3.54[3)]	0.06[3)]	2911[4)]	4000
X_7	oyster shells				36.88[3)]	0.16[3)]		500
X_8	Limestone				37.75[3)]	0.08[3)]		800
X_9	Mineral supplement				32.50[5)]	1.00[5)]		10000

Footnote: Values for X_1–X_3 are expressed as predicted nutrient values ± standard error of prediction (SEP) derived from NIRS, indicating prediction uncertainty rather than standard deviation, while single values for other ingredients reflect conventional analyses due to the lack of available NIRS calibrations. Source: [1)] predicted based on NIRS data (analysis conducted at the Central Laboratory of Universitas Andalas, Padang, Indonesia.). [2)] Leeson and Summers (2008). [3)]. Analysis conducted at the Non-Ruminant Laboratory, Faculty of Animal Science, Universitas Andalas, Padang, Indonesia. [4)] Mahgoub *et al*. (2018).

Table 2: Nutrient requirements based on fuzzy membership values (λ = 0 and λ = 1).

No	Nutrient and ME	λ = 0	References	λ = 1	References
1	Crude Protein (minimum) (%)	15	National Standardization Agency of Indonesia (BSN, 2024)	17	Alwi *et al*. (2019)
2	Metabolizable Energy (minimum) (Kcal/kg)	2500	Alwi *et al*. (2019)	2700	Alwi *et al*. (2019); Utami (2023)
3	Crude Fat (maximum)	7	González-Muñoz (2009)	6	Leeson and Summers (2008)
4	Crude Fiber (maximum)	7	Utami (2023)	7	Utami (2023)
5	Calcium (minimum)	3.25	Utami (2023)	3.25	Utami (2023)
6	Total Phosphorus (minimum)	0.45	Utami (2023)	0.45	Utami (2023)

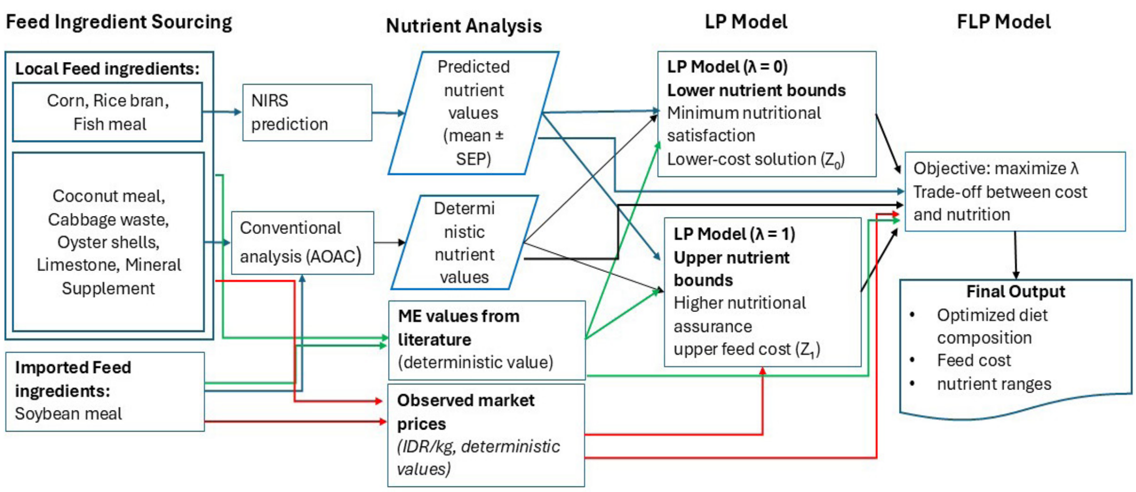

Figure 1: Experimental design and optimization workflow. Schematic overview of the experimental design and optimization workflow used in this study. The process begins with sourcing local feed ingredients, followed by nutrient characterization using Near-infrared spectroscopy (NIRS) for corn, rice bran, and fish meal, and conventional laboratory analyses for other ingredients. NIRS outputs are expressed as predicted nutrient values ± standard error of prediction (SEP), while conventionally analyzed ingredients are represented by deterministic values. Two linear programming (LP) models are then constructed to represent the lower-bound (λ = 0) and upper-bound (λ = 1) nutritional scenarios. These boundary models are integrated into a Fuzzy Linear Programming (FLP) framework, in which the fuzzy membership value (λ) is maximized to obtain a compromise solution under nutrient uncertainty. The final outputs include the fuzzy-optimal diet formulation, feed cost, and nutrient composition ranges for native laying chickens.

