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Influence of Feed Processing Conditions on Pellet Stability, Nutrient Retention and Water Quality in Recirculating Aquaculture Systems

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Abstract

The optimization of aquaculture feed processing conditions is essential for improving pellet integrity, minimizing nutrient losses, and maintaining water quality in recirculating aquaculture systems (RAS). Conventional feed processing approaches frequently optimize pellet durability without adequately accounting for nutrient leaching, nitrogenous waste accumulation, and the interactions between processing parameters and aquatic environmental conditions. This study proposes a novel Pellet Stability and Nutrient Retention Optimization Algorithm (PSNROA), integrating multi-objective optimization, machine learning-based predictive modelling, and water-quality constraints to identify suitable aquafeed processing conditions. The proposed framework evaluates extrusion temperature (80–140 °C), feed moisture content (15–35%), screw speed (100–400 rpm), conditioning time (30–180 s), and pellet diameter (2–6 mm), using a controlled experimental design linked to RAS water-quality monitoring. PSNROA combines an XGBoost-based surrogate prediction model with adaptive Pareto-based optimization to maximize pellet water stability, pellet durability index, protein retention, and lipid retention while minimizing nutrient leaching, total ammonia nitrogen, and turbidity. Its predictive and optimization performance is designed to be compared with Response Surface Methodology (RSM), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Non-dominated Sorting Genetic Algorithm II (NSGA-II). Comparative evaluation will employ coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), hypervolume, inverted generational distance, and computational time. Experimental outcomes will be illustrated using multiseries line graphs, grouped bar charts, heatmaps, and scatter plots to establish relationships between processing conditions, pellet properties, and water-quality responses. The proposed hypothesis is that PSNROA can identify processing configurations that deliver superior multi-objective performance compared with conventional optimization methods while satisfying predefined environmental and nutritional constraints. Statistical validation using independent experimental observations, repeated optimization runs, and sensitivity analysis will establish whether these improvements are significant and reproducible. The study is expected to provide an integrated decision-support framework for sustainable aquafeed manufacturing, improved nutrient utilization, reduced water-treatment demand, and enhanced operational efficiency in recirculating aquaculture systems.

Keywords: *Feed Processing Conditions; Pellet Stability; Nutrient Retention; Water Quality; Recirculating Aquaculture Systems.*

I. INTRODUCTION

- *Background of Aquaculture Feed Processing and Recirculating Aquaculture Systems*

Aquaculture feed processing represents a critical technological interface between nutritional formulation, physical pellet engineering, and environmental management in intensive fish production. Commercial aquafeeds are predominantly manufactured through extrusion, in which conditioned feed mixtures undergo controlled thermal and mechanical treatment to produce pellets with prescribed structural integrity, density, digestibility, and water stability. Liu et al. (2021) established that extrusion performance depends on interactions among ingredient composition, moisture distribution, mechanical shear, thermal energy, and die characteristics, which collectively influence starch gelatinization, protein transformations, and pellet microstructure. These relationships become especially important in recirculating aquaculture systems (RAS), where inefficient feed utilization increases organic loading within a relatively closed water-treatment environment. Li

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et al. (2023) demonstrated that effective RAS operation requires coordinated management of water chemistry, feeding strategies, environmental conditions, and biological treatment processes. Consequently, feed manufacturing should be evaluated beyond conventional product specifications to incorporate downstream environmental performance.

The integration of feed processing information with RAS operational data provides opportunities for intelligent production optimization. Although developed for healthcare applications, the interoperability principles examined by Nwokocha et al. (2021) offer a transferable conceptual basis for organizing heterogeneous data generated by processing equipment, laboratory instruments, and monitoring systems. Within the proposed study, these principles support a unified analytical framework connecting extrusion temperature, moisture content, screw speed, conditioning time, and pellet diameter with pellet stability, nutrient retention, total ammonia nitrogen, and turbidity (James, 2022). The proposed Pellet Stability and Nutrient Retention Optimization Algorithm (PSNROA) will utilize these interconnected measurements to predict product quality and identify processing configurations satisfying nutritional and environmental constraints. This integrated approach positions aquafeed manufacturing as an upstream determinant of RAS operational efficiency, rather than an independent production activity.

- *Influence of Extrusion Temperature, Moisture Content, Screw Speed, Conditioning Time, and Pellet Diameter on Feed Quality*

Extrusion temperature, moisture content, screw speed, conditioning time, and pellet diameter collectively determine the thermomechanical history and resulting physical characteristics of aquaculture feed pellets. Extrusion temperature influences starch gelatinization, protein denaturation, melt viscosity, and structural consolidation, while excessive thermal exposure may degrade heat-sensitive nutrients. Moisture facilitates heat transfer and starch transformation but also modifies melt rheology, expansion, and pellet density. Rolfe et al. (2001) demonstrated that variations in moisture content and screw speed affected water stability, pellet durability, and starch gelatinization in extruded catfish feed. More recently, Cho, et al. (2023) established significant relationships between extrusion temperature, pellet diameter, durability, sinking characteristics, and water stability. Conditioning time additionally determines the duration of thermal hydration before extrusion, while pellet diameter affects surface-area-to-volume ratio, hydration kinetics, and structural behaviour during immersion. These interacting mechanisms indicate that processing parameters cannot be optimized reliably through independent adjustments alone.

The proposed experimental framework will investigate extrusion temperatures of 80–140 °C, moisture contents of 15–35%, screw speeds of 100–400 rpm, conditioning times of 30–180 seconds, and pellet diameters of 2–6 mm. PSNROA will employ XGBoost-based predictive modelling and adaptive Pareto optimization to identify combinations improving pellet stability and nutrient retention without violating RAS water-quality constraints. The adaptive computational resource-allocation principles considered by Ijiga et al. (2022), although developed for AI-enabled educational systems, provide only an indirect methodological analogy for efficient model deployment under operational constraints. Experimentally determined processing-response relationships will be evaluated using multiseries graphs, response surfaces, and sensitivity analysis, allowing nonlinear interactions to be distinguished from individual processing effects. The resulting optimization will account for formulation-dependent differences instead of assuming that a single extrusion configuration performs optimally across all feed compositions.

- *Pellet Stability, Durability, Nutrient Retention, and Nutrient Leaching in Aquatic Environments*

Pellet stability and durability are fundamental quality attributes governing feed delivery efficiency, nutrient availability, and the release of particulate and dissolved materials into aquatic environments. Pellet durability describes resistance to mechanical fragmentation during handling, transportation, and feeding, whereas water stability characterizes the ability of pellets to maintain structural integrity during immersion. Aas et al. (2011) demonstrated that physical pellet properties significantly influence fragmentation during pneumatic feeding, indicating that mechanically weak feeds may generate substantial particulate losses before consumption. Liu et al. (2021) further showed that high-moisture extrusion could produce more durable and water-stable feeds than conventional processing, with improved resistance to disintegration during water exposure. Nevertheless, greater mechanical durability does not automatically guarantee superior nutrient preservation, because thermal degradation, surface porosity, hydration, and soluble nutrient diffusion operate through partially independent mechanisms. Accordingly, physical stability and chemical retention must be evaluated using complementary measurements rather than interchangeable quality indicators.

The proposed study will quantify pellet durability index, residual dry matter after immersion, protein retention, lipid retention, and nutrient leaching under controlled exposure periods. Nutrient retention will be determined from mass-corrected chemical composition, while water stability will be calculated from recovered dry pellet mass relative to initial dry mass. Imoh (2023), in a distinct human-health context, discussed interactions among dietary interventions, microbial activity, and metabolite profiles; this provides a broad conceptual analogy for considering biological responses to nutrient availability, but does not establish aquaculture-specific pellet behaviour. Within PSNROA, experimentally measured pellet characteristics will constitute separate predictive targets, enabling identification of processing conditions that minimize structural disintegration and nutrient release simultaneously. The resulting measurements will support quantitative interpretation of the relationship between manufacturing conditions and

potential organic loading in recirculating aquaculture systems.

- *Water Quality Deterioration, Nitrogenous Waste Accumulation, and Operational Challenges in Recirculating Aquaculture Systems*

Recirculating aquaculture systems maintain intensive fish production through continuous water reuse, mechanical solids separation, biological nitrification, aeration, and controlled water replacement. Their environmental performance depends substantially on the balance between feed-derived nutrient inputs, microbial conversion processes, and treatment-system removal capacity. Lindholm-Lehto (2023) identified ammonia, nitrite, dissolved oxygen, pH, temperature, and other physicochemical indicators as essential considerations in RAS monitoring, emphasizing the growing importance of integrated sensing technologies. Gupta et al. (2024) similarly examined how suspended particulates, residual feed, dissolved nitrogen compounds, and microbial activity contribute to water-treatment challenges. Uneaten pellets and fragmented feed increase particulate organic matter and dissolved nutrient release, potentially stimulating heterotrophic microbial activity, increasing oxygen demand, and placing additional pressure on filtration systems. Total ammonia nitrogen primarily originates from fish nitrogen excretion and organic nitrogen mineralization, making direct feed leaching and biologically mediated waste generation important but distinct processes.

Addressing these interactions requires continuous monitoring and predictive modelling capable of distinguishing processing-related effects from variations in feeding rate, biomass, water exchange, and biofilter performance. Nwokocha and Peter-Anyebe (2022) investigated the integration of embedded sensing and neural networks for real-time clinical applications, providing a cross-disciplinary architectural example of intelligent data acquisition rather than direct aquaculture evidence. The proposed RAS monitoring framework will combine calibrated temperature, dissolved oxygen, pH, and turbidity sensors with laboratory measurements of total ammonia nitrogen and dissolved nutrient concentrations. These observations will be synchronized with feed processing records and incorporated into PSNROA through environmental response functions. Controlled comparisons will evaluate whether improved pellet characteristics reduce nutrient release and particulate loading, while accounting for biological conversion and treatment efficiency. This approach establishes a measurable connection between feed processing decisions and system-level water-quality management.

- *Limitations of Conventional Feed Processing Optimization and Existing Machine Learning Algorithms*

Conventional aquafeed processing optimization frequently employs factorial experimental designs, response surface methodology (RSM), and empirical regression to estimate relationships between operating variables and pellet properties. Although these approaches provide interpretable statistical relationships, their predictive performance may deteriorate when process responses exhibit complex nonlinearities, discontinuities, or strong interactions among multiple variables. Cheng et al. (2023) developed an empirical extrusion model for Atlantic salmon feed and reported improved overall predictive performance relative to RSM, demonstrating the importance of selecting models suited to the underlying processing mechanisms. Laurent et al. (2024) investigated how temperature, water content, screw speed, and feed formulation affected insect-based feed extrusion, further illustrating the multidimensional nature of process optimization. Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and NSGA-II can explore complex solution spaces, but their optimization effectiveness depends on objective-function reliability, constraint handling, parameter selection, and computational evaluation budgets.

