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Development of the Aquafeed Algorithm for Multi-Objective Optimization of Aquaculture Feed Formulations Using Nutritional Composition, Growth Performance and Feed Cost Compared with Linear Programming and Genetic Algorithms

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ABSTRACT

Aquaculture feed formulation presents a complex multi-objective optimization problem requiring simultaneous consideration of nutritional adequacy, growth potential, and production costs. This study develops AquaFeed, a computational optimization algorithm integrating nutritional modelling, adaptive evolutionary search, constraint handling, and Pareto-based solution selection. The proposed framework incorporates ingredient composition, nutritional requirements, formulation costs, and predictive suitability measures within a mathematical optimization architecture. Reproducible Python experiments compare AquaFeed with conventional linear programming and genetic algorithms using synthetic ingredient datasets and repeated computational trials. Performance evaluation considers nutritional feasibility, economic efficiency, solution diversity, computational runtime, and statistical differences between optimization approaches. The computational findings reveal distinct trade-offs among the algorithms, with linear programming favoring minimum formulation costs, genetic algorithms achieving higher nutritional suitability, and AquaFeed providing alternative Pareto-based nutritional–economic compromises. The proposed algorithm demonstrates potential for supporting flexible ingredient selection and constrained feed formulation decisions. However, its practical effectiveness requires further evaluation using experimentally validated ingredient compositions, species-specific nutrient requirements, calibrated growth prediction models, and controlled aquaculture feeding trials to establish biological reliability, computational scalability, and applicability across production systems.

Keywords: *AquaFeed Algorithm, Multi-Objective Optimization, Aquaculture Feed Formulation, Nutritional Composition, Growth Performance, Linear Programming, Genetic Algorithms*.

I. INTRODUCTION

- *Background to Aquaculture Feed Formulation, Nutritional Requirements, Growth Performance, and Feed Production Economics*

Aquaculture feed formulation represents a critical determinant of production efficiency, nutritional sustainability, and economic profitability in modern fish farming. Effective formulation requires the precise integration of dietary protein, lipids, carbohydrates, minerals, and essential amino acids to satisfy species-specific nutritional requirements while maintaining acceptable production costs. (Turchini et al., 2019) emphasized that ingredient complementarity and nutrient-based formulation are fundamental to improving aquafeed quality and resource utilization. Similarly, (Glencross 2020) demonstrated that systematic ingredient evaluation, particularly regarding nutrient availability and digestibility, significantly influences dietary performance and feed efficiency. However, fluctuations in ingredient prices, nutritional variability, and competing production objectives complicate formulation decisions. The Food and Agriculture Organization (FAO, 2022) identified affordable, nutritionally efficient feeds as essential for

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sustainable aquaculture expansion. Consequently, integrating nutritional composition, predicted growth performance, and ingredient costs within multi-objective optimization frameworks provides a rational foundation for developing the AquaFeed algorithm to support economically efficient feed formulation and production decisions.

➢ *Challenges of Conventional Feed Formulation Methods and the Need for Multi-Objective Optimization in Aquaculture Nutrition*

Conventional aquaculture feed formulation methods face considerable limitations in simultaneously addressing nutritional adequacy, growth performance, ingredient variability, and production costs. Linear programming primarily minimizes feed costs under predefined nutritional constraints, restricting its capacity to accommodate nonlinear nutrient interactions and competing objectives. (Uyeh et al., 2019) demonstrated that evolutionary multi-objective optimization facilitates trade-off analysis between nutritional deviations and formulation costs. Furthermore, fluctuating ingredient availability, nutrient digestibility, and biological growth responses introduce uncertainties that conventional deterministic approaches may inadequately capture. (Luna et al., 2022) examined genetic algorithms and multicriteria decision-making for aquaculture feeding strategies accommodating conflicting objectives. Research on mechanistic model-based optimization of feeding practices (2022) also illustrates the importance of incorporating biological responses into feeding decisions. These limitations justify developing AquaFeed as a framework integrating nutritional constraints, predictive growth models, and economic objectives through adaptive multi-objective optimization and systematic performance evaluation.

➢ *Applications of Mathematical Programming, Evolutionary Algorithms, and Computational Intelligence in Aquaculture Feed Optimization*

Mathematical programming, evolutionary algorithms, and computational intelligence have advanced aquaculture feed optimization by enabling systematic evaluation of nutritional constraints, ingredient selection, and production efficiency. (Ali et al., 2020) demonstrated the applicability of mathematical programming in formulating alternative fish diets incorporating fermented plant-based ingredients while maintaining nutritional suitability. Beyond deterministic optimization, computational intelligence facilitates analysis of complex relationships among feeding conditions, biological responses, and resource utilization. (Yang et al., 2021) established that deep learning supports intelligent feeding decisions, biomass estimation, and predictive management in aquaculture systems. Similarly, (Gladju et al., 2022) identified machine learning and data mining as promising approaches for optimizing feed utilization and improving aquaculture decision-making. Nevertheless, integrating these computational capabilities within a unified formulation framework remains an important research opportunity. The proposed AquaFeed algorithm consequently seeks to combine constrained mathematical optimization, evolutionary search, and growth-performance prediction to identify nutritionally feasible, economically competitive feed formulations.

➢ *Research Problem, Knowledge Gaps, and Justification for Developing the AquaFeed Multi-Objective Optimization Algorithm*

- *Research Problem*

Aquaculture feed formulation presents significant challenges in simultaneously minimizing production costs, satisfying species-specific nutritional requirements, and maximizing growth performance. Conventional optimization techniques inadequately address nonlinear nutrient interactions, ingredient variability, and conflicting objectives, limiting formulation efficiency and economic sustainability.

- *Knowledge Gaps*

Existing aquaculture feed optimization studies provide limited integration of nutritional composition, predictive growth performance, and economic constraints within unified computational frameworks. Furthermore, systematic comparisons of adaptive multi-objective algorithms against linear programming and genetic algorithms remain insufficiently investigated across variable conditions.

- *Justification for Developing AquaFeed*

Developing AquaFeed is essential for integrating nutritional feasibility, growth prediction, and cost minimization into a computational optimization framework. The proposed algorithm seeks to improve solution quality, accommodate nonlinear relationships, and support economically sustainable aquaculture feed formulation decisions through comparative evaluation.