In this study, different authoritative literature sources were therefore used to define conservative and permissive bounds for these nutrients, allowing the FLP model to explicitly account for knowledge-based uncertainty in nutrient requirements.

Differences in nutrient coefficients across the lower-bound (λ= 0), upper-bound (λ= 1), and integrated FLP models are intentionally introduced to represent ingredient-level uncertainty associated with NIRS predictions. In this study, the interpretation of each formulation is based on nutritional risk management under prediction uncertainty rather than on the statistical magnitude of the nutrient coefficients. In the integrated FLP model, the predicted nutrient value of each feed ingredient is used as the central estimate. The lower-bound formulation (λ= 0) incorporates the predicted nutrient value plus the standard error of prediction (SEP). Although this results in higher assumed nutrient coefficients at the formulation stage, it may increase the risk of unintended nutrient deficiency if actual nutrient values are overestimated by the prediction model. Conversely, the upper-bound formulation (λ= 1) adopts a conservative worst-case assumption at the ingredient level by using predicted minus SEP values, thereby producing a nutritionally robust diet that remains adequate even under unfavorable nutrient realizations. These bounds represent a practical expression of NIRS prediction uncertainty rather than a formal statistical confidence interval.

Lower-bound LP model (λ = 0)

Feed cost: Minimized $Z_0 = 6500X_1 + 2500X_2 + 6000X_3 + 10000X_4 + 4400X_5 + 4000X_6 + 500X_7 + 800X_8 + 10000X_9$

Subject to:

Crude protein: $6.86X_1 + 8.36X_2 + 53.06X_3 + 41.06X_4 + 24.34X_5 + 17.23X_6 \geq 15.00$

ME: $3313X_1 + 1900X_2 + 2750X_3 + 2540X_4 + 2200X_5 + 2911X_6 \geq 2500$

Crude fat: $3.66X_1 + 9.53X_2 + 8.67X_3 + 4.35X_4 + 8.00X_5 + 5.07X_6 \leq 7.00$

Crude fiber: $3.61X_1 + 14.48X_2 + 0.30X_3 + 5.33X_4 + 13.00X_5 + 12.39X_6 \leq 7.00$

Calcium: $1.07X_1 + 0.10X_2 + 4.88X_3 + 0.35X_4 + 0.38X_5 + 3.54X_6 + 36.88X_7 + 37.75X_8 + 32.50X_9 \geq 3.25$

Phosphorus: $0.31X_1 + 1.39X_2 + 2.70X_3 + 0.35X_4 + 0.38X_5 + 0.06X_6 + 0.16X_7 + 0.08X_8 + 1.00X_9 \geq 0.45$

Fish meal limitation (Alemayehu *et al.*, 2015): $X_3 \leq 10.00\%$

Coconut meal limitation (Leeson and Summers, 2008): $X_5 \leq 10.00\%$

Cabbage waste limitation (Mahgoub *et al.*, 2018): $X_6 \leq 12.00\%$

Total: $X_1 + X_2 + X_3 + X_4 + X_5 + X_6 + X_7 + X_8 + X_9 = 100\%$

Non negative variables: $X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9 \geq 0$

Upper-bound LP model (λ = 1)

Feed Cost: Minimized Z1 = 6500X1 + 2500X2 + 6000X3 + 10000X4 + 4400X5 + 4000X6 + 500 X7 + 800X8 + 10000X9

Subject to:

Crude protein 6.38X1 + 8.24X2+ 45.88X3 + 41.06X4 + 24.34X5+ 17.23X6 ≥ 17.00

ME: 3313X1 + 1900X2 + 2750X3 + 2540X4 + 2200X5+ 2911X6 ≥ 2700

Crude fat: 3.34X1 + 9.17X2 + 8.43X3 + 4.35X4 + 8.00X5+ 5.07X6 ≤ 6.00

Crude fiber: 3.39X1 + 14.12X2 + 0.20X3 + 5.33X4 + 13.00X5+ 12.39X6 ≤ 7.00

Calcium: 0.65X1 + 0.08X2 + 3.50X3 + 0.35X4 + 0.38X5+ 3.54X6
+ 36.88X7 + 37.75X8 + 32.50X9 ≥ 3.25