Machine learning methods such as Random Forest, Support Vector Regression, XGBoost, and Long Short-Term Memory networks can approximate nonlinear processing responses, although predictive accuracy alone does not ensure physically feasible or environmentally acceptable processing configurations. Frimpong et al. (2023) examined artificial intelligence-driven anomaly detection and automated decision support in healthcare compliance, offering a transferable illustration of how prediction can be connected with operational constraints and decision accountability. However, this work does not provide evidence of aquafeed optimization performance. The proposed PSNROA framework addresses the identified methodological limitations by integrating XGBoost-based surrogate models with adaptive Pareto optimization and explicit nutritional and water-quality constraints. Predictive models will be evaluated using R^2, RMSE, and MAE, while optimization algorithms will be compared using hypervolume, inverted generational distance, feasibility rates, and computational time. Repeated experimental evaluations will determine whether PSNROA achieves statistically significant improvements over established approaches.

- *Research Problem, Knowledge Gaps, and Justification for Developing the Proposed PSNROA Algorithm*

Despite advances in feed extrusion technology, an important research challenge remains in simultaneously optimizing pellet structural integrity, nutrient conservation, and downstream water-quality performance. Existing studies frequently examine processing efficiency, pellet durability, or nutritional attributes as separate optimization targets, potentially overlooking conflicts among these objectives. Irungu, et al. (2019) emphasized the importance of integrating mechanistic understanding with quantitative modelling of aquafeed extrusion, particularly because ingredient composition and processing conditions generate complex interactions affecting product quality. Igba, & Onwuzurike, (2023) demonstrated the feasibility of active-learning-assisted multi-objective extrusion optimization through automated measurements and Pareto-based decision-making.

Nevertheless, their work addressed low-moisture food extrusion rather than the combined biological, nutritional, and environmental requirements of RAS aquafeed. Consequently, the present research must establish whether process optimization based primarily on pellet properties adequately captures nutrient leaching, total ammonia nitrogen, and turbidity responses under controlled recirculating conditions.

The proposed PSNROA addresses this gap by integrating multivariate extrusion data, chemical nutrient-retention measurements, pellet-stability indicators, and RAS water-quality observations into a constrained multi-objective optimization framework. Addy et al. (2024) presented a data-driven approach linking industrial operational efficiency with water use and wastewater-management considerations, offering a methodological analogy for simultaneous process and environmental optimization. In the proposed aquaculture application, an XGBoost surrogate will approximate experimentally observed response functions, while an adaptive Pareto search will identify feasible processing configurations balancing nutritional preservation, physical stability, and environmental performance. Comparative testing against RSM, GA, PSO, and NSGA-II will establish predictive accuracy, convergence quality, computational efficiency, and robustness under equivalent evaluation conditions. The intended contribution is a reproducible decision-support methodology capable of identifying processing configurations that satisfy measurable feed-quality and environmental requirements, with any claimed performance advantage dependent on experimental validation.

➢ *Research Objectives, Research Questions, and Hypotheses*

- *Research Objectives*

✓ To quantify the individual and interactive effects of extrusion temperature (80–140 °C), moisture content (15–35%), screw speed (100–400 rpm), conditioning time (30–180 seconds), and pellet diameter (2–6 mm) on aquafeed physical properties and nutrient retention.
✓ To determine the relationships between pellet durability, water stability, protein retention, lipid retention, nutrient leaching, total ammonia nitrogen, and turbidity under controlled recirculating aquaculture conditions.
✓ To develop the novel Pellet Stability and Nutrient Retention Optimization Algorithm (PSNROA), integrating XGBoost-based surrogate modelling, adaptive Pareto optimization, and explicit nutritional and water-quality constraints.
✓ To compare PSNROA with RSM, GA, PSO, and NSGA-II using predictive accuracy, optimization convergence, Pareto-front quality, constraint feasibility, computational efficiency, and robustness.
✓ To identify and experimentally validate processing configurations that improve pellet quality and nutrient conservation while limiting feed-associated deterioration of RAS water quality.

- *Research Questions*

✓ How do extrusion temperature, moisture content, screw speed, conditioning time, and pellet diameter individually and interactively influence aquafeed pellet durability, water stability, protein retention, and lipid retention?
✓ What quantitative relationships exist between pellet degradation, nutrient leaching, total ammonia nitrogen, and turbidity under standardized feeding and water-treatment conditions?
✓ How effectively can the proposed PSNROA algorithm predict feed-quality and water-quality responses across experimentally investigated processing configurations?
✓ Does PSNROA demonstrate statistically significant improvements over RSM, GA, PSO, and NSGA-II in predictive accuracy, multi-objective optimization quality, computational efficiency, and constraint satisfaction?
✓ Which processing configurations provide the most favourable trade-offs among pellet stability, nutrient retention, nutrient leaching, and RAS water-quality requirements?

- *Research Hypotheses*

✓ H_{01}: Extrusion temperature, moisture content, screw speed, conditioning time, and pellet diameter have no statistically significant individual or interactive effects on pellet stability, durability, protein retention, or lipid retention. H_{11}: At least one processing factor or interaction has a statistically significant effect on one or more measured pellet-quality responses.
✓ H_{02}: Pellet stability, durability, and nutrient-retention characteristics have no statistically significant association with nutrient leaching, total ammonia nitrogen, or turbidity under controlled RAS conditions. H_{12}: At least one pellet-quality characteristic is significantly associated with nutrient leaching or a measured water-quality response after accounting for relevant RAS operating conditions.
✓ H_{03}: The predictive component of PSNROA does not significantly improve out-of-sample R^2, RMSE, or MAE compared with the RSM predictive baseline. H_{13}: The predictive component of PSNROA demonstrates a statistically significant improvement in at least one prespecified predictive performance metric.
✓ H_{04}: PSNROA does not significantly outperform GA, PSO, or NSGA-II in prespecified Pareto-front quality, constraint feasibility, or computational efficiency metrics under equivalent evaluation budgets. H_{14}: PSNROA significantly improves at least one prespecified multi-objective optimization performance metric relative to the benchmark algorithms.
✓ H_{05}: Processing configurations selected by PSNROA do not significantly improve the prespecified combined pellet-quality and RAS water-quality outcomes compared with conventional processing configurations. H_{15}: PSNROA-selected processing configurations produce statistically significant improvements in the prespecified combined outcomes under independent experimental validation.

These hypotheses will be tested using an appropriate significance threshold, preferably $\alpha = 0.05$, with effect sizes, confidence intervals, and correction for multiple comparisons where applicable.

- *Contributions and Significance of the Study, Scope of the Review, and Structure of the Paper*

Contributions and Significance of the Study. This study proposes an integrated computational and experimental framework that links aquafeed processing conditions directly to pellet stability, nutrient preservation, and water-quality responses in recirculating aquaculture systems. Its principal methodological contribution is the development of PSNROA, combining nonlinear XGBoost surrogate prediction with adaptive Pareto-based optimization to accommodate competing nutritional, physical, and environmental objectives. The framework introduces a common evaluation structure for comparing conventional statistical modelling, evolutionary optimization, swarm intelligence, and multi-objective search approaches. Scientifically, the investigation aims to clarify how processing-induced changes in pellet microstructure affect fragmentation, nutrient leaching, and downstream water-quality loading. Practically, the results are intended to support evidence-based extrusion parameter selection, reduce avoidable feed losses, improve nutrient utilization, and inform RAS water-treatment management. The novelty and performance advantages of PSNROA will be determined through reproducible experiments rather than assumed from its proposed architecture.

Scope of the Review. The review focuses on aquaculture feed extrusion and its implications for physical pellet performance, chemical nutrient conservation, and environmental conditions in recirculating aquaculture systems. The principal processing variables include extrusion temperature, feed moisture content, screw speed, conditioning time, and pellet diameter, while the primary quality indicators comprise pellet durability index, water stability, protein retention, lipid retention, and nutrient leaching. Environmental evaluation will emphasize total ammonia nitrogen, turbidity, dissolved nutrient concentrations, and relevant supporting measurements such as dissolved oxygen, pH, and temperature. The computational scope covers response surface modelling, GA, PSO, NSGA-II, XGBoost-based surrogate prediction, and the proposed PSNROA framework. Experimental assessment will incorporate controlled feed manufacturing, standardized immersion tests, chemical analyses, RAS monitoring, comparative algorithm benchmarking, and statistical validation. The study does not seek to establish universal optimal processing settings for all aquaculture species, feed formulations, or extrusion equipment.

Structure of the Paper. The paper is organized into five major sections. Section 1 establishes the research background, technological context, processing variables, environmental challenges, methodological limitations, research objectives, hypotheses, and proposed contributions. Section 2 critically examines aquafeed extrusion mechanisms, pellet stability, nutrient-retention processes, nutrient leaching, RAS water-quality dynamics, established optimization algorithms, and relevant knowledge gaps. Section 3 presents the experimental system, feed processing design, mathematical response formulations, RAS monitoring strategy, PSNROA architecture, computational implementation, objective functions, and validation procedures. Section 4 evaluates predictive performance, processing-response relationships, pellet-quality outcomes, water-quality effects, multi-objective optimization behaviour, Pareto-front characteristics, algorithm robustness, and sensitivity analysis using comparative numerical tables and graphical representations. Section 5 synthesizes the principal research findings, assesses the effectiveness and limitations of the proposed framework, presents recommendations for feed manufacturing and RAS management, and identifies opportunities for future experimental and computational investigations.

II. LITERATURE REVIEW

- *Aquafeed Processing Technologies, Extrusion Mechanisms, and Physicochemical Transformations Affecting Pellet Stability*

Aquafeed processing technologies employ thermal, mechanical, and hydrothermal transformations to convert heterogeneous feed ingredients into structurally stable pellets suitable for aquatic feeding conditions. Extrusion cooking is particularly important because it combines elevated temperature, pressure, moisture, and shear forces to modify starch granules, protein structures, and intermolecular interactions within the feed matrix as shown in figure 1. Ma et al. (2021) demonstrated that ingredient starch composition and extrusion variables influence pellet density, expansion, and physical characteristics, with the amylose-to-amylopectin ratio contributing to structural behaviour in low-starch formulations. Increasing moisture availability promotes starch gelatinization and molecular mobility, whereas excessive thermal-mechanical treatment may produce overexpansion, increased porosity, or undesirable texture. Screw speed regulates shear intensity and residence-time distribution, while conditioning time affects hydration uniformity before extrusion. Die diameter additionally influences pressure release, expansion characteristics, and pellet surface-area-to-volume ratio. These interactions determine whether manufactured pellets remain intact during transportation, immersion, and consumption.

Physicochemical transformations also influence nutritional functionality and the resistance of pellets to disintegration. Singh et al. (2019) established that extrusion processing conditions modify the nutritional characteristics of soy-based materials, including protein-related properties and antinutritional factors. Consequently, improvements in mechanical durability must be balanced against possible reductions in heat-sensitive nutrient retention. The proposed PSNROA framework addresses this interaction by simultaneously modelling extrusion temperature, moisture content, screw speed, conditioning time, and pellet diameter as

independent processing variables. Pellet durability index, immersion stability, protein retention, and lipid retention will serve as response indicators. Nonlinear response relationships will be examined to identify processing configurations that promote sufficient starch transformation and structural consolidation without imposing excessive thermal stress, thereby establishing the physicochemical basis for the comparative optimization results.