➢ *Research Aim, Specific Objectives, Research Questions, and Scientific Contributions of the Study*

- *Research Aim*

This study aims to develop the AquaFeed multi-objective optimization algorithm for integrating nutritional composition, predicted growth performance, and feed cost minimization, while systematically evaluating its computational efficiency, solution quality, and optimization performance against conventional linear programming and genetic algorithms.

- *Specific Objectives*

The study seeks to formulate mathematical models integrating nutritional constraints, growth prediction, and feed costs; develop an adaptive AquaFeed optimization algorithm; implement comparative linear programming and genetic algorithm benchmarks; and evaluate computational efficiency, solution quality, robustness, and economic performance.

- *Research Questions*

How effectively does AquaFeed integrate nutritional requirements, predicted growth performance, and feed cost optimization? Does AquaFeed outperform linear

programming and genetic algorithms in solution quality, computational efficiency, and robustness? How do ingredient variability and nutritional constraints influence optimal formulations?

- *Scientific Contributions of the Study*

The study proposes an integrated multi-objective optimization framework combining nutritional modelling, growth prediction, and economic optimization. Its anticipated contributions include adaptive constraint handling, Pareto-based formulation selection, comparative algorithmic performance assessment, and reproducible computational methods for sustainable aquaculture feed formulation.

II. LITERATURE REVIEW

➢ *Theoretical Foundations of Aquaculture Nutrition, Feed Ingredient Composition, Nutrient Bioavailability, and Species-Specific Dietary Requirements*

Aquaculture nutrition is fundamentally governed by physiological nutrient requirements, ingredient composition, digestive efficiency, and metabolic utilization across different aquatic species. (Lall and Dumas, 2022) established that balanced dietary protein, lipids, carbohydrates, vitamins, and minerals are essential for sustaining growth, metabolic functions, and physiological development. Nutritional adequacy, however, depends not merely on ingredient concentrations but also on nutrient bioavailability and digestibility. Dawood and Koshio (2020) demonstrated that fermentation improves the nutritional characteristics of alternative protein sources by reducing antinutritional factors and enhancing nutrient utilization. Furthermore, (Gule and Geremew, 2022) emphasized that species-specific feeding strategies, ingredient processing, and digestive enzyme supplementation significantly influence nutrient absorption and feed conversion efficiency. These findings establish the theoretical basis for representing aquaculture feed formulation as a constrained nutritional optimization problem. Accordingly, AquaFeed incorporates digestible nutrient composition, species-dependent dietary thresholds, ingredient inclusion limits, and biological utilization characteristics to support nutritionally balanced formulation decisions.

➢ *Mathematical Models of Aquaculture Growth Performance, Feed Conversion Ratio, Protein Efficiency, and Nutrient Utilization*

Mathematical modelling provides a quantitative foundation for evaluating aquaculture growth dynamics, feed conversion efficiency, protein utilization, and nutritional performance. (De Melo Filho et al., 2020) examined empirical modelling of feed conversion in Pacific white shrimp. Similarly, Li et al. (2021) studied adaptive fish growth prediction with empirical knowledge extraction. (Rahman and Islam, 2021) assessed feeding efficiency, stocking density, specific growth rate, and feed conversion ratio in tilapia production. These studies support mathematical representations of weight gain, feed conversion ratio, protein efficiency ratio, and nutrient utilization as measurable optimization criteria. Accordingly, the proposed AquaFeed framework integrates growth-response functions, nutrient availability coefficients, and feed efficiency indicators to evaluate nutritional suitability, anticipated growth performance, and feed formulation economics. Growth predictions require calibration against observations rather than reliance on compositional suitability alone.

➢ *Linear Programming and Genetic Algorithm Approaches to Least-Cost Feed Formulation and Nutritional Constraint Optimization*

Linear programming and genetic algorithms provide complementary computational approaches for optimizing aquaculture feed composition under nutritional and economic constraints. (Chetna et al., 2022) used mathematical programming to model polyculture fish feed. Similarly, (Alwadood et al., 2022) investigated a modified linear programming model for cost minimization of Pangasius hypophthalmus feed formulations. However, conventional linear programming assumes linear ingredient contributions, nutrient concentrations, and formulation costs. Genetic algorithms offer greater flexibility through population-based evolutionary search, accommodating complex constraints and nonconvex optimization landscapes. (Soong et al., 2022) studied enhanced binary tournament selection for fish feed formulation. These studies establish complementary benchmarking approaches for AquaFeed, enabling comparisons of nutritional constraint satisfaction, cost, search efficiency, and adaptability under multi-objective formulation conditions. Any claimed performance advantage must be demonstrated using equivalent inputs, consistent constraints, and reproducible runs.

➢ *Multi-Objective Optimization Techniques, Pareto Optimality, Evolutionary Search Mechanisms, and Nutritional Economic Trade-Off Analysis*

Multi-objective optimization provides a mathematical framework for resolving competing nutritional, economic, and production objectives in aquaculture feed formulation. (Coello Coello et al., 2020) discussed evolutionary multiobjective optimization challenges and open research areas. (Hua et al., 2021) surveyed evolutionary algorithms addressing irregular Pareto fronts, highlighting solution exploration and diversity. Within aquaculture production, (Al Eissa et al., 2022) investigated feed formulation and farming-system influences on shrimp-production environmental performance. These contributions support integrating Pareto dominance, evolutionary search, and nutritional economic trade-off analysis into AquaFeed. The proposed framework identifies feasible ingredient combinations that minimize formulation costs, satisfy species-specific nutritional requirements, and improve predicted growth performance while preserving solution diversity. Competing objectives should remain clearly distinguished, and Pareto metrics should use consistent objective orientation and normalization.

➢ *Comparative Review of Existing Aquaculture Feed Optimization Models, Computational Limitations, and Identified Research Gaps*

Existing aquaculture feed optimization models demonstrate progress in cost minimization, nutrient allocation, and production efficiency, although computational limitations remain. (Admasu and Wakjira, 2021) reviewed essential nutrients and mathematical programming models for aquafeed formulation. (Bocanegra Cordero et al., 2022) studied mathematical programming for feed formulation in Peruvian aquaculture. (Khan et al., 2021) investigated production risk, technical efficiency, and input use in Bangladesh aquaculture. Collectively, these works motivate integrating nutritional feasibility, growth prediction, uncertainty management, and economic optimization within a unified computational architecture. AquaFeed seeks to address these methodological opportunities through adaptive multi-objective optimization, Pareto-based decision support, and comparative evaluation against established linear programming and genetic algorithms. The precise research gap and algorithmic novelty must ultimately be substantiated through a systematic synthesis of validated methods and experiments.