Phosphorus: 0.19X1 + 1.13X2 + 2.04X3 + 0.35X4 + 0.38X5+ 0.06X6+ 0.16X7 + 0.08X8 + 1.00X9 ≥ 0.45

Fish meal limitation: X3 ≤ 10.00%

Coconut meal limitation: X5 ≤ 10.00%

Cabbage waste limitation: X6 ≤ 12.00%

Total: X1 + X2+X3 + X4 +X5+X6+X7 + X8 + X9 = 100%

Non negative variables: X1, X2, X3, X4, X5, X6, X7, X8, X9 ≥ 0

Z0= total cost at λ=0, Z1= total cost at λ=1, X1=corn, X2=rice bran, X3=fish meal, X4=soybean meal, X5=coconut meal, X6=cabbage waste, X7=oyster shell, X8=limestone, X9=mineral supplement and λ= fuzzy membership value. All costs are in Indonesian Rupiah (IDR) per kilogram.

Integrated FLP model

To integrate the two extreme fuzzy scenarios, namely the lower-bound LP model (λ= 0) and the upper-bound LP model (λ= 1), into a single optimization framework, an Integrated FLP model was formulated by introducing the membership variable λ ∈ [0,1]. The objective function of the integrated FLP model is to maximize λ, which quantifies the overall degree of satisfaction of the formulated diet with respect to both economic efficiency and nutritional adequacy. Maximizing λ therefore identifies the highest feasible satisfaction level that can be achieved while simultaneously satisfying feed cost constraints and nutrient requirements within the fuzzy-defined bounds.

Maximization of the fuzzy membership value (λ)

In this formulation, the feed cost constraint is restricted to remain below the upper cost bound obtained from the upper-bound LP model (λ= 1, Z_1), while allowing gradual relaxation toward the lower-bound LP solution (λ= 0) as λ decreases. Similarly, each nutritional constraint is constructed such that nutrient levels are maintained above those corresponding to the lower-bound membership level and below those associated with the upper-bound membership level through linear interpolation between the two formulations. Consequently, the integrated FLP model represents a compromise solution that maximizes overall satisfaction while ensuring feed cost control and nutritional adequacy within the fuzzy-defined bounds.

Fuzzy constraint formulation based on membership functions

The fuzzy membership functions shown in Figures 2–5 illustrate the linear relationships between the fuzzy membership value (λ) and the corresponding economic and nutritional constraints used in the FLP model. These figures visually define how allowable feed cost and nutrient requirements are interpolated between the lower-bound (λ= 0) and upper-bound (λ= 1) LP solutions. The linear relationship between the fuzzy membership value and the corresponding feed cost is illustrated in Figure 2. As illustrated, λ ranges between 0 and 1, while the feed cost Z varies between the lower and upper bounds Z_0 and Z_1, respectively. Accordingly, the feed cost corresponding to a given fuzzy membership level is obtained by linear interpolation between Z_0 and Z_1, resulting in the following constraint:

$$Z \le Z_0 + \lambda\,(Z_1 - Z_0)$$

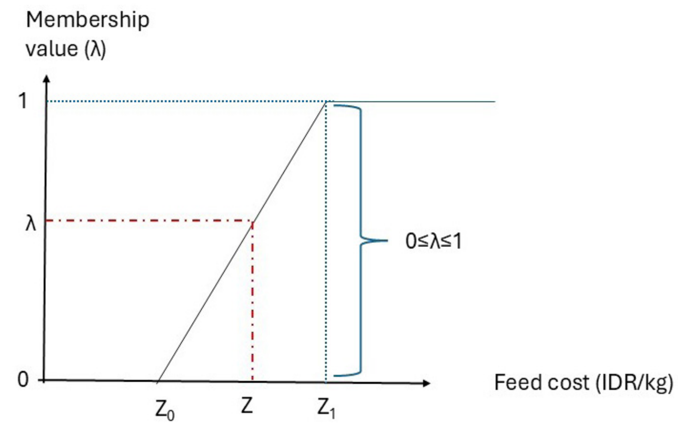

Figure 2: Fuzzy membership function for feed cost constraint in the FLP model.
The horizontal axis represents feed cost (Z, IDR/kg), ranging from the lower-cost solution at λ = 0 (Z_0) to the upper-cost solution at λ = 1 (Z_1), while the vertical axis represents the fuzzy membership value (0 ≤ λ ≤ 1). The straight line indicates linear interpolation between Z_0 and Z_1, defining the allowable maximum feed cost at a given λ level, expressed mathematically as $Z \le Z_0 + \lambda(Z_1 - Z_0)$.