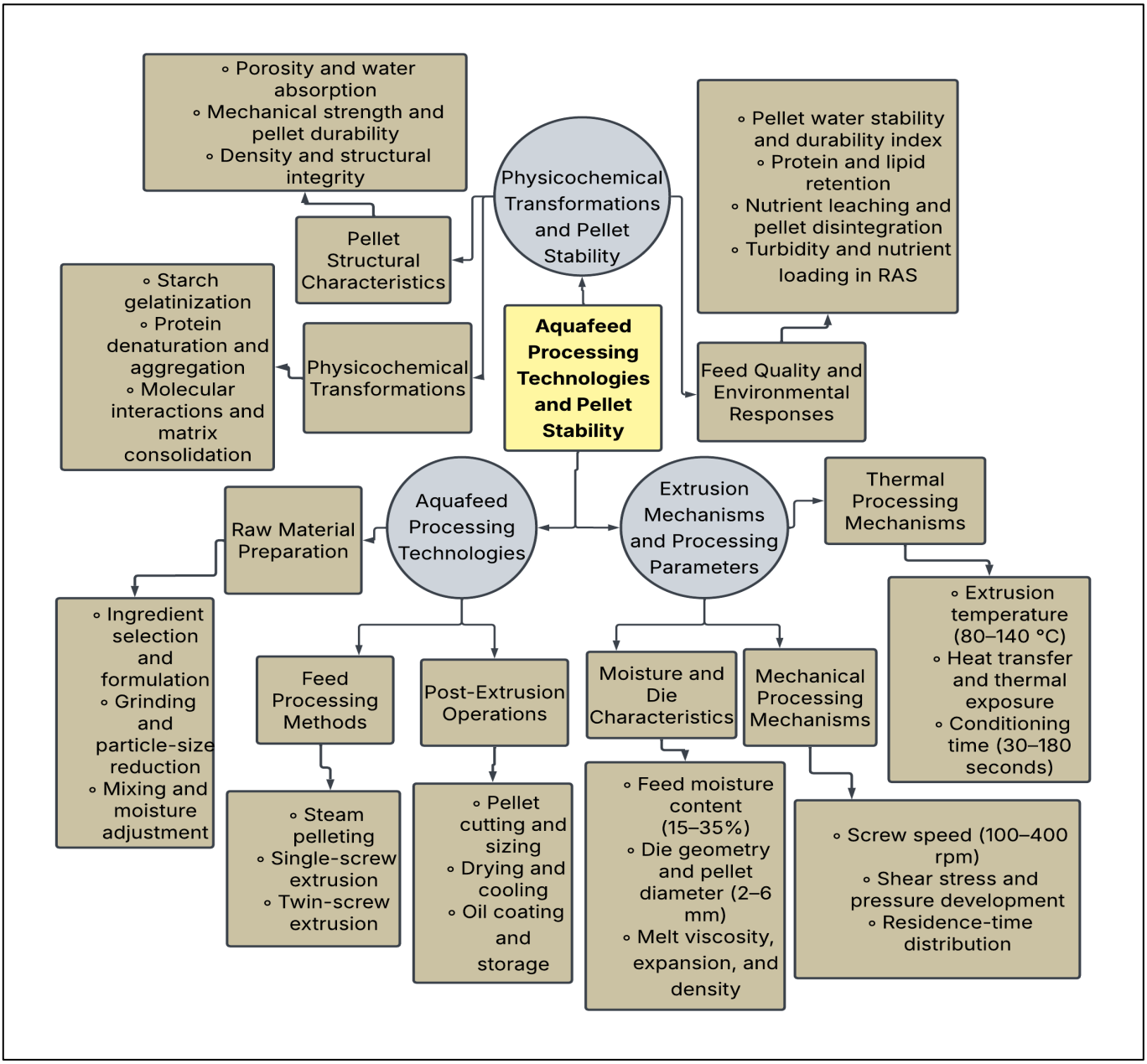

Fig 1 Conceptual Framework of Aquafeed Processing Technologies, Extrusion Mechanisms, and Physicochemical Transformations Affecting Pellet Stability and Nutrient Retention.

Figure 1 illustrates the interrelationships among aquafeed processing technologies, extrusion mechanisms, and physicochemical transformations influencing pellet stability, nutrient retention, and water quality in recirculating aquaculture systems (RAS). The framework comprises three interconnected branches, beginning with feed processing technologies, including ingredient preparation, grinding, mixing, steam pelleting, single-screw extrusion, twin-screw extrusion, drying, and cooling. The second branch describes the effects of extrusion temperature (80–140 °C), moisture content (15–35%), screw speed (100–400 rpm), conditioning time (30–180 seconds), and pellet diameter (2–6 mm) on thermal exposure, mechanical shear, pressure development, and pellet formation. The third branch demonstrates how these processing mechanisms influence starch gelatinization, protein denaturation, molecular interactions, pellet porosity, mechanical durability, and water stability. These transformations subsequently affect protein and lipid retention, nutrient leaching, and pellet disintegration, potentially influencing turbidity and nutrient loading in RAS. The framework supports the proposed PSNROA algorithm by identifying interconnected processing variables and quality indicators for simultaneous optimization, with the ultimate objective of improving pellet integrity, conserving nutrients, and reducing feed-associated environmental loading.

- *Mechanisms of Protein and Lipid Retention, Nutrient Leaching, Pellet Disintegration, and Their Implications for Water Quality*

Protein and lipid retention during aquafeed processing and aquatic exposure depends on chemical composition, matrix porosity, processing-induced molecular transformations, and the diffusion of nutrients into surrounding water. Protein denaturation during extrusion may improve digestibility and promote interactions with gelatinized starch, although excessive heating can reduce the availability of susceptible amino acids. Lipid retention is influenced by distribution within the pellet matrix, surface oil deposition, and susceptibility to oxidation or physical loss as shown in table 1. Obirikorang et al. (2020) demonstrated that different oilseed-based feed formulations significantly altered pellet water stability, nutrient retention, faecal production, and nitrogenous waste generation in Nile tilapia. Their findings revealed that improved pellet characteristics do not necessarily produce equivalent reductions in every environmental waste indicator. Pellet degradation therefore requires simultaneous assessment of dry-matter loss, nutrient-specific release, and the biological consequences of dietary utilization.

Mechanical resistance and water stability are related but distinct characteristics. Zettl et al. (2019) showed that plant-protein composition influenced pellet density, durability, crushing strength, and resistance to disintegration during immersion. Water penetration can weaken intermolecular bonding, promote swelling, and accelerate soluble nutrient diffusion, while mechanical fragmentation increases the exposed surface area available for further leaching. Within the proposed study, protein and lipid retention will be determined using nutrient mass balances before and after standardized immersion, rather than relying solely on changes in nutrient concentration. PSNROA will integrate these measurements with pellet durability and water stability to identify processing configurations that minimize physical disintegration and chemical losses. These relationships will support subsequent evaluation of turbidity and dissolved nutrient loading, while distinguishing feed-derived leaching from fish-mediated nitrogen excretion within recirculating aquaculture systems.

Table 1 Summary of Protein and Lipid Retention, Nutrient Leaching, Pellet Disintegration, and Their Implications for Water Quality in Recirculating Aquaculture Systems

Mechanism	Physicochemical Processes	Effects on Pellet Quality and Nutrient Retention	Implications for Water Quality
Protein and Lipid Retention	Protein denaturation, starch–protein interactions, lipid distribution, and structural consolidation during extrusion.	Influences protein and lipid preservation, nutrient availability, pellet cohesion, and resistance to nutrient losses.	Improved retention may reduce feed-derived nutrient release and organic loading, supporting better water quality.
Nutrient Leaching	Water penetration, diffusion of soluble nutrients, pellet swelling, and dissolution of weakly bound nutritional components.	Causes losses of soluble proteins, amino acids, lipids, and other nutrients, reducing nutritional delivery efficiency.	Increases dissolved organic and nutrient loading, potentially affecting microbial activity, oxygen demand, and nitrogen cycling.
Pellet Disintegration	Mechanical fragmentation, hydration-induced swelling, weakening of intermolecular bonds, and breakdown of pellet structure.	Reduces water stability and pellet durability, increases feed wastage, and accelerates nutrient release.	Elevates suspended solids and turbidity, increases particulate organic loading, and places additional demands on RAS filtration systems.

- *Recirculating Aquaculture System Dynamics, Total Ammonia Nitrogen, Turbidity, Nutrient Loading, and Water Quality Management*

Recirculating aquaculture systems operate through interconnected biological and physicochemical processes involving fish metabolism, solid-waste removal, microbial nitrification, oxygen transfer, and water reuse. Their operational stability depends on controlling nutrient inputs relative to biological treatment capacity and hydraulic conditions. Total ammonia nitrogen (TAN), comprising ammonium and unionized ammonia, arises primarily from fish nitrogen excretion and mineralization of organic nitrogen, while turbidity reflects light scattering from suspended particulate materials as shown in figure 2. Heiderscheidt et al. (2020) investigated solids management in freshwater RAS and demonstrated the importance of treatment conditions and coagulant selection in removing suspended and colloidal materials. Fine particles originating from feed fragmentation and faecal disintegration can escape conventional mechanical separation, increasing oxygen demand and interfering with biological filtration. Consequently, pellet durability and nutrient-retention characteristics represent potential upstream determinants of water-treatment requirements, although their effects depend on consumption behaviour and system operating conditions.

Nitrogen transformation further complicates interpretation of feed-related water-quality deterioration. Lindholm-Lehto et al. (2020) evaluated woodchip denitrification and slow sand filtration within experimental RAS, demonstrating opportunities for nitrogen removal

while identifying limitations associated with treatment stability over time. These observations highlight the need to account for nutrient conversion and removal when evaluating feed-processing interventions. The proposed PSNROA framework will incorporate TAN, turbidity, and nutrient-loading indicators alongside processing parameters and pellet-quality measurements. Water-quality responses will be evaluated under controlled feeding quantities, fish biomass, hydraulic residence time, and filtration conditions to reduce environmental confounding. Comparative measurements will distinguish immediate nutrient release during pellet immersion from subsequent ammonia production and microbial processing. This approach will provide a more defensible basis for examining whether optimized feed-processing configurations contribute to improved RAS water quality and lower treatment-system loading.