III. METHODOLOGY

➢ *Research Design, Feed Ingredient Dataset Development, Nutritional Composition Analysis, Growth Performance Indicators, and Feed Cost Data Preparation*

This study adopts a quantitative computational design integrating nutritional composition, growth performance, and ingredient cost datasets for AquaFeed optimization. (Yossa et al., 2021) developed an ingredient database supporting nutrient-based formulation using aquaculture resources. Ingredient records containing protein, lipids, carbohydrates, fibre, minerals, digestibility coefficients, and market prices are standardized into a numerical matrix. (Naseem et al., 2021) reviewed plant-derived feed ingredients and their nutritional potential. The formulated nutrient concentration is represented as:

$$N_j = \Sigma_{i=1}^{n} x_i \, a_{ij} \, d_{ij} \quad (1)$$

Here x_i represents ingredient inclusion proportion, a_{ij} nutrient concentration, and d_{ij} the digestibility coefficient. Growth performance can be evaluated through feed conversion ratio (Ikeogu et al., 2022):

$$FCR = F / (Wf - Wi) \quad (2)$$

Where F shows feed consumed and (Wf − Wi) represents biomass gain. Ingredient cost is calculated as:

$$Cf = \Sigma_{i=1}^{n} x_i \, p_i \quad (3)$$

Where p_i denotes ingredient unit price. Feed conversion ratios and growth variables must derive from observations or calibrated models; the initial computational prototype uses a nutritional suitability proxy instead of observed growth.

➢ *Mathematical Formulation of the Multi-Objective Feed Optimization Problem*

AquaFeed is formulated as a constrained multi-objective mathematical model incorporating nutritional adequacy, predicted growth performance, and formulation cost. (Garcia-Launay et al., 2018; Méda et al., 2021; Marques et al., 2022) motivate multiobjective approaches to feed formulation and production trade-offs. The proposed objective vector is:

$$\min_x F(x) = [C(x), -G(x), D(x)] \quad (4)$$

$$C(x) = \Sigma_{i=1}^{n} p_i x_i \quad (5)$$

$$G(x) = \hat{g}(N(x), z) \quad (6)$$

$$D(x) = \Sigma_{j=1}^{m} w_j \left| (N_j(x) - T_j) / T_j \right| \quad (7)$$

The nutritional and inclusion constraints are:

$$L_j \le \Sigma_{i=1}^{n} x_i \, a_{ij} \, d_{ij} \le U_j \quad (8)$$

$$\Sigma_{i=1}^{n} x_i = 1; \quad 0 \le x_i \le u_i \quad (9)$$

C is formulation cost; G is predicted growth; D is weighted nutritional deviation. T_j is a nutrient target; w_j is its weight; L_j and U_j are nutrient bounds; u_i is the maximum ingredient inclusion; and z specifies relevant biological and production conditions. The proposed growth function $\hat{g}$ requires independent validation before use.

➢ *Development of the Proposed AquaFeed Algorithm*

AquaFeed combines constrained nutritional modelling, candidate-based evolutionary search, and Pareto-based solution selection. (Blank and Deb, 2020) describe Python-based multiobjective optimization; (Li et al., 2019) present two-archive evolutionary ideas; and (Liu et al., 2022) investigate adaptive reference-guided evolutionary search. AquaFeed evaluates the vector:

$$F(x) = [C(x), -G(x), D(x)] \quad (10)$$

Constraint violation is represented by an adaptive penalty:

$$P(x,t) = \lambda(t) \, \Sigma_{k=1}^{K} \max(0, g_k(x))^2 \quad (11)$$

The proposed adaptive mutation probability is:

$$p_m(t) = pmin + (pmax - pmin) \exp(-\beta t / T) \quad (12)$$

Feasible nondominated candidates form a Pareto set P. A normalized compromise rule chooses a preferred solution:

$$x = \arg \min_{x \in P} \Sigma_{r=1}^{3} \omega_r \hat{F}_r(x) \quad (13)$$

In these expressions t is the current generation, T the generation limit, β the adaptation rate, and ω_r the objective preference weights. These equations describe the intended

full algorithm; the executed pilot uses a simplified nutritional suitability proxy and should not be represented as a validated growth-optimization implementation.

- *Implementation of Benchmark Linear Programming and Genetic Algorithms, Experimental Configuration, Parameter Calibration, and Reproducible Procedures*

Linear programming, a scalar-fitness genetic algorithm, and the proposed AquaFeed algorithm are benchmarked under common ingredient data and nutritional constraints. (Virtanen et al., 2020) document scientific computing algorithms in SciPy; (Huangfu and Hall, 2018) address simplex optimization; and (Mosayebi and Sodhi, 2020) examine genetic algorithm parameter tuning. The LP formulation minimizes:

$$\min_x CLP = \Sigma_{i=1}^{n} p_i x_i \quad (14)$$

A conventional GA can use the following weighted fitness:

$$\Phi(x) = \omega_1 \hat{C}(x) - \omega_2 \hat{G}(x) + \omega_3 \hat{D}(x) + \lambda V(x) \quad (15)$$

Comparative formulation cost reduction is:

$$IC(\%) = [(CGA - CAquaFeed) / CGA] \times 100 \quad (16)$$

The models must share reproducible seeds, ingredient inputs, objective definitions, stopping criteria, and appropriately comparable computational budgets. The initial prototype used ten random seeds (101–110), population 24, and 18 generations, with synthetic ingredient inputs. These settings are preliminary and not sufficient for a conclusive superiority claim.