Crude protein constraint

The crude protein requirement increases with the fuzzy membership value (Figure 3). At λ=0 the minimum crude protein requirement is 15%, whereas at λ=1 the minimum requirement increases to 17%. Therefore, the crude protein content under fuzzy conditions is expressed as:

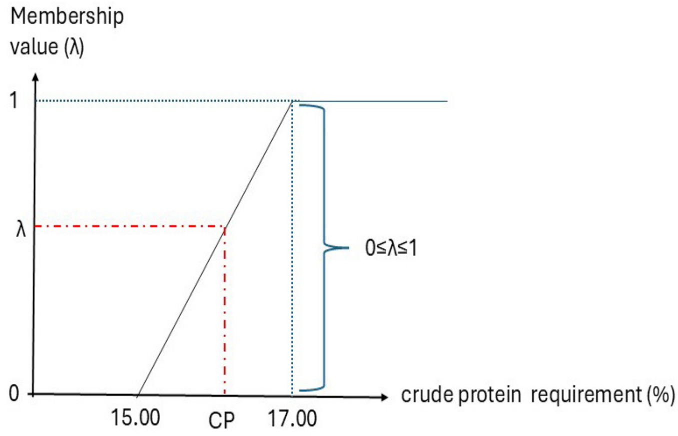

Figure 3: Fuzzy membership function for crude protein requirement in the FLP model.
The horizontal axis represents crude protein content (CP, %), increasing from the lower-bound requirement of 15% at λ = 0 to the upper-bound requirement of 17% at λ = 1, while the vertical axis represents the fuzzy membership value (0 ≤ λ ≤ 1). The linear segment illustrates the progressive tightening of the minimum crude protein requirement as λ increases within the FLP framework.

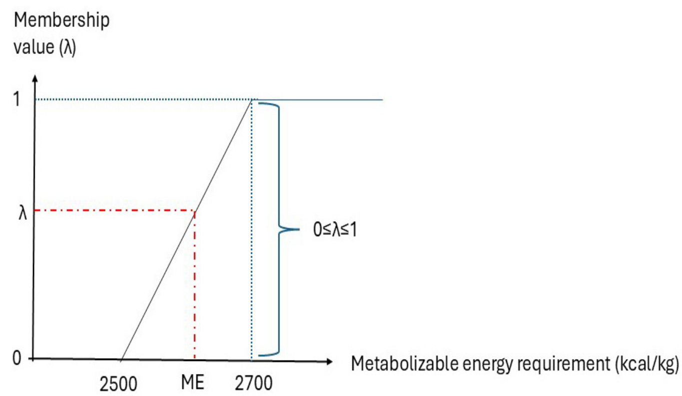

Figure 4: Fuzzy membership function for metabolizable energy requirement in the FLP model.
The horizontal axis represents metabolizable energy (ME, kcal/kg), increasing linearly from the lower-bound requirement of 2500 kcal/kg at λ = 0 to the upper-bound requirement of 2700 kcal/kg at λ = 1, while the vertical axis represents the fuzzy membership value (0 ≤ λ ≤ 1). The straight line indicates linear interpolation between these two bounds, defining the λ-dependent energy constraint applied in the FLP formulation.

$$6.62X_1 + 8.30X_2 + 49.47X_3 + 41.06X_4 + 24.34X_5 + 17.23X_6 \ge 15.00 + \lambda\,(17\text{-}15)$$

By rearranging the terms and transferring the λ-dependent component to the left-hand side, the constraint can be written as:

$$6.62X_1 + 8.30X_2 + 49.47X_3 + 41.06X_4 + 24.34X_5 + 17.23X_6 - 2\lambda \ge 15.00$$

ME constraint

The relationship between ME requirement and the fuzzy membership value is shown in Figure 4. At λ-0, the minimum ME requirement is 2500 kcal/kg while at λ=1 increases to 2700 kcal/kg. Thus, the ME constraint under fuzzy conditions is formulated as:

$$3313X_1 + 1900X_2 + 2750X_3 + 2540X_4 + 2200X_5 + 2911X_6 \geq 2500 + \lambda\,(2700 - 2500)$$