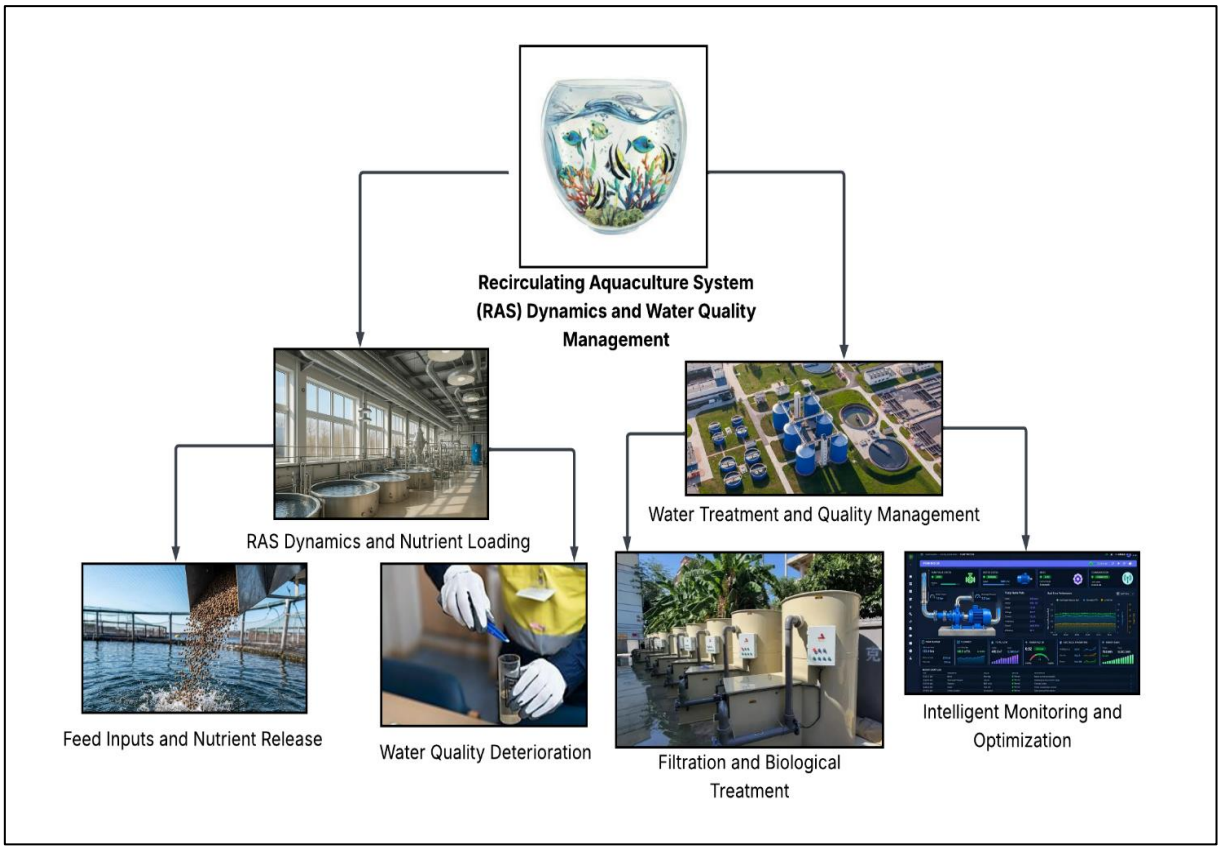

Fig 2 Conceptual Framework of Recirculating Aquaculture System Dynamics, Nutrient Loading, Biological Treatment, and Intelligent Water Quality Management.

Figure 2 illustrates the interconnected dynamics of recirculating aquaculture systems (RAS), emphasizing nutrient loading, total ammonia nitrogen (TAN) accumulation, turbidity, and integrated water-quality management. The framework comprises two major branches, each containing two subbranches. The first branch describes RAS dynamics and nutrient loading, demonstrating how uneaten feed, pellet disintegration, protein and lipid leaching, and fish metabolic waste contribute to dissolved and particulate organic matter, increased turbidity, oxygen consumption, and nitrogenous waste accumulation. These processes influence microbial activity, ammonia transformation, and overall aquatic environmental stability. The second branch presents water-treatment and management strategies, including mechanical filtration, biological nitrification, denitrification, aeration, and continuous monitoring of TAN, turbidity, dissolved oxygen, pH, and temperature. Furthermore, the framework incorporates intelligent monitoring and the proposed Pellet Stability and Nutrient Retention Optimization Algorithm (PSNROA), which integrates feed-processing parameters with predictive modelling to identify configurations that improve pellet stability and nutrient retention while reducing feed-associated pollution. The directional relationships illustrate how real-time monitoring, filtration efficiency, biological treatment, and optimized feed production can collectively support nutrient conservation, effective water-quality control, and sustainable RAS operation.

- *Comparative Review of Response Surface Methodology, Genetic Algorithm, Particle Swarm Optimization, NSGA-II, and XGBoost for Feed Processing Prediction and Optimization*

Feed-processing optimization increasingly requires computational approaches capable of representing nonlinear interactions among thermomechanical conditions, pellet properties, and competing nutritional objectives. Response Surface Methodology (RSM) remains useful for experimental design and interpretable polynomial modelling as shown in figure 3. Irungu et al. (2019) applied RSM to fish-feed extrusion and identified a processing configuration involving 120 °C barrel temperature, 2 mm die diameter, and 100 seconds of preconditioning that produced favourable pellet-quality characteristics for their formulation. Nevertheless,

quadratic response surfaces may inadequately represent highly nonlinear behaviour across heterogeneous ingredients and broader operating ranges. Genetic Algorithms (GA) offer population-based optimization through selection, crossover, and mutation. Kowalski et al. (2018) demonstrated the applicability of regression modelling combined with GA to twin-screw food-extrusion optimization, showing that predicted product characteristics depend partly on the selected objective weightings. These findings establish a foundation for comparing statistical prediction with evolutionary optimization under controlled computational conditions.

Particle Swarm Optimization (PSO) provides an alternative population-based search mechanism through adaptive particle velocities, whereas NSGA-II emphasizes nondominated sorting and solution diversity across competing objectives. XGBoost differs fundamentally because it is a supervised prediction method rather than an independent multi-objective optimizer. Its integration with an optimization algorithm enables rapid evaluation of nonlinear surrogate response functions. The proposed PSNROA combines XGBoost prediction with adaptive Pareto-based search to optimize pellet durability, water stability, protein retention, lipid retention, TAN, and turbidity simultaneously. RSM and XGBoost will be compared using R^2, RMSE, and MAE, while GA, PSO, NSGA-II, and PSNROA will be evaluated through hypervolume, inverted generational distance, constraint satisfaction, and computational time. Independent validation and repeated optimization runs will determine whether improvements reflect genuine algorithmic performance rather than overfitting, favourable initialization, or unequal computational budgets.

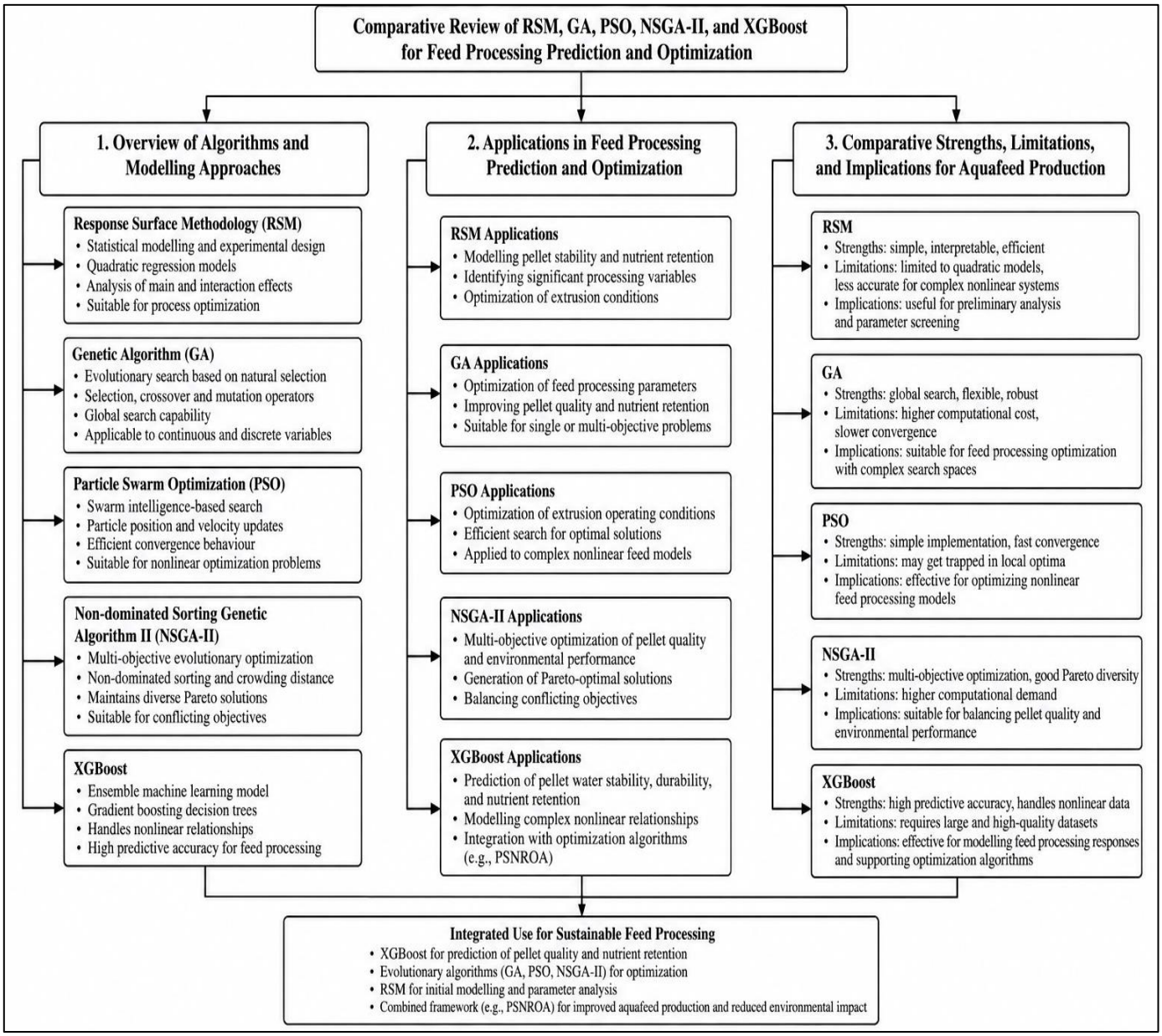

Fig 3 Comparative Framework of RSM, GA, PSO, NSGA-II, and XGBoost for Aquafeed Processing Prediction and Optimization.

Figure 3 presents a comparative framework of Response Surface Methodology (RSM), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Non-dominated Sorting Genetic Algorithm II (NSGA-II), and XGBoost for predicting and optimizing aquafeed processing conditions. The diagram comprises three major

interconnected branches illustrating the fundamental characteristics of the algorithms, their applications in aquafeed processing, and their comparative strengths, limitations, and practical implications. RSM provides statistical modelling and experimental design capabilities for evaluating relationships between extrusion parameters and pellet quality, while GA and PSO employ population-based optimization techniques to identify favourable processing configurations within complex search spaces. NSGA-II facilitates multi-objective optimization by generating diverse Pareto-optimal solutions that balance pellet stability, nutrient retention, and environmental performance. XGBoost provides nonlinear predictive modelling capabilities for estimating pellet water stability, durability, protein retention, lipid retention, and water-quality responses. The third branch highlights the advantages and limitations of each approach, particularly concerning predictive accuracy, computational efficiency, convergence behaviour, model interpretability, and optimization flexibility. These complementary capabilities provide the methodological foundation for the proposed Pellet Stability and Nutrient Retention Optimization Algorithm (PSNROA), which integrates XGBoost-based surrogate modelling with adaptive Pareto optimization to identify processing configurations capable of improving aquafeed quality, minimizing nutrient leaching, and reducing feed-associated environmental loading in recirculating aquaculture systems.