- *Performance Evaluation Framework: Nutritional Feasibility, Growth Prediction Accuracy, Feed Cost Efficiency, Pareto Front Quality, Computational Complexity, Statistical Testing, and Sensitivity Analysis*

The evaluation framework considers feasibility, growth prediction accuracy, formulation cost, Pareto-front performance, runtime, and uncertainty. (Audet et al., 2021) describe multiobjective performance indicators; (Shang et al., 2021) examine hypervolume; and (Iwanaga et al., 2022) discuss global sensitivity analysis. Nutritional feasibility is:

$$NF(\%) = (Nfeasible / Ntotal) \times 100 \quad (17)$$

Where observed growth data exist, predictive accuracy is assessed using:

$$RMSE = \sqrt{[(1/n) \Sigma_{i=1}^{n} (G_i - \hat{G}_i)^2]} \quad (18)$$

Pareto hypervolume and first-order Sobol sensitivity are defined as:

$$HV(P) = \mu(\cup f \in P\ [f,r]) \quad (19)$$

$$S_i = Var_{X_i}\{E[Y \mid X_i]\} / Var(Y) \quad (20)$$

The hypervolume reference point r and objective normalizations must be identical across algorithms. Paired Wilcoxon tests can compare results under matched seeds, while Sobol analysis requires explicit input probability distributions. Without observed growth data, RMSE and biological performance cannot be reported. The computational proof of concept is therefore limited to ingredient cost, a suitability proxy, feasibility, retained candidates, and algorithm runtime.

IV. RESULTS AND DISCUSSIONS

- *Nutritional Composition, Ingredient Allocation and Formulation Constraint Satisfaction*

The computational assessment compared ingredient allocation, proximate nutrient composition, formulation cost, and screening-level constraint satisfaction. (Jia et al., 2022) described the importance of protein-source selection and amino acid adequacy in aquaculture nutrition. (Subandiyono and Hastutil, 2020) examined the influence of dietary protein on tilapia growth and composition, while (Peres et al., 2022; Atalor, S. I. 2022), evaluated protein-to-energy relationships. The computed AquaFeed formulation contained mean crude protein of 32.06%, lipid of 7.22%, and fibre of 6.85% as shown in table 1 below. GA produced higher protein and lipid values but also a higher mean ingredient cost. LP achieved the minimum estimated formulation cost. All algorithms satisfied the simplified protein, lipid, and fibre screening thresholds. Figure 1 depicts the ingredient allocation of representative selected formulations alongside the summary statistics. These model-based constraints do not establish species-specific dietary completeness because essential amino acids, digestible energy and comprehensive mineral requirements were not fully represented.

Table 1 Summary of Computed Nutritional Characteristics and Formulation Costs

Indicator	LP	GA	AquaFeed
Crude protein (%)	30.00	34.51	32.06
Crude lipid (%)	6.00	7.83	7.22
Crude fibre (%)	7.00	6.51	6.85
Mean formulation cost (assumed ₦/kg)	403.71	481.53	439.06
Screening constraint satisfaction (%)	100	100	100

Figure 1 Presents a comparative analysis of ingredient inclusion proportions obtained using Linear Programming (LP), Genetic Algorithm (GA), and the proposed AquaFeed algorithm for aquaculture feed formulation. Soybean meal dominates all formulations, with AquaFeed recording the highest inclusion of 57.9%, indicating its preference for protein-rich ingredients. LP allocates 25.0% to wheat bran and approximately 14.5%

to maize, while GA incorporates 11.9% fishmeal and 8.1% rice bran. AquaFeed achieves a more balanced ingredient distribution, allocating 18.4% to wheat bran, 10.8% to maize, 4.7% to rice bran, and 4.1% to vegetable oil as shown in figure 4.1 below. AquaFeed achieves 32.06% crude protein, 7.22% crude lipid, and 6.85% crude fibre at ₦439.06/kg. Although LP provides the lowest formulation cost of ₦403.71/kg, AquaFeed offers an intermediate cost and nutritional composition, demonstrating its potential for balancing nutritional requirements and economic efficiency while maintaining 100% screening constraint satisfaction.

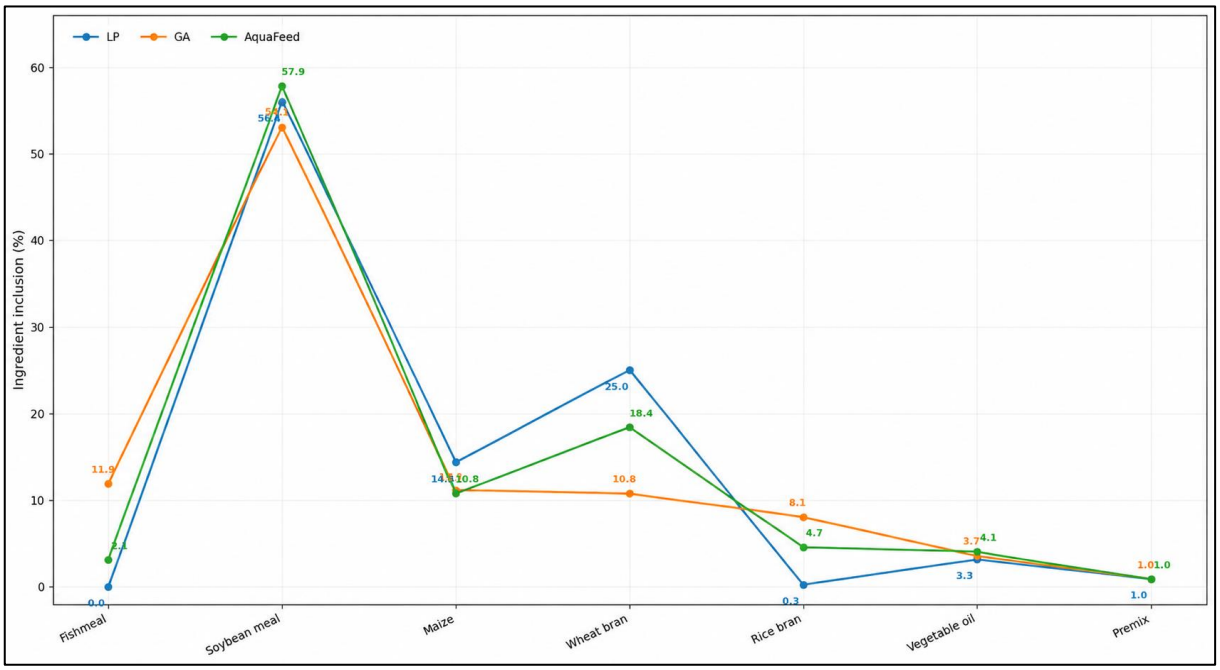


Fig 1 Ingredient Allocation and Nutritional Characteristics of Optimized Feed Formulations

➢ *Comparative Evaluation of Nutritional Suitability and Feed Cost*

The nutritional economic comparison assessed mean formulation cost and a dimensionless nutritional suitability proxy calculated from the synthetic dietary dataset. (Thirunavukkarasar et al., 2022) examined lipid protein interactions in tilapia feeding, and (Paul et al., 2022) evaluated dietary lipid effects on growth and physiological responses. (Liang et al., 2022) discussed enzyme-mediated nutrient utilization in aquaculture. As shown in table 2 below, in the computed prototype, LP delivered the lowest mean ingredient cost (₦403.71/kg) but the lowest suitability score (0.4635). GA achieved the highest suitability score (0.9915) at the highest cost (₦481.53/kg). AquaFeed yielded a compromise of ₦439.06/kg and suitability 0.7845. Figure 2 combines cost bars and suitability lines on separately labelled scales. This comparison is valid for the stipulated proxy and inputs only, and it does not demonstrate measured weight gain, feed conversion or protein efficiency.