After simplification, this constraint becomes:

$$3313X_1 + 1900X_2 + 2750X_3 + 2540X_4 + 2200X_5 + 2911X_6 - 200\,\lambda \geq 2500$$

Crude fat constraint

Figure 5 illustrates how the crude fat limitation is adjusted as a function of the fuzzy membership value (λ) within the FLP framework. At λ=0 the maximum crude fat level is 7%, while at λ=1 it decreases to 6%. Based on these limits, the crude fat constraint is formulated as:

$$3.50X_1 + 9.35X_2 + 8.55X_3 + 4.35X_4 + 8.00X_5 + 5.07X_6 \leq 7.00 - \lambda\,(7.00 - 6.00)$$

This expression can be simplified to:

$$3.50X_1 + 9.35X_2 + 8.55X_3 + 4.35X_4 + 8.00X_5 + 5.07X_6 + \lambda \leq 7.00$$

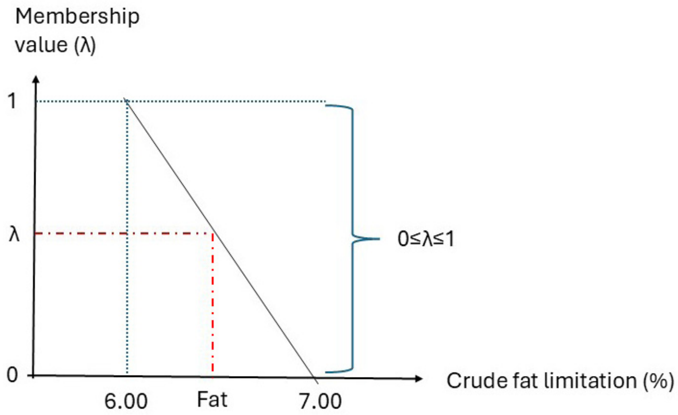

Figure 5: Fuzzy membership function for crude fat limitation in the FLP model.
The horizontal axis represents crude fat content (%), while the vertical axis represents the fuzzy membership value (0 ≤ λ ≤ 1). As λ increases, the allowable maximum crude fat level decreases linearly from 7% at λ = 0 to 6% at λ = 1, indicating a progressively stricter fat constraint under higher nutritional assurance.

Other nutritional constraints

Based on Table 2, the remaining nutritional requirements are identical for both λ=0 and λ=1. Calcium, phosphorus, and crude fiber were treated as deterministic constraints. Calcium and phosphorus requirements for laying hens are relatively well established and were supplied primarily from mineral sources with stable nutrient concentrations. Crude fiber was defined as a fixed upper-limit constraint to control dietary bulkiness rather than as a target nutrient subject to uncertainty. Therefore, identical reference values were applied for these nutrients across λ scenarios to ensure biological safety and model stability. Therefore, these constraints do not involve the membership variable λ and are expressed as:

Crude fiber: $3.50X_1 + 14.30X_2 + 0.25X_3 + 5.33X_4 + 13.00X_5 + 12.39X_6 \leq 7.00$
Calcium: $0.85X_1 + 0.09X_2 + 4.19X_3 + 0.35X_4 + 0.38X_5 + 3.54X_6 + 36.88X_7 + 37.75X_8 + 32.50X_9 \geq 3.25$
Phosphorus: $0.25X_1 + 1.26X_2 + 2.37X_3 + 0.35X_4 + 0.38X_5 + 0.06X_6 + 0.16X_7 + 0.08X_8 + 1.00\,X_9 \geq 0.45$

The inclusion levels of selected ingredients were restricted as follows:

$$X_3 \leq 10.00\%,\ X_5 \leq 10.00\%,\ X_6 \leq 12.00\%$$

The mass balance constraint is given by:

$$X_1 + X_2 + X_3 + X_4 + X_5 + X_6 + X_7 + X_8 + X_9 = 100\%$$

All decision variables are non-negative and the membership value is bounded within:

$$X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9 \geq 0$$
$$0 \leq \lambda \leq 1$$

In the FLP formulation, fixed right-hand side values represent literature-derived reference nutrient thresholds, while fuzziness is introduced by λ-dependent terms on the left-hand side of the constraints, allowing nutrient requirements to be progressively tightened or relaxed as the membership value changes. The objective function is to maximize the fuzzy membership value (λ), which represents the overall degree of satisfaction of the nutritional constraints. Feed cost (Z) is treated as a constraint rather than an objective function, incorporated via linear interpolation between the minimum-cost solution (Z_0 at λ = 0) and the maximum-nutrition solution (Z_1 at λ = 1). This formulation ensures that λ increases only within the feasible cost range defined by Z_0 and Z_1.