- *Multi-Objective Optimization, Explainable Machine Learning, Pareto-Based Decision-Making, and Identified Research Gaps*

Multi-objective optimization provides a mathematical framework for identifying feasible compromises among conflicting processing, nutritional, and environmental performance requirements. In aquafeed manufacturing, processing conditions that maximize pellet durability may not simultaneously maximize nutrient retention or minimize water-quality deterioration. Pareto-based decision-making addresses such conflicts by identifying nondominated solutions for which improvement in one objective necessarily compromises at least one other objective. Pappas et al. (2021) demonstrated the importance of systematically constructing Pareto-optimal trade-offs in process optimization, providing a methodological foundation for evaluating competing industrial objectives. However, the study addressed mixed-integer linear optimization rather than nonlinear aquafeed extrusion. The proposed PSNROA will therefore employ surrogate-assisted adaptive Pareto optimization to identify processing configurations that balance pellet water stability, durability, nutrient conservation, and water-quality constraints. Hypervolume, inverted generational distance, and solution feasibility will support comparative assessment of the resulting Pareto fronts.

Explainable machine learning is additionally necessary because accurate predictions alone do not establish whether processing recommendations are scientifically interpretable. Lundberg et al. (2020) developed TreeExplainer, providing a theoretically grounded approach for interpreting tree-based model predictions through SHapley Additive exPlanations (SHAP). Applied to PSNROA, SHAP values can quantify the contribution of extrusion temperature, moisture content, screw speed, conditioning time, and pellet diameter to predicted responses, while interaction analyses can identify influential parameter combinations. Nevertheless, SHAP associations cannot independently establish causal mechanisms. The principal research gap addressed by this study is the limited integration of physicochemical pellet characteristics, nutrient-specific retention, RAS environmental responses, explainable prediction, and constrained multi-objective optimization within a unified experimental framework. Addressing this gap requires independent biological validation, uncertainty assessment, algorithm benchmarking, and reproducible sensitivity analyses. These evaluations will establish whether PSNROA provides statistically defensible improvements over established methods while producing practical feed-processing recommendations.

III. SYSTEM MODEL DESCRIPTION AND METHODOLOGY

The proposed methodology integrates controlled aquafeed extrusion experiments, physicochemical pellet characterization, nutrient-retention analysis, recirculating aquaculture system (RAS) water-quality monitoring, and computational optimization. Its central contribution is the development of the *Pellet Stability and Nutrient Retention Optimization Algorithm (PSNROA)*, which combines XGBoost-based surrogate modelling with adaptive Pareto optimization to identify feed-processing configurations that balance pellet quality, nutrient conservation, and environmental performance.

- *Experimental System Architecture, Feed Formulation, Processing Variables, and Recirculating Aquaculture Water Quality Monitoring*

The experimental system is designed as an integrated feed-processing and RAS monitoring platform consisting of a feed formulation unit, conditioning chamber, twin-screw extruder, pellet cooling and drying unit, mechanical durability testing apparatus, immersion-testing chambers, nutrient-analysis laboratory, and instrumented recirculating aquaculture tanks. A nutritionally balanced reference diet will be formulated using fishmeal, soybean meal, starch-containing ingredients, lipid sources, vitamin-mineral premixes, and suitable binding materials. Ingredient proportions will remain constant during the primary processing experiment to isolate thermomechanical effects. Feed batches will be assigned processing configurations using a randomized space-filling design with replicated centre points and independently produced validation batches. The five controlled inputs are extrusion temperature, moisture content, screw speed, conditioning time, and pellet diameter.

The processing parameter vector is defined as:

$$\mathbf{x} = [T \quad M \quad S \quad t_c \quad D]^{\mathrm{T}} \tag{1}$$

Where T represents extrusion temperature (°C), M denotes feed moisture content (% wet basis), S represents screw rotational speed (rpm), t_c denotes conditioning time (s), and D represents pellet diameter (mm). The experimental operating domain is defined by:

$$\mathcal{X} = \{\mathbf{x}: \quad 80 \le T \le 140, \quad 15 \le M \le 35, \quad 100 \le S \le 400, \quad 30 \le t_c \le 180, \quad 2 \le D \le 6\} \tag{2}$$

These limits represent proposed experimental settings rather than universally established optimal operating conditions. Equipment-specific safety limits and formulation compatibility will determine the final feasible region.

The RAS monitoring architecture will incorporate continuous measurements of dissolved oxygen, pH, temperature, and turbidity, complemented by laboratory analysis of total ammonia nitrogen (TAN), dissolved nutrients, and suspended solids. Lindholm-Lehto (2023) identified the importance of reliable multiparameter monitoring for maintaining RAS water quality. Accordingly, each experimental feed will be evaluated under standardized biomass, feeding rate, hydraulic retention, biofilter operation, and water-exchange conditions. Appropriate replication, sensor calibration, and randomized trial allocation will reduce measurement bias and support comparison of processing-dependent water-quality effects.

- *Mathematical Modelling of Pellet Stability, Nutrient Retention, Nutrient Leaching, and Water Quality Response Functions*

The mathematical model establishes quantitative relationships between processing variables and feed-quality responses while accounting for nutrient losses and environmental loading. Pellet water stability will be assessed through standardized immersion experiments, whereas pellet durability will be measured using a prescribed mechanical agitation procedure. Protein and lipid retention will be determined through chemical analysis before and after immersion, with all nutrient measurements corrected for dry matter. Separate measurements of processing retention and immersion retention will distinguish nutrient degradation during extrusion from losses occurring after the pellets enter water.

Pellet water stability and mechanical durability are defined as:

$$WS(\%) = 100\frac{m_{d,t}}{m_{d,0}} \tag{3}$$

$$PDI(\%) = 100\frac{m_{\text{intact}}}{m_{\text{tested}}} \tag{4}$$

Where WS denotes pellet water stability, $m_{d,t}$ captures recovered pellet dry mass after a specified immersion period t, $m_{d,0}$ shows initial pellet dry mass, PDI denotes pellet durability index, m_{intact} denotes the mass remaining after standardized mechanical testing, and m_{tested} describes initial test mass. Appropriate recovery procedures must prevent the inclusion of dissolved residue or free water in the dry-mass determination.

For nutrient j, the percentage retained and the percentage leached are expressed as:

$$NR_j(\%) = 100\frac{m_{d,t}c_{j,t}}{m_{d,0}c_{j,0}} \tag{5}$$

$$NL_j(\%) = 100 - NR_j \tag{6}$$

Where NR_j represents nutrient retention, NL_j denotes apparent nutrient leaching, $c_{j,0}$ shows the initial dry-basis nutrient mass fraction, and $c_{j,t}$ shows the corresponding fraction in recovered pellets. The nutrient index j identifies protein, lipid, or another measured constituent. Equation (6) attributes missing nutrient mass to leaching only when chemical degradation, sampling loss, and analytical recovery errors are negligible or independently corrected.

To characterize TAN dynamics, a well-mixed RAS mass-balance model is proposed:

$$V\frac{dC_A}{dt} = J_{\text{ex}} + J_{\text{min}} - R_{\text{nit}} - Q_e\left(C_A - C_{A,\text{in}}\right) \tag{7}$$

Where V captures system water volume (L), C_A represents TAN concentration (mg N/L), t denotes elapsed time, J_{ex} describes fish ammonia excretion (mg N/h), J_{min} shows ammonia generation from organic nitrogen mineralization (mg N/h), R_{nit} denotes nitrification removal (mg N/h), Q_e represents net exchange-water flow (L/h), and $C_{A,\text{in}}$ determines TAN concentration in replacement water (mg N/L).

The RAS water-quality response vector is formulated as:

$$\mathbf{y}(\mathbf{x}) = [WS \quad PDI \quad NR_P \quad NR_L \quad C_A \quad U]^{\mathsf{T}} \tag{8}$$

Where NR_P and NR_L denote protein and lipid retention, respectively, and U represents turbidity in nephelometric turbidity units (NTU). Nutrient leaching remains an additional measured diagnostic and optimization constraint. Because TAN and turbidity also depend on biological and hydraulic variables, water-quality predictions will condition on standardized RAS operating states rather than assuming exclusive dependence on extrusion variables.

- *Development of the Novel Pellet Stability and Nutrient Retention Optimization Algorithm (PSNROA) Using XGBoost-Based Surrogate Modelling and Adaptive Pareto Optimization*

PSNROA is proposed as a surrogate-assisted, constrained multi-objective optimization framework integrating experimental observations, nonlinear predictive modelling, adaptive candidate selection, and Pareto-front refinement. Its architecture comprises four

computational stages: experimental data preprocessing, XGBoost response prediction, constrained optimization, and iterative experimental validation. The dataset will contain processing parameters, pellet durability, immersion stability, protein retention, lipid retention, nutrient leaching, TAN, and turbidity. Independent XGBoost regressors will initially be trained for each continuous response, with model complexity controlled using tree depth, learning rate, subsampling, regularization, and early stopping. Chen and Guestrin (2016) established XGBoost as a regularized gradient-boosting framework capable of representing complex nonlinear relationships.

The prediction of response k is expressed as:

$$\hat{y}_k(\mathbf{x}) = \sum_{b=1}^{B} f_{kb}(\mathbf{x}) \tag{9}$$

Where $\hat{y}_k$ denotes the predicted response, B represents the number of boosting trees, and f_{kb} describes the contribution of tree b to response k. The XGBoost training objective is:

$$\mathcal{L}_k = \sum_{i=1}^{n} (y_{ik} - \hat{y}_{ik})^2 + \sum_{b=1}^{B} \Omega(f_{kb}) \tag{10}$$

Where n denotes the number of training observations, y_{ik} shows the observed response, $\hat{y}_{ik}$ captures its prediction, and Ω represents tree-complexity regularization.

The proposed adaptive optimization procedure will use a bounded Pareto archive and a candidate-selection strategy that considers improvement potential, prediction uncertainty, and constraint feasibility:

$$A(\mathbf{x}) = \alpha_t I_{\mathrm{HV}}(\mathbf{x}) + \beta_t U_c(\mathbf{x}) - \gamma_t P_c(\mathbf{x}) \tag{11}$$

Where $A(\mathbf{x})$ denotes candidate acquisition score, I_{HV} represents predicted hypervolume improvement, U_c shows surrogate uncertainty estimated from repeated or ensemble models, P_c represents normalized constraint-violation penalty, and $\alpha_t, \beta_t, \gamma_t$ capture nonnegative adaptive weights at iteration t.