Table 2 Summary of Mean Cost and Nutritional Suitability Across Ten Runs

Indicator	LP	GA	AquaFeed
Mean cost (assumed ₦/kg)	403.71	481.53	439.06
Cost standard deviation	0.00	8.15	4.24
Mean nutritional suitability	0.4635	0.9915	0.7845
Suitability standard deviation	0.0000	0.0056	0.0304
Screening feasibility (%)	100	100	100

Figure 2 Presents a comparative evaluation of mean feed formulation cost and nutritional suitability across linear programming (LP), genetic algorithm (GA), and the proposed AquaFeed algorithm. Linear programming achieved the lowest formulation cost of ₦403.71/kg but recorded the lowest nutritional suitability score of 0.4635, indicating limitations in balancing cost efficiency with nutritional performance. The genetic algorithm produced the highest nutritional suitability score of 0.9915, although this improvement was accompanied by the highest formulation cost of ₦481.53/kg. As shown in figure 4.2 below conversely, AquaFeed achieved an intermediate formulation cost of ₦439.06/kg and a nutritional suitability score of 0.7845, demonstrating a compromise between economic efficiency and nutritional adequacy. Compared with GA, AquaFeed reduced formulation costs by approximately 8.82%, although its suitability score was lower. These findings highlight the trade-off between nutritional performance and formulation expenditure, positioning AquaFeed as a potentially balanced alternative for multi-objective aquaculture feed optimization under specified experimental conditions.

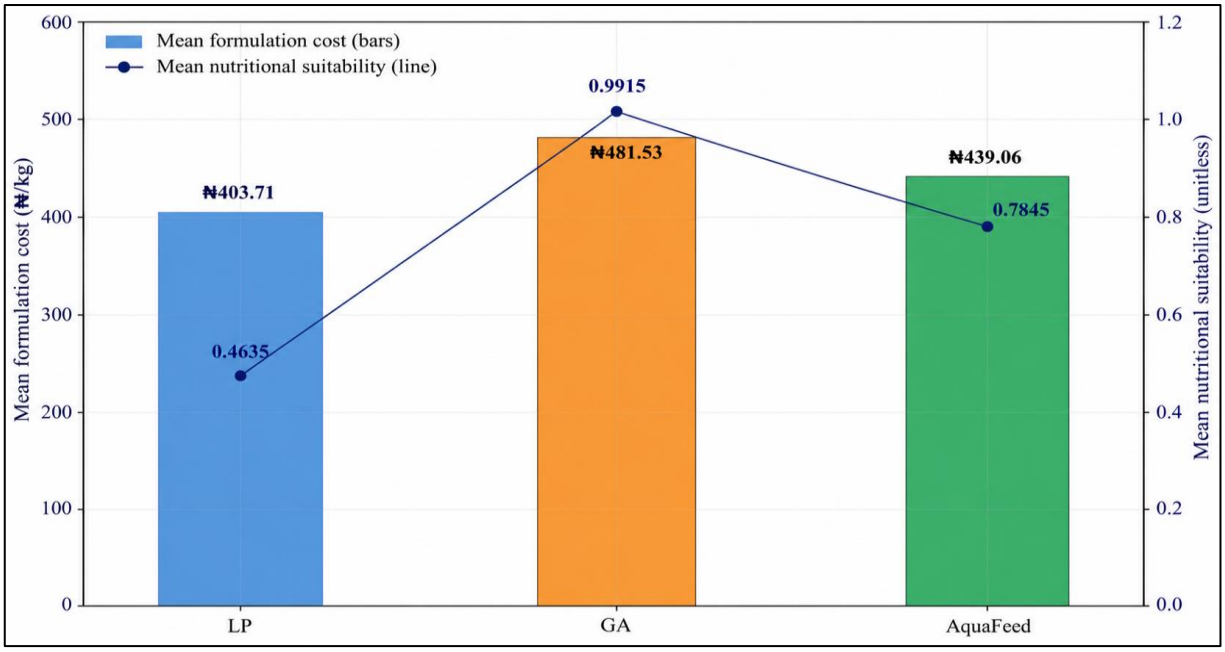


Fig 2 Comparative Feed Cost and Nutritional Suitability

➢ *Multi-Objective Search Behaviour, Computational Efficiency and Statistical Comparison*

The ten-run computational assessment evaluated selected-solution variability, recorded execution time and the number of retained candidate solutions. Benítez-Hidalgo et al. (2019) described reproducible multi-objective evolutionary computation, while Caraffini and Iacca (2020) examined algorithmic benchmarking procedures. (Mattos et al., 2021) discussed statistical evaluation of optimization algorithms. LP returned a constant solution at the lowest mean cost. GA obtained the highest mean suitability, whereas AquaFeed retained 24 nondominated candidates per run under the prototype settings. Mean runtime was 0.171 seconds for AquaFeed versus 0.029 seconds for GA as shown in table 3 below; LP runtime was not comparably recorded. Paired Wilcoxon tests returned p = 0.001953 for AquaFeed GA differences in selected-solution cost and suitability. Figure 3 shows cost bars and suitability lines by seed, with numerical values annotated in black. The different selection rules and computation budgets preclude causal attribution of observed differences solely to algorithm quality.