In this study, the fuzzy membership value (λ) is not intended to represent a biological performance index or a predefined production target. Instead, λ serves as an endogenous decision variable that quantifies the degree of simultaneous satisfaction of nutritional and economic constraints within a fuzzy-defined feasible space. The optimization process identifies the maximum feasible λ that can be achieved without violating any constraints, thereby yielding a mathematically optimal compromise between cost efficiency and nutritional robustness rather than a biological optimum.

Diet formula and nutrient calculation

After the diet formulation was obtained for each λ scenario, the nutrient composition of the final diet was calculated as the weighted sum of ingredient inclusion levels and their predicted nutrient contents. To account for ingredient-level uncertainty derived from NIRS analysis, dietary nutrient ranges were subsequently computed by applying the predicted nutrient value minus SEP as the lower bound and the predicted nutrient value plus SEP as the upper bound for each ingredient. This deterministic calculation was performed for λ = 0, λ = 1, and the λ-optimal solution.

All LP and FLP models were solved using Microsoft Excel with the Solver add-in, applying the Simplex LP algorithm. Non-negativity constraints were enforced, and the fuzzy membership value was bounded within $0 \leq \lambda \leq 1$.

RESULTS AND DISCUSSIONS

Feed formulation under different scenario

Based on the optimization framework defined in feed formulation, the FLP model generated three alternative feed formulations corresponding to λ = 0, λ = 1, and the fuzzy-optimal condition ($0 \leq \lambda \leq 1$). The optimal membership value was obtained at λ = 0.33, representing the best compromise between cost minimization and nutrient adequacy under uncertainty. The detailed ingredient compositions for each formulation are presented in Table 3.

Table 3: Feed formulation composition based on fuzzy linear programming.

Variable	Feed ingredients	Feed formulation (%)		
		λ=0	λ=1	Fuzzy (λ=0.33)
X_1	Corn	37.29	42.73	44.32
X_2	Rice bran	18.62	8.39	8.95
X_3	Fish meal	10.00	10.00	10.00
X_4	Soybean meal	2.62	11.05	6.73
X_5	Coconut meal	10.00	10.00	10.00
X_6	Cabbage waste	12.00	12.00	12.00
X_7	Oyster shells	7.47	3.83	6.00
X_8	Limestone	1.00	1.00	1.00
X_9	Mineral supplement	1.00	1.00	1.00
	Total	100	100	100
	Feed cost (IDR/kg)	4817	5739	5436

At λ = 0, which emphasizes minimum nutrient requirements and cost minimization, the model prioritizes locally available feed ingredients such as corn, rice bran, coconut meal, and cabbage waste, while minimizing soybean meal inclusion. This pattern is consistent with previous findings reporting that appropriate balancing of local ingredients can substantially reduce feed costs (Akhadiarto, 2019; Winarti and Wiranti, 2016). The resulting feed price (IDR 4,817/kg) is the lowest among the formulated scenarios, reflecting the cost-minimizing nature of the lower-bound solution rather than a nutritionally robust formulation.

Under λ= 1, the formulation reflects upper nutrient constraints designed to represent nutritionally stringent conditions associated with higher production potential. This requires greater reliance on high-quality protein sources, particularly soybean meal, consistent with previous observations that imported soybean meal is often indispensable for achieving upper-bound protein targets in poultry diets (Adrizal *et al.*, 2025). The increased use of soybean meal elevates the feed cost to IDR 5,739/kg, illustrating the trade-off between nutrient precision and economic feasibility.

The fuzzy-optimal formulation at λ = 0.33 represents a balanced compromise solution. Soybean meal inclusion decreases relative to λ= 1, while local ingredients remain predominant. This balanced strategy supports the findings of Adrizal *et al.* (2025), who reported that fuzzy optimization effectively handles uncertainties in nutrient composition, especially when incorporating agricultural by-products in rural feed systems. The resulting feed cost of IDR 5,436/kg represents a practical compromise between the two extreme fuzzy scenarios, achieving an additional 5.28% cost saving compared with the λ = 1 formulation. Moreover, this cost is substantially lower than the commercial feed currently used by farmers (IDR 7,920/kg), corresponding to a total cost reduction of 31.37%. These results highlight the real-world economic relevance of FLP for small-scale and cooperative-based feed producers.