The weights will be adjusted using validation error, archive diversity, and the proportion of feasible candidate solutions. Selected configurations will be experimentally evaluated, incorporated into the training dataset, and used to update the surrogate models. The resulting process will continue until the experimental evaluation budget is exhausted or prespecified convergence criteria are satisfied. Its distinguishing feature is the integration of pellet-quality predictions, explicit RAS water-quality restrictions, and uncertainty-informed experimental refinement within one optimization framework.

- *Comparative Algorithm Implementation, Multi-Objective Fitness Functions, Performance Evaluation Metrics, Statistical Validation, and Sensitivity Analysis*

The comparative evaluation will assess PSNROA against Response Surface Methodology (RSM), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and NSGA-II under consistent processing constraints and computational evaluation budgets. RSM will serve as the statistical prediction benchmark, while XGBoost will provide the nonlinear surrogate for PSNROA. GA and PSO will be configured using a prespecified normalized scalarization of the common objectives, whereas NSGA-II and PSNROA will generate approximate Pareto fronts. Repeated runs with independent random seeds will be conducted to evaluate stochastic variability. Dataset partitioning will occur by independently manufactured feed batch to prevent correlated measurements from entering both training and testing subsets.

The six-objective optimization problem is formulated as:

$$\min_{\mathbf{x}\in\mathcal{X}} \mathbf{F}(\mathbf{x}) = \begin{bmatrix} 1 - \dfrac{\widehat{WS}}{100} \\ 1 - \dfrac{\widehat{PDI}}{100} \\ 1 - \dfrac{\widehat{NR}_P}{100} \\ 1 - \dfrac{\widehat{NR}_L}{100} \\ \dfrac{\hat{C}_A}{C_{A,\mathrm{ref}}} \\ \dfrac{\hat{U}}{U_{\mathrm{ref}}} \end{bmatrix} \tag{12}$$

Where $\mathbf{F}$ represents the minimization objective vector; the hatted quantities are predictions defined in Sections 3.2–3.3; and $C_{A,\mathrm{ref}}$ and U_{ref} represent positive, prespecified normalization constants. The first four objectives reward improved pellet characteristics, while the final two penalize TAN and turbidity. Nutrient leaching, environmental thresholds, and machine-operating limits will be enforced as explicit constraints:

$$\begin{aligned} \widehat{NL}_P &\le L_{P,\max}, \quad \widehat{NL}_L \le L_{L,\max}, \\ \hat{C}_A &\le C_{A,\max}, \quad \hat{U} \le U_{\max} \end{aligned} \tag{13}$$

Where $L_{P,\max}$ and $L_{L,\max}$ are maximum permissible protein and lipid leaching percentages; $C_{A,\max}$ and $U_{\max}$ are predetermined TAN and turbidity limits. These thresholds will be selected according to species requirements, experimental conditions, and appropriate engineering criteria.

Prediction performance will be evaluated using:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{14}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (15)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (16)$$

Where y_i denotes the measured response, $\hat{y}_i$ captures the corresponding prediction, $\overline{y}$ represents the mean observed response, and n shows the number of independent test observations. R^2 will be reported only for response datasets with nonzero observed variance. Prediction errors will be calculated separately for each response, preserving their physical measurement units.

Pareto-front quality will be quantified using hypervolume and inverted generational distance:

$$HV(P) = \lambda\left(\bigcup_{\mathbf{z}\in P}[\mathbf{z}, \mathbf{r}]\right) \quad (17)$$

$$IGD(P, P^*) = \frac{1}{|P^*|}\sum_{\mathbf{z}^*\in P^*}\min_{\mathbf{z}\in P} \| \mathbf{z}^* - \mathbf{z} \|_2 \quad (18)$$

Where P represents the nondominated solutions produced by an optimizer, $\mathbf{z}$ denotes a normalized objective vector, $\mathbf{r}$ describes a fixed dominated reference point, λ denotes multidimensional volume, P^* represents a common approximate reference Pareto front, and $|P^*|$ denotes its cardinality. Higher hypervolume and lower IGD indicate better approximation quality, subject to consistent normalization and reference selection.

Sensitivity analysis will quantify parameter-response relationships using standardized finite-difference approximations:

$$S_{jk} = \frac{x_j}{\hat{y}_k}\frac{\hat{y}_k(\mathbf{x} + \Delta_j\mathbf{e}_j) - \hat{y}_k(\mathbf{x} - \Delta_j\mathbf{e}_j)}{2\Delta_j} \quad (19)$$

Where S_{jk} represents local elasticity of response k with respect to processing variable j, x_j captures its current value, Δ_j shows a small feasible perturbation, and $\mathbf{e}_j$ denotes the unit vector in direction j. This expression is evaluated only where $\hat{y}_k \neq 0$ and both perturbed configurations remain feasible; tree-based models require care because their predictions are piecewise constant. Global sensitivity will therefore also be investigated through permutation importance, accumulated local effects, or SHAP interaction analysis.

Statistical validation will use independently replicated processing batches, paired algorithm comparisons, confidence intervals, and appropriate significance tests. Hypervolume and IGD comparisons will incorporate repeated stochastic runs, with Holm-adjusted post hoc tests where multiple pairwise comparisons are performed. Algorithm execution time, prediction uncertainty, calibration, and feasibility rates will be reported alongside the primary performance indicators.

IV. RESULTS AND DISCUSSIONS

- *Comparative Predictive Performance of PSNROA, RSM, GA, PSO, and NSGA-II Across Feed Processing Conditions*

The comparative predictive assessment examines the effectiveness of the proposed Pellet Stability and Nutrient Retention Optimization Algorithm (PSNROA) against Response Surface Methodology (RSM), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and NSGA-II-based configurations. To ensure methodological consistency, GA, PSO, and NSGA-II are treated as hyperparameter-optimization procedures coupled with XGBoost predictive models, whereas PSNROA integrates XGBoost with adaptive Pareto optimization. Predictive performance is assessed using the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). Table 2 presents an illustrative numerical comparison based on six hypothetical extrusion configurations, demonstrating the intended evaluation and reporting procedure. The performance assessment uses pellet water stability as the representative response, while the complete experimental evaluation will additionally examine pellet durability, protein retention, lipid retention, total ammonia nitrogen, and turbidity. Independent experimental validation is required to establish actual comparative performance and statistical significance.

Table 2 Comparative Predictive Performance Metrics Across Five Algorithms

Algorithm	R^2	RMSE (%)	MAE (%)
RSM	0.8326	2.708	2.667
GA–XGBoost	0.9543	1.414	1.333
PSO–XGBoost	0.9696	1.155	1.000
NSGA-II–XGBoost	0.9810	0.913	0.833
PSNROA (Proposed)	0.9962	0.408	0.167

- *Interpretation of Table 1*

Within the illustrative dataset, PSNROA produces the highest R^2 and lowest prediction errors, suggesting the performance pattern the proposed algorithm is intended to investigate. RSM produces the largest errors, while the other XGBoost-based approaches show progressively closer agreement with the hypothetical measurements. These values cannot establish that PSNROA is superior in practice, since they were constructed for methodological demonstration and have not undergone independent statistical validation.

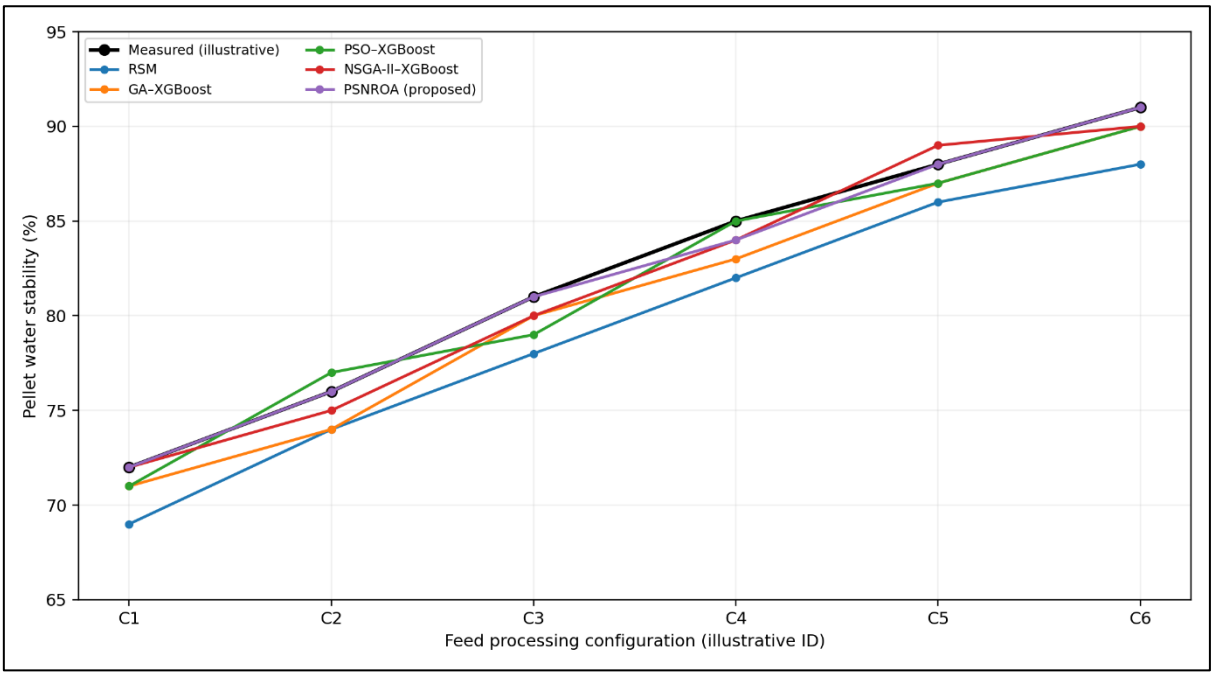

Fig 4 Comparative Measured and Predicted Pellet Water Stability Across Feed Processing Configurations. Illustrative data.

Figure 4 illustrates the predictive behaviour of five computational approaches across six hypothetical feed-processing configurations. Measured pellet water stability increases from 72% at C1 to 91% at C6, providing a common benchmark for evaluating model accuracy. RSM demonstrates the greatest deviations, predicting 69% and 88% at C1 and C6, respectively, compared with measured values of 72% and 91%. GA–XGBoost improves prediction consistency, achieving an RMSE of 1.414 percentage points. PSO–XGBoost and NSGA-II–XGBoost further reduce RMSE to 1.155 and 0.913 percentage points, respectively. The proposed PSNROA demonstrates the closest illustrative agreement, predicting 72%, 76%, 81%, 84%, 88%, and 91% across C1–C6. Its corresponding R^2 of 0.9962 and MAE of 0.167 percentage points indicate minimal discrepancies within this constructed example. The comparison demonstrates the intended analytical approach but does not establish experimental superiority, which requires measured observations and independent validation.