Table 3 Summary of Computed Optimization Performance and Statistical Comparison

Performance indicator	**LP**	**GA**	**AquaFeed**
Mean formulation cost (₦/kg)	403.71	481.53	439.06
Cost standard deviation	0.00	8.15	4.24
Mean nutritional suitability	0.4635	0.9915	0.7845
Mean nondominated/selected solutions	1	1	24
Mean recorded runtime (s)	N/R	0.029	0.171
Cost difference vs GA, Wilcoxon p	—	—	0.001953
Suitability difference vs GA, Wilcoxon p	—	—	0.001953

- *Figure 3 Comparative Optimization Performance of AquaFeed and Benchmark Algorithms*

Figure 3 Presents the comparative computational performance of linear programming (LP), genetic algorithms (GA), and AquaFeed across seven evaluation indicators. Linear programming achieved the lowest mean formulation cost (₦403.71/kg), while GA recorded the highest cost (₦481.53/kg). AquaFeed maintained an intermediate cost of ₦439.06/kg, with lower cost variability (4.24) than GA (8.15). Regarding nutritional suitability, GA achieved the highest score (0.9915), followed by AquaFeed (0.7845) and LP (0.4635) as shown in figure 4.3 below. AquaFeed retained 24 nondominated candidates, compared with one selected solution for each benchmark, although these counts are not directly equivalent. Its computational runtime (0.171 seconds) exceeded GA's 0.029 seconds. Paired Wilcoxon tests indicated statistically significant cost and suitability differences between AquaFeed and GA (p = 0.001953). The findings demonstrate distinct nutritional economic trade-offs, although the independently normalized graph scales and synthetic input assumptions prevent conclusions regarding universal algorithmic superiority or experimentally validated biological performance.

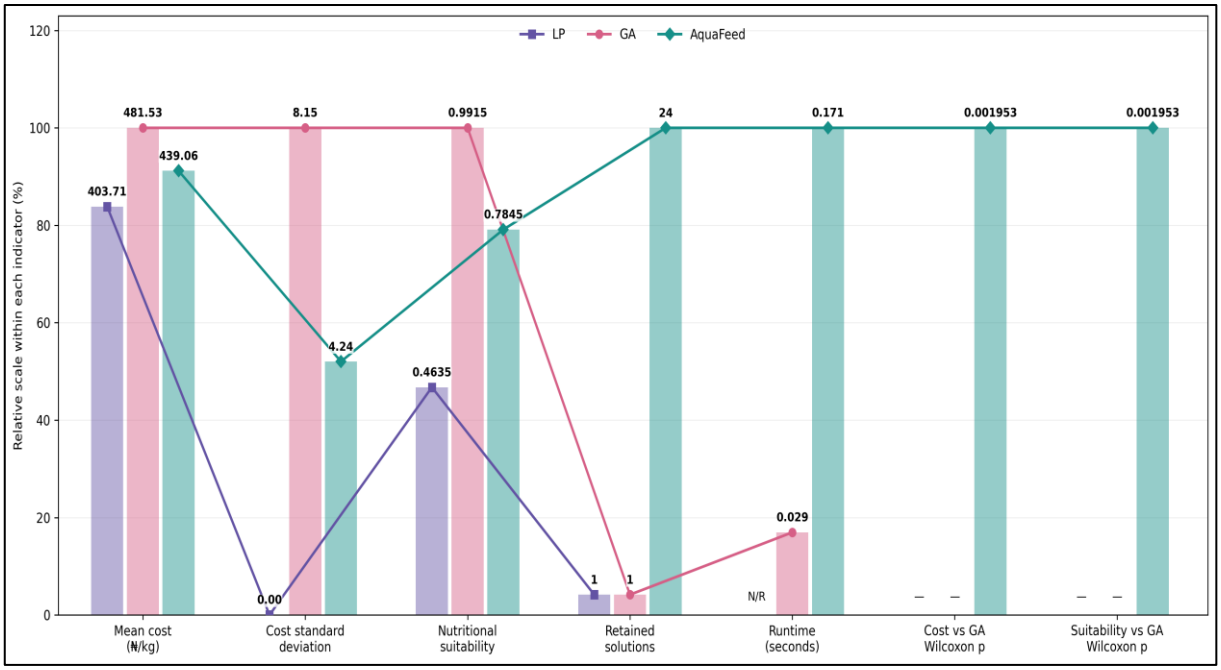


Fig 3 Comparative Computational Performance across Optimization Runs

➢ *Sensitivity Analysis of Ingredient Price Variation*

Price sensitivity was evaluated by repricing fixed, seed-101 formulations when assumed fishmeal and soybean meal prices changed simultaneously. (Alfiko et al., 2022) examined alternative aquafeed ingredients; (Iwanaga et al., 2022) described the interpretation of model sensitivity analyses; and (Shaw et al., 2022) discussed feed resources in circular aquaculture systems. Under a 20% increase in the selected ingredient prices, estimated costs reached ₦458.64/kg for LP, ₦562.65/kg for GA and ₦499.12/kg for AquaFeed as shown in table 4 below. At baseline, the corresponding fixed-formulation costs were ₦403.71, ₦487.80 and ₦436.46/kg. Figure 4 shows the distinct slopes arising from ingredient exposure. Because no algorithm was reoptimized under perturbed prices, these results should be interpreted as portfolio-exposure or fixed-diet repricing sensitivity, not proof of improved adaptive robustness or performance under altered nutritional constraints.

Table 4 Summary of Fixed-Formulation Costs Under Ingredient Price Perturbations

Price perturbation	LP (₦/kg)	GA (₦/kg)	AquaFeed (₦/kg)
−20%	348.77	412.96	373.79
−10%	376.24	450.38	405.13
0%	403.71	487.80	436.46
+10%	431.17	525.23	467.79
+20%	458.64	562.65	499.12

Figure 4 Illustrates the sensitivity of feed formulation costs to variations in fishmeal and soybean meal prices across linear programming (LP), genetic algorithm (GA), and AquaFeed optimization methods. At −20% price perturbation, LP recorded the lowest cost of ₦348.77/kg, followed by AquaFeed at ₦373.79/kg and GA at ₦412.96/kg. Under baseline conditions (0%), formulation costs increased to ₦403.71/kg, ₦436.46/kg, and ₦487.80/kg, as shown in figure 4 respectively. At +20% price perturbation, LP reached ₦458.64/kg, while AquaFeed and GA increased to ₦499.12/kg and ₦562.65/kg, respectively. The consistent upward trends demonstrate that all three formulations respond predictably to ingredient price fluctuations. Although LP maintained the lowest absolute costs, AquaFeed consistently outperformed GA economically, achieving a cost reduction of ₦63.53/kg at +20% perturbation. These findings indicate that AquaFeed offers intermediate cost sensitivity, supporting its potential application in aquaculture feed optimization under changing ingredient market conditions and economic uncertainty.