The fuzzy-optimal solution at λ= 0.33 should therefore be interpreted as a computational compromise rather than a biologically optimal diet. This solution reflects an intermediate nutritional scenario that balances feed cost reduction and nutrient adequacy under ingredient-level uncertainty. It does not correspond to a specific physiological state such as maintenance or maximum egg production, but instead represents the highest attainable satisfaction level within the defined fuzzy bounds.

Because no biological performance trial was conducted in the present study, the alignment between the mathematical optimum and biological response cannot be assumed. Consequently, the λ = 0.33 formulation should be regarded as a candidate diet generated through decision-support optimization, which requires subsequent *in vivo* validation to confirm its effects on egg production, feed efficiency, and bird health.

Nutrient composition and nutritional adequacy

Nutrient composition ranges generated from the three formulations (Table 4) demonstrate that the FLP model generally operates within recommended nutrient levels for native laying hens, even in the presence of ingredient quality uncertainty. The nutrient composition ranges in Table 4 were obtained by recalculating the final diet using ingredient nutrient values adjusted by ± SEP as a deterministic sensitivity analysis, thereby providing lower and upper bounds of dietary nutrient content for each λ scenario. The crude protein in the λ = 0 model (14.39–15.30 %) is formulated to meet the minimum requirement of 15% (BSN, 2024). While the upper end of this range satisfies the standard, the lower bound reflects the inherent uncertainty in ingredient composition, indicating that in some realizations, the diet might marginally fall below the target. Within the FLP framework, λ= 0 represents a boundary solution with minimal nutritional satisfaction and is not intended to guarantee adequacy under all possible variability.

Table 4: Range of nutrient composition of diets formulated using fuzzy linear programming.

No.	Nutrient criteria	λ = 0	λ = 1	λ = 0.33
1	Crude protein (%)	14.39-15.30	17.00-17.98	15.38-16.36
2	Crude fat (%)	5.20–5.41	4.93–5.12	4.85–5.05
3	Crude fiber (%)	6.65–6.81	6.04–6.17	5.93–6.07
4	Calcium (%)	4.73–5.02	3.25–3.57	4.05–4.37
5	Phosphorus (%)	0.54–0.69	0.48–0.62	0.48–0.62
6	Metabolizable energy (kcal/kg)	2,500	2,700	2670

The λ= 1 formulation increases protein content substantially (17.00–17.98%), which could support higher production potential and aligning with National Research Council (1994) recommendations for maximizing egg output. In the fuzzy-optimal formulation at λ= 0.33, crude protein ranges from 15.38–16.36%, which falls within and slightly above the recommended range for native layers. This intermediate protein level indicates that the FLP model successfully balances nutrient sufficiency and cost efficiency by producing a formulation with protein levels higher than λ= 0 but lower than λ= 1. The result demonstrates the model's ability to accommodate nutrient uncertainty while maintaining protein adequacy without excessive reliance on costly protein sources such as soybean meal.

Crude fat levels remain stable across formulations, aligning with established recommendations for layer diets (4–6%) to maintain energy density without adversely affecting feed intake (Leeson and Summers, 2008). Crude fiber values are slightly higher than those commonly observed in commercial layer diets but remain physiologically acceptable for native chickens, which possess a greater tolerance for fibrous ingredients (Munawaroh *et al*., 2021). Importantly, this range still complies with the maximum crude fiber limit of 7% established for both λ = 0 and λ = 1 in Table 2, as recommended by Utami (2023), indicating that all formulations satisfy the required standard despite variability in ingredient composition.

Calcium content varies substantially across λ values. The λ = 0 formulation yields high calcium levels (4.73–5.02%) due to increased oyster shell inclusion, which supports eggshell formation but may exceed the minimum requirement for native layers. In contrast, the λ = 1 formulation produces lower calcium content (3.25–3.57%), aligning with the minimum Ca requirement of 3.25% established by Utami (2023) in Table 2. The fuzzy-optimal range (4.05–4.37%) falls well within the recommended threshold and provides adequate calcium to support consistent eggshell quality while maintaining mineral balance across formulations.