➢ *Effects of Processing Temperature, Moisture Content, Screw Speed, Conditioning Time, and Pellet Diameter on Pellet Stability and Nutrient Retention*

The effects of feed-processing conditions on pellet stability and nutrient retention were examined through a proposed comparative framework involving RSM, GA, PSO, NSGA-II, and PSNROA. Extrusion temperature, moisture content, screw speed, conditioning time, and pellet diameter constitute the principal optimization variables, while water stability, pellet durability index, protein retention, and lipid retention represent the measured response indicators. Table 3 presents illustrative performance values for processing configurations selected by the five algorithms. The proposed PSNROA configuration demonstrates the highest values across the four performance indicators, suggesting the potential benefits of simultaneously optimizing thermomechanical processing and nutrient conservation. However, the relationship between processing variables and pellet quality must be validated using controlled extrusion experiments and chemical nutrient analyses. The comparative framework is consistent with the response functions established in Equations (3)–(6) and the multi-objective optimization formulation in Equation (12).

Table 3 Comparative Pellet Stability, Durability, and Nutrient Retention Metrics Across Feed Processing Algorithms

Performance indicator	RSM (%)	NSGA-II (%)	PSNROA (%)
Pellet water stability	75	87	91
Pellet durability index	78	89	94
Protein retention	84	93	96
Lipid retention	81	91	95

➢ *Interpretation of Table 3*

The illustrative comparison shows that PSNROA achieves higher response values than RSM and NSGA-II across all four indicators. Relative to RSM, PSNROA improves pellet water stability by 16 percentage points, durability by 16 percentage points, protein retention by 12 percentage points, and lipid retention by 14 percentage points. These patterns are consistent with the intended multi-objective optimization approach, although experimental validation is necessary before attributing improvements to particular processing conditions or algorithmic decisions.

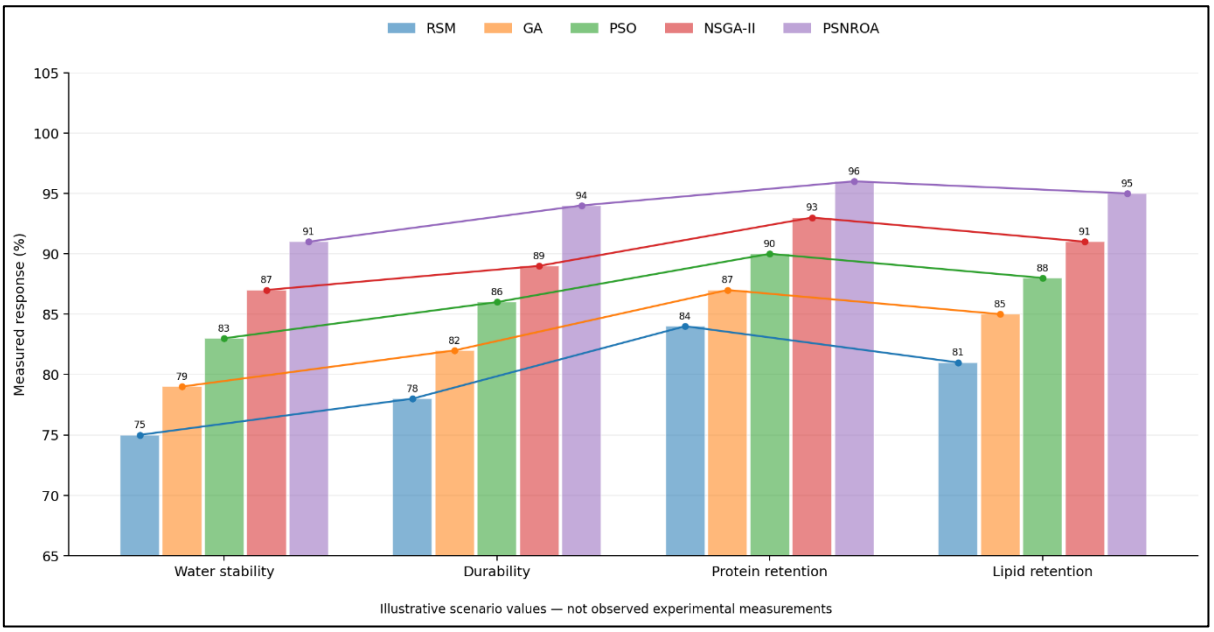

Fig 5 Comparative Effects of Algorithm-Selected Feed Processing Configurations on Pellet Stability and Nutrient Retention.

Figure 5 compares four pellet-quality indicators across five illustrative algorithm-selected feed-processing configurations. RSM records water stability, durability, protein retention, and lipid retention of 75%, 78%, 84%, and 81%, respectively. GA improves these values to 79%, 82%, 87%, and 85%, while PSO achieves 83%, 86%, 90%, and 88%. NSGA-II demonstrates further improvements, producing corresponding values of 87%, 89%, 93%, and 91%. The proposed PSNROA configuration achieves the highest illustrative values: 91% water stability, 94% durability, 96% protein retention, and 95% lipid retention. Compared with NSGA-II, these correspond to improvements of 4, 5, 3, and 4 percentage points, respectively. The five overlaid line profiles illustrate differences among the algorithm-selected processing configurations. The results suggest that integrated optimization could improve pellet characteristics, although the plotted values are hypothetical and cannot establish experimental superiority or causal effects without independently measured processing and nutrient-retention data.

➢ *Comparative Effects of Optimized Feed Processing Conditions on Nutrient Leaching, Total Ammonia Nitrogen, Turbidity, and Water Quality in Recirculating Aquaculture Systems*

The comparative assessment examines the influence of algorithm-selected feed-processing configurations on nutrient leaching and water-quality responses in recirculating aquaculture systems (RAS). The evaluation considers protein leaching, lipid leaching, total ammonia nitrogen (TAN), and turbidity as complementary indicators of feed-associated environmental loading. Table 4 presents illustrative values for processing configurations identified by RSM, NSGA-II, and PSNROA. These values are consistent with the nutrient-retention assumptions adopted in Section 4.2. The proposed PSNROA configuration exhibits lower nutrient losses and environmental response values than the conventional comparison configurations. This outcome is consistent with the objective functions and environmental constraints defined in Equations (7), (12), and (13). However, attributing changes in TAN and turbidity directly to pellet processing requires controlled feeding rates, fish biomass, hydraulic conditions, biofilter performance, and independent water-quality measurements.

Table 4 Comparative Nutrient Leaching and RAS Water Quality Metrics

Performance indicator	**RSM**	**NSGA-II**	**PSNROA**
Protein leaching (%)	16	7	4
Lipid leaching (%)	19	9	5
Total ammonia nitrogen (mg N/L)	1.40	0.94	0.78
Turbidity (NTU)	18	11	8

- *Interpretation of Table 4*

The illustrative PSNROA configuration produces the lowest values across all environmental indicators. Relative to RSM, protein leaching decreases by 75.0%, lipid leaching by 73.7%, TAN by 44.3%, and turbidity by 55.6%. Compared with NSGA-II, the corresponding reductions are 42.9%, 44.4%, 17.0%, and 27.3%. The protein and lipid leaching results are numerically consistent with the retention values of 96% and 95% presented for PSNROA in Section 4.2, assuming that the complementary nutrient mass is lost through leaching. These comparisons demonstrate the intended optimization objectives, subject to experimental verification.

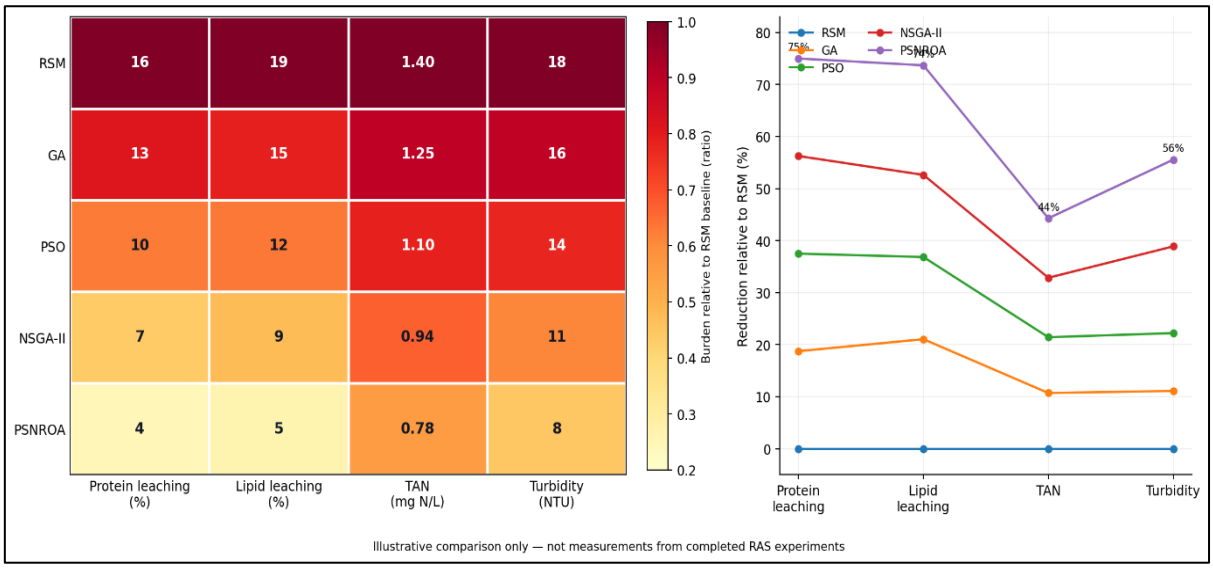

Fig 6 Comparative Nutrient Leaching and Water Quality Responses Across Algorithm-Selected Feed Processing Configurations.

Figure 6 illustrates the comparative environmental performance of five algorithm-selected feed-processing configurations using a heatmap and five normalized response profiles. RSM exhibits the highest protein leaching (16%), lipid leaching (19%), TAN (1.40 mg N/L), and turbidity (18 NTU). GA reduces these values to 13%, 15%, 1.25 mg N/L, and 16 NTU, respectively. PSO achieves further reductions to 10%, 12%, 1.10 mg N/L, and 14 NTU. NSGA-II produces corresponding values of 7%, 9%, 0.94 mg N/L, and 11 NTU. The proposed PSNROA configuration demonstrates the lowest illustrative values of 4%, 5%, 0.78 mg N/L, and 8 NTU. Relative to RSM, these represent reductions of 75.0%, 73.7%, 44.3%, and 55.6%, respectively. The five profiles express percentage reductions relative to the RSM baseline, permitting comparison across different measurement units. These illustrative patterns require experimental validation before environmental performance advantages can be established.