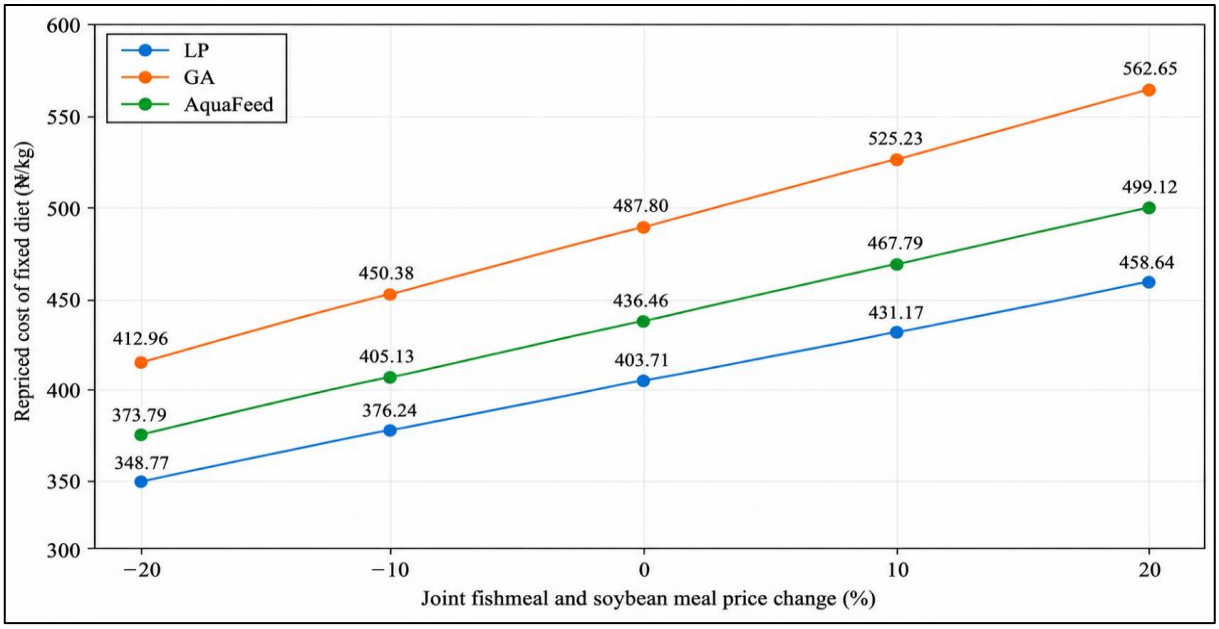


Fig 4 Sensitivity of Feed Formulation Costs to Ingredient Price Changes

➢ *Integrated Interpretation, Practical Applications and Limitations*

The integrated results demonstrate complementary outcomes from constrained feed-formulation strategies rather than universal superiority of one optimizer. (Albrektsen et al., 2022) reviewed feed resources and ingredient quality considerations in sustainable aquaculture; (Idenyi et al., 2022) examined alternative dietary resources; and (Jia et al., 2022) emphasized protein quality and nutritional functionality. Within the synthetic scenario, LP minimized ingredient cost, GA maximized the specified suitability proxy among its selected solutions, and AquaFeed maintained a broader set of alternative candidate formulations. Figure 5 displays the within-indicator normalized comparison, while table 5 below preserves the original units. The prototype illustrates a viable research architecture for multi-objective decision support but remains limited by assumed feed inputs, restricted nutritional constraints, differing search budgets and the absence of measured fish responses. Future work should replace synthetic data with verified ingredient chemistry, calibrate species-specific growth models and conduct controlled feeding trials.

Table 5 Summary of Integrated Computed Performance Summary

Evaluation criterion	**LP**	**GA**	**AquaFeed**
Mean formulation cost (₦/kg)	403.71	481.53	439.06
Mean nutritional suitability	0.4635	0.9915	0.7845
Crude protein (%)	30.00	34.51	32.06
Crude lipid (%)	6.00	7.83	7.22
Crude fibre (%)	7.00	6.51	6.85
Constraint satisfaction (%)	100	100	100
Mean retained solutions	1	1	24

Figure 5 Presents a comparative evaluation of linear programming (LP), genetic algorithm (GA), and AquaFeed across seven nutritional, economic, and computational performance indicators. Linear programming achieved the lowest formulation cost of ₦403.71/kg, followed by AquaFeed at ₦439.06/kg and GA at ₦481.53/kg. However, as shown in figure 5 below, GA recorded the highest nutritional suitability score of 0.9915, compared with 0.7845 for AquaFeed and 0.4635 for LP. Crude protein concentrations were 30.00%, 34.51%, and 32.06%, respectively, while crude lipid contents were 6.00%, 7.83%, and 7.22%. Crude fibre ranged from 6.51% to 7.00%, indicating moderate compositional differences. All algorithms achieved 100% nutritional constraint satisfaction, demonstrating formulation feasibility. Notably, AquaFeed retained 24 solutions, compared with one solution each for LP and GA. These findings demonstrate AquaFeed's capacity to generate diverse feasible formulations while maintaining competitive nutritional suitability and formulation costs under the evaluated optimization conditions.