Phosphorus ranges (0.48–0.69%) remain within recommended limits (0.45–0.60%) for layers, supporting metabolic and skeletal functions (National Research Council, 1994). These values also meet the minimum phosphorus requirement of 0.45% established by Utami (2023) in Table 2, indicating that all formulations supply adequate phosphorus to sustain bone development, eggshell mineralization, and overall physiological function despite variability in ingredient quality.

The ME values (2,500–2,700 kcal/kg) fall within the typical ME recommendations for native hens, confirming the ability of FLP to maintain energy adequacy despite reliance on variable-quality local ingredients. This energy range is also consistent with the minimum ME requirement of 2,500 kcal/kg for λ= 0 and the upper target of 2,700 kcal/kg for λ= 1 as outlined by Alwi *et al*. (2019) in Table 2, indicating that all formulations meet the energy thresholds necessary to support optimal production performance in native laying hens.

Overall, these results support the conclusion that FLP is a robust method for formulating cost-effective and nutritionally reliable diets under nutrient uncertainty. The approach reduces dependence on imported soybean meal, promotes utilization of local ingredients, and provides flexible solutions that remain consistent with nutritional standards.

CONCLUSION

This study concludes that fuzzy linear programming (FLP) is a robust and flexible decision-support method for formulating native chicken layer diets under conditions of nutrient uncertainty. By incorporating nutrient intervals rather than fixed values, FLP effectively addresses the variability inherent in locally sourced feed ingredients.

The formulation at λ = 0 achieved the lowest feed cost by maximizing the use of affordable local ingredients while satisfying minimum nutrient constraints. In contrast, the λ = 1 formulation emphasized upper nutrient thresholds, resulting in higher soybean meal inclusion and increased feed cost. The fuzzy-optimal solution (λ = 0.33) produced a balanced formulation that optimally reconciled nutrient adequacy and economic efficiency.

Overall, the FLP approach reduces dependence on imported ingredients, stabilizes diet quality under fluctuating nutrient profiles, and provides a practical framework for small-scale feed industries. These findings support the development of sustainable and cost-effective native chicken production systems in rural Indonesia. However, the fuzzy-optimal solution represents a mathematical compromise within a fuzzy-defined feasible space rather than a definitive biological optimum, and therefore requires *in vivo* validation.

Future studies should include controlled performance trials using native laying hens, in which the λ= 0.33 formulation is evaluated against both the λ= 1 formulation and a conventional commercial-type diet. Such trials should assess egg production, feed conversion ratio, egg quality, and overall hen health, while also examining feed cost efficiency under practical farm conditions. Although the λ= 0 formulation yields the lowest feed cost, it constitutes a boundary solution with minimal satisfaction of fuzzy nutrient constraints and higher sensitivity to ingredient variability, and was therefore not prioritized as the primary candidate for biological validation.

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NOVELTY STATEMENT

This study presents a novel application of fuzzy linear programming (FLP) for formulating diets for native laying chickens under nutrient uncertainty by integrating variable nutrient profiles of local feed ingredients with flexible nutrient requirement intervals. Unlike conventional deterministic linear programming approaches, the proposed method explicitly incorporates uncertainty in both ingredient composition and nutrient requirements, resulting in a more robust and practically relevant formulation framework for small-scale feed industries. To the best of our knowledge, this is the first study to develop and evaluate an FLP-based feed formulation specifically tailored for native laying chickens in Indonesia using NIRS-derived data to characterize nutrient variability.

AUTHOR'S CONTRIBUTION

Adrizal conceptualized the research, designed the methodology, developed the software, supervised data collection, conducted the investigation, and led the writing and editing of the manuscript. Ahadiyah Yuniza contributed to data curation, investigation activities, and interpretation of the findings, as well as manuscript review and editing. Zurmiati supported data curation, investigation, and interpretation, and participated in manuscript review and editing. Firda Arlina assisted with data curation, field and laboratory work, and contributed to drafting and revising the manuscript. Winda Sartika participated in the investigation, supported data interpretation, and assisted with manuscript review and editing. All authors contributed to the discussion of the results and approved the final version of the manuscript.

Generative AI and AI-assisted technology statement

ChatGPT was used solely for language editing purposes. The authors are fully responsible for the content of the manuscript.

Conflict of interest

The authors have declared no conflict of interest.

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