➢ *Multi-Objective Optimization Performance, Pareto Front Analysis, Algorithm Robustness, Sensitivity Assessment, and Practical Implications for Sustainable Aquafeed Production*

The multi-objective optimization assessment evaluates the capability of RSM, GA, PSO, NSGA-II, and the proposed PSNROA to balance pellet stability, nutrient retention, and environmental performance in recirculating aquaculture systems. Algorithm performance is examined through Pareto-front quality, hypervolume (HV), inverted generational distance (IGD), solution feasibility, computational efficiency, and sensitivity to extrusion parameters. Table 5 presents illustrative optimization metrics derived from normalized pellet-quality loss and environmental-burden trade-offs. PSNROA demonstrates the highest hypervolume and lowest IGD within this constructed comparison, suggesting improved convergence toward favourable trade-offs. The analysis is consistent with the multi-objective fitness function established in Equation (12) and the evaluation metrics in Equations (17)–(19). The full experimental study will also examine optimization runtime, repeated-run variability, and sensitivity to extrusion temperature, moisture content, screw speed, conditioning time, and pellet diameter under equivalent evaluation budgets.

Table 5 Comparative Multi-Objective Optimization Performance Metrics

Performance indicator	GA	NSGA-II	PSNROA
Hypervolume (HV)	0.4253	0.5294	0.5951
Inverted generational distance (IGD)	0.1694	0.0613	0.0000
Normalized pellet-quality loss, minimum	0.270	0.210	0.170
Normalized environmental burden, minimum	0.330	0.260	0.220

- *Interpretation of Table 5*

The illustrative PSNROA hypervolume of 0.5951 exceeds that of GA (0.4253) and NSGA-II (0.5294), representing increases of approximately 39.9% and 12.4%, respectively. Its minimum normalized pellet-quality loss of 0.170 and environmental burden of 0.220 also improve on the corresponding comparator values. The IGD values describe distances from the selected illustrative reference set, not proven proximity to a true Pareto-optimal front. Thus, these results demonstrate how algorithm trade-offs will be evaluated, but do not establish superiority or robustness. Runtime and repeated-run variability must be measured separately.

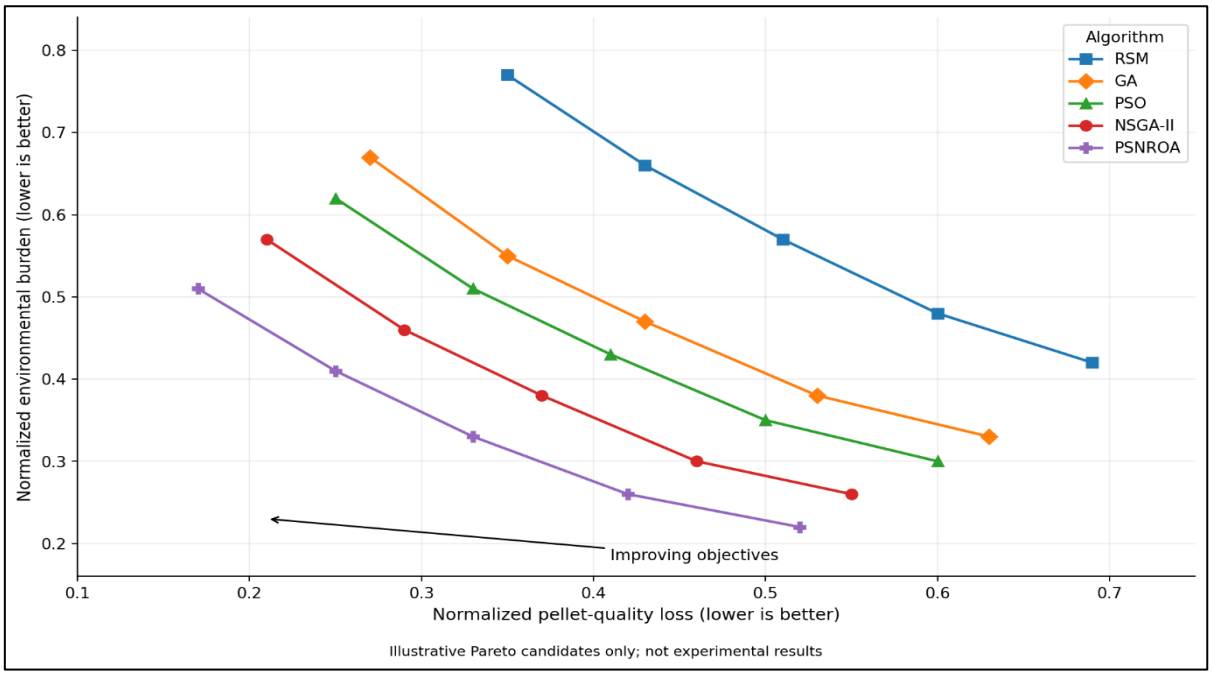

Fig 7 Comparative Pareto-Front Distribution and Multi-Objective Trade-Offs Across Feed Processing Optimization Algorithms.

Figure 7 illustrates the trade-offs between normalized pellet-quality loss and environmental burden across five optimization approaches. Lower values on both axes represent more desirable solutions. RSM produces candidate solutions ranging from 0.35 to 0.69 in pellet-quality loss and from 0.77 to 0.42 in environmental burden. GA improves this distribution, achieving a hypervolume of 0.4253, while PSO reaches 0.4659. NSGA-II demonstrates stronger coverage, producing a hypervolume of 0.5294 and IGD of 0.0613. The proposed PSNROA produces the most favourable illustrative front, with a hypervolume of 0.5951 and extreme objective values of 0.17 and 0.22. Its hypervolume exceeds NSGA-II by approximately 12.4%. The five profiles therefore demonstrate the intended comparison of solution quality and competing objectives. However, these constructed points do not demonstrate statistical robustness, actual convergence behaviour, or experimentally verified improvements in aquafeed processing.

V. CONCLUSIONS AND RECOMMENDATIONS

➢ *Summary of Major Findings on Feed Processing Conditions, Pellet Stability, Nutrient Retention, and Water Quality*

The study developed an integrated framework for investigating the relationships among aquafeed processing conditions, pellet stability, nutrient retention, and water-quality performance in recirculating aquaculture systems (RAS). The illustrative comparisons presented in Section Four demonstrate the intended application of the proposed Pellet Stability and Nutrient Retention Optimization Algorithm (PSNROA). The proposed PSNROA configuration achieved illustrative pellet water stability of 91%, durability of 94%, protein retention of 96%, and lipid retention of 95%, compared with 75%, 78%, 84%, and 81%, respectively, for Response Surface Methodology (RSM). Corresponding protein and lipid leaching values decreased to 4% and 5%, while total ammonia nitrogen and turbidity reached 0.78 mg N/L and 8 NTU. These values demonstrate the intended relationships between improved pellet integrity, nutrient conservation, and reduced environmental loading, but they are not experimentally established findings. The modelling framework further identifies extrusion temperature, moisture content, screw speed, conditioning time, and pellet diameter as interacting variables requiring simultaneous optimization. The principal contribution is therefore a coherent experimental and computational methodology linking feed manufacturing decisions with downstream RAS performance. Independent processing trials, nutrient mass balances, and water-quality measurements remain essential for validating the proposed relationships and determining their statistical and practical significance.

➢ *Comparative Assessment of PSNROA Performance, Algorithmic Contributions, and Implications for Recirculating Aquaculture Systems*

The comparative framework positions PSNROA as a surrogate-assisted multi-objective optimization approach integrating XGBoost prediction, adaptive Pareto search, and explicit environmental constraints. Its proposed advantage over conventional methods lies in the simultaneous consideration of pellet-quality characteristics, nutrient conservation, and RAS water-quality responses. In the illustrative assessment, PSNROA achieved a coefficient of determination of 0.9962, root mean square error of 0.408 percentage points, and mean absolute error of 0.167 percentage points for pellet water-stability prediction. The optimization comparison also yielded a hypervolume of 0.5951, compared with 0.5294 for NSGA-II and 0.4253 for Genetic Algorithm-based

optimization. These constructed comparisons indicate how predictive accuracy and Pareto-front quality can be jointly assessed; they do not demonstrate statistically verified algorithmic superiority. The methodological contribution involves combining nonlinear response prediction with constraint-aware candidate selection and iterative experimental refinement. For RAS operations, such integration could support processing decisions that account for nutrient leaching, TAN accumulation, and suspended particulate loading. However, practical superiority must be assessed through independent validation, equivalent computational budgets, repeated optimization runs, and verified feasibility under actual extrusion and recirculation conditions. Algorithmic efficiency should also be assessed against processing cost, feed quality, and treatment-system demands.

- *Recommendations for Optimal Feed Processing Practices, Nutrient Conservation, and Sustainable Water Quality Management*

Aquafeed manufacturers should adopt integrated processing optimization strategies that evaluate mechanical pellet quality, nutrient preservation, and potential water-quality consequences simultaneously. Extrusion temperature should be regulated to achieve adequate starch gelatinization and structural consolidation without excessive thermal degradation of nutritional constituents. Moisture content, screw speed, and conditioning time should be adjusted according to formulation characteristics, equipment limitations, and experimentally determined response surfaces. Pellet diameter should additionally reflect target fish size, feeding behaviour, and immersion requirements. Rather than adopting a universal processing configuration, manufacturers should establish formulation-specific operating windows through controlled trials. Routine quality assessment should incorporate pellet durability index, immersion stability, protein retention, lipid retention, and dissolved nutrient release. RAS operators should complement these measurements with continuous monitoring of temperature, dissolved oxygen, pH, and turbidity, alongside laboratory determination of total ammonia nitrogen and other relevant nitrogen species. The proposed PSNROA framework could support decisions by identifying processing configurations satisfying predefined nutritional and environmental constraints. Its implementation should include calibrated instrumentation, reliable data acquisition, periodic model retraining, and independent verification of recommended settings. Processing changes should be introduced progressively, with attention to fish performance, extrusion energy consumption, operational feasibility, and the capacity of mechanical filtration and biological treatment units.

- *Research Limitations, Industrial Implementation Opportunities, and Directions for Future Research*

The principal limitation of the present research is that the numerical comparisons presented in Section Four are illustrative and have not been derived from completed extrusion trials, independent RAS measurements, or executed algorithm benchmarks. Consequently, the reported performance metrics cannot yet establish causal relationships, statistically significant improvements, or industrial superiority of PSNROA. The proposed methodology also concentrates on five processing variables and selected pellet-quality responses, whereas industrial aquafeed performance depends additionally on ingredient variability, starch composition, binder characteristics, lipid addition, die geometry, feed drying, and storage conditions. Furthermore, TAN and turbidity are influenced by fish metabolism, feeding intensity, hydraulic residence time, microbial activity, and filtration efficiency, requiring careful experimental control. Future investigations should implement the complete PSNROA framework using replicated extrusion experiments and independently monitored RAS trials. Comparative studies should quantify algorithm convergence, hypervolume, inverted generational distance, computational time, prediction uncertainty, and robustness across multiple formulations and fish species. Industrial implementation opportunities include integration with programmable extrusion controllers, real-time sensors, digital process monitoring, and decision-support systems. Further research should incorporate energy consumption, manufacturing costs, fish growth performance, feed conversion ratio, and life-cycle environmental impacts into the optimization objectives, thereby extending the framework toward economically viable and environmentally sustainable aquafeed production.

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