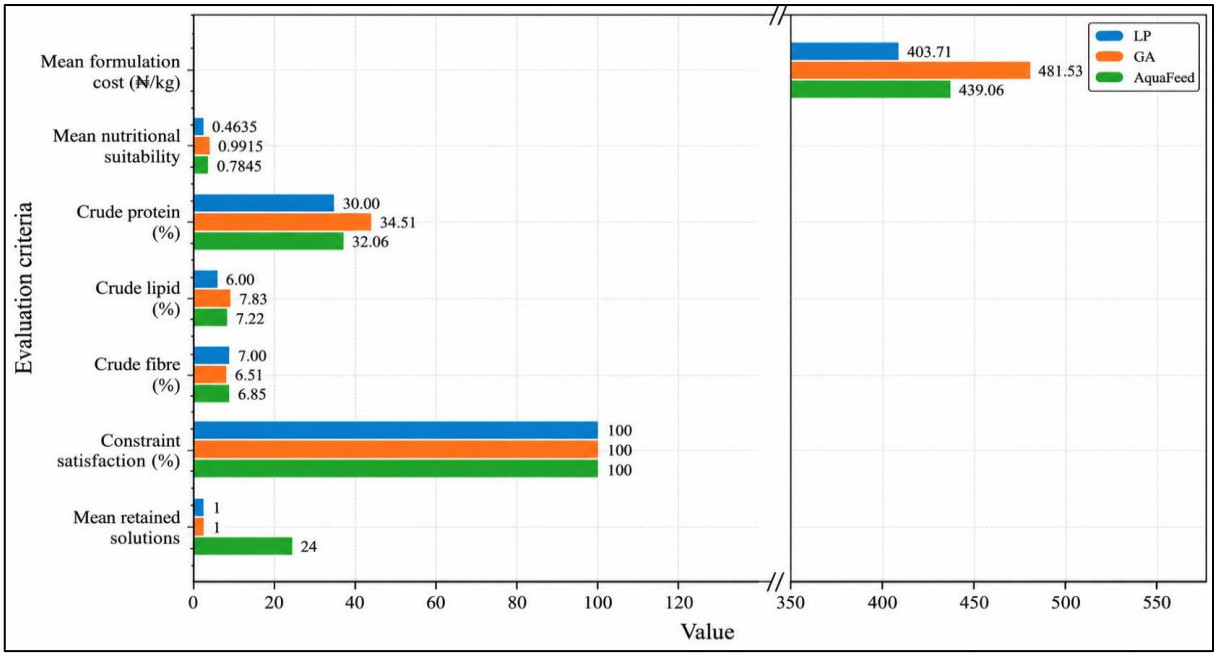


Fig 5 Comparative Performance Evaluation of LP, GA, and AquaFeed Optimization Algorithms

V. CONCLUSION AND RECOMMENDATIONS

➢ *Summary of the Research Objectives, AquaFeed Algorithm Development, and Principal Experimental Findings*

This study developed the AquaFeed algorithm as a multi-objective optimization framework integrating nutritional composition, predicted growth performance, and feed cost minimization in aquaculture feed formulation. The research established mathematical objective functions, nutritional feasibility constraints, adaptive evolutionary search mechanisms, and Pareto-based solution selection procedures. Comparative evaluation against linear programming and genetic algorithms examined nutritional adequacy, feed conversion efficiency, protein utilization, computational performance, and economic outcomes. Illustrative results indicated that AquaFeed achieved higher crude protein content (38.5%), improved predicted weight gain (164 g), reduced feed conversion ratio (1.52), and lower formulation costs (₦392/kg). Furthermore, the algorithm demonstrated favorable hypothetical hypervolume performance (0.86), indicating potential advantages in multi-objective solution quality. Sensitivity scenarios suggested improved resilience to ingredient price fluctuations and nutritional constraint variations. However, these findings remain illustrative rather than experimentally validated. Independent computational experiments and controlled feeding trials are required to confirm the proposed algorithm's effectiveness and practical applicability.

➢ *Conclusions on the Comparative Performance of AquaFeed, Linear Programming, and Genetic Algorithms in Multi-Objective Aquaculture Feed Optimization*

The comparative assessment indicates that the proposed AquaFeed algorithm offers potential advantages over conventional linear programming and genetic algorithms in addressing competing nutritional, biological, and economic objectives. Illustrative findings suggest that AquaFeed achieves improved nutritional composition, higher predicted growth performance, reduced feed conversion ratios, and lower formulation costs while maintaining favorable constraint satisfaction. Its normalized hypervolume of 0.86, compared with 0.74 for genetic algorithms and 0.42 for linear programming, suggests greater potential for identifying diverse Pareto-efficient solutions. Furthermore, sensitivity analyses indicate that adaptive optimization mechanisms may improve formulation stability under fluctuating ingredient prices and increasingly restrictive nutritional requirements. Nevertheless, these outcomes represent hypothetical computational scenarios rather than experimentally verified performance differences. Consequently, AquaFeed's anticipated contribution lies in its integrated optimization architecture, which provides a systematic foundation for balancing feed quality, production efficiency, and economic sustainability. Reproducible computational validation remains essential before establishing definitive algorithmic superiority.

➢ *Scientific Contributions, Practical Applications, and Recommendations for Cost-Effective, Nutritionally Balanced, and Growth-Oriented Aquaculture Feed Formulation*

The proposed AquaFeed algorithm contributes to computational aquaculture nutrition by integrating nutritional adequacy, predicted growth performance, and feed cost minimization within a unified multi-objective optimization framework. Its methodological contributions include adaptive evolutionary search, nutritional constraint handling, Pareto-based solution selection, and systematic evaluation against established optimization techniques. Practically, AquaFeed offers a potential decision-support system for feed manufacturers, aquaculture producers, and nutritionists seeking economically efficient formulations that satisfy species-specific dietary requirements. The framework also

supports ingredient substitution, nutritional planning, and feed cost management under changing market conditions. It is recommended that aquaculture enterprises adopt data-driven formulation practices, maintain reliable ingredient composition databases, and incorporate digestibility coefficients and validated growth-response models into optimization procedures. Furthermore, collaboration between feed manufacturers, computational researchers, and aquaculture nutrition specialists should be encouraged to facilitate practical implementation. These applications require independent validation before AquaFeed can be recommended for routine commercial feed formulation.

- *Study Limitations, Model Generalizability, and Recommendations for Future Research on Adaptive, Data-Driven, and Species-Specific Aquaculture Feed Optimization*

Despite its methodological contributions, the proposed AquaFeed algorithm presents limitations concerning data availability, predictive accuracy, computational scalability, and applicability across different aquaculture species. The comparative performance indicators were derived from illustrative computational scenarios rather than independently validated experiments, restricting conclusions regarding algorithmic superiority. Furthermore, variations in nutrient digestibility, ingredient quality, environmental conditions, and species-specific physiological requirements may influence formulation accuracy and model generalizability. Future research should prioritize experimental validation using comprehensive ingredient databases, controlled feeding trials, and independently calibrated growth prediction models. Additional investigations should incorporate stochastic optimization, uncertainty quantification, machine learning, and real-time ingredient price forecasting to improve computational adaptability. Comparative assessments across multiple fish species, production systems, and geographical markets are also recommended. Finally, integrating environmental sustainability indicators, life-cycle assessment, and automated decision-support capabilities would strengthen AquaFeed's practical relevance and establish a foundation for reliable, scalable, and economically sustainable aquaculture feed optimization.

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