

Multi-objective configuration of water quality indicators in tilapia production systems using artificial intelligence

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ABSTRACT

Objective: To constrain the operational costs of water quality management within acceptable thresholds while preserving “excellent” quality standards, thereby ensuring optimal growth conditions for tilapia.

Design/methodology/approach: Aquaculture has emerged as a key global source of protein. The application of Artificial Intelligence (AI) to manage water quality indicators enables optimization of efficiency, sustainability, and costs. However, the multi-objective integration of parameters and their joint application in aquaculture systems remains an emerging challenge.

Results: The optimization results provide practical references for the design of decision-support systems in aquaculture plants, offering a structured methodology to balance water quality improvement with cost minimization.

Limitations on study/implications: The study was based on simulated data validated through the literature. The current value of the research lies in its conceptual and methodological foundation. Future work could integrate real-time data obtained from sensors.

Findings/conclusions: The proposed methodology demonstrates the potential of combining Artificial Neural Networks (ANNs) and Multi-Objective Genetic Algorithms (MOGA) as a decision-support tool in aquaculture management. By optimizing both water quality and costs, it contributes to improving the efficiency, resilience, and sustainability of intensive tilapia farming.

Keywords: multi-objective optimization, Pareto front, genetic algorithms, artificial neural networks, tilapia farming.

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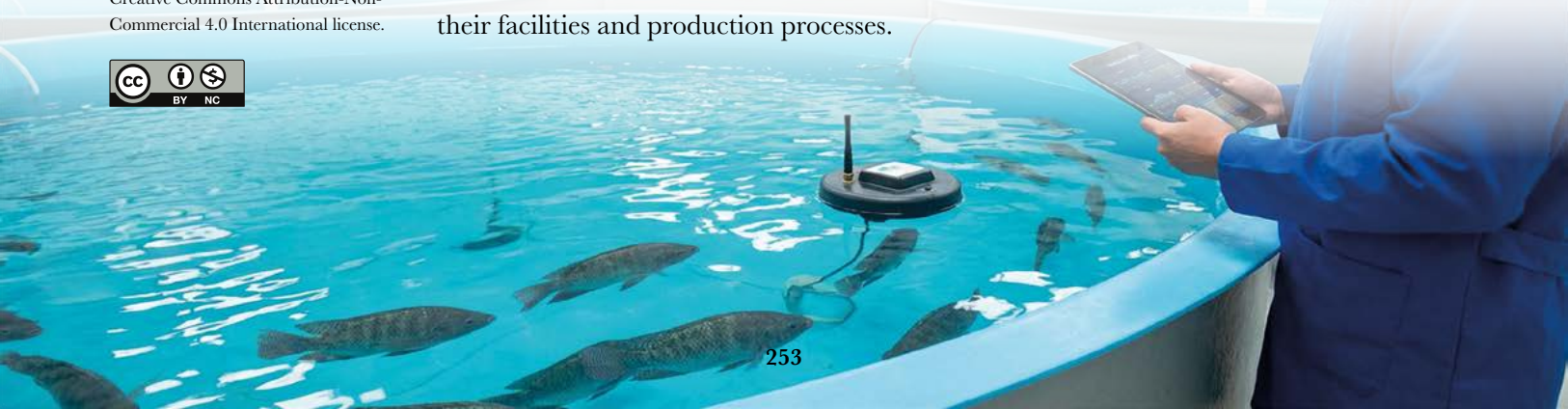
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INTRODUCTION

This study was conducted for the Ingeniería Agropecuaria del Papaloapan S.P.R. de R.L. farm, registered under the National Registry of Fisheries and Aquaculture of the State of Veracruz, México. Aquaculture has experienced significant growth over recent decades, becoming a key global source of protein. Despite technological advances, most aquaculture farms in México still face the need to make substantial financial investments to modernize their facilities and production processes.



This research examines whether predictive models derived from Artificial Neural Networks (ANNs), in combination with a Multi-Objective Genetic Algorithm (MOGA), can provide decision-support tools that optimize both water quality and cost management in tilapia farming systems.

Process optimization within aquaculture production facilities is essential to enhance efficiency, sustainability, and profitability. In this context, the implementation of water quality indicators and their management through Artificial Intelligence (AI) techniques represents a significant advancement toward informed decision-making and process automation.

The importance of monitoring critical indicators for tilapia survival such as temperature, dissolved oxygen, pH, TAN (Total Ammonia Nitrogen), nitrites, nitrates, transparency, hardness, alkalinity, and carbon dioxide has been well established to maintain optimal conditions within production systems. (Comité de Pesca. 36^o Período de Sesiones. Directrices Para La Acuicultura Sostenible, 2024). However, most of these approaches have been limited to single objective control strategies, prioritizing only one parameter without accounting for the interactions among multiple indicators. AI-based methods have demonstrated great potential in predicting and detecting environmental issues within aquaculture systems. AI-based methods have demonstrated great potential in predicting and detecting environmental issues in aquaculture systems (Vásquez-Quispesivana *et al.*, 2022; Yang *et al.*, 2023). Algorithms such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Genetic Algorithms (GAs) have been applied to model water dynamics and optimize conditions in real time. However, the integration of these models to simultaneously configure multiple indicators remains an emerging field.

Based on these premises, a simulated database (DB) will be created using reference ranges for the variables considered critical to water quality. The expected results aim to achieve high levels of efficiency and accuracy, with an estimated similarity of approximately 99% compared to the simulated behavior of Water Quality (WQ) and Total Cost (TC). The mathematical models derived from the ANNs for WQ and TC will provide a predictive tool due to their strong ability to interpolate and extrapolate water quality indicator values, enabling the immediate estimation of WQ and TC behaviors. Considering the predictive capabilities of ANNs, it is expected that the company will be able to make strategic decisions and maintain proper process management through model adaptation.

The selection of this algorithm is justified by its efficiency in identifying Pareto Fronts in dual objective problems, which aligns with the evolutionary optimization methodologies reported in the current literature (Ray *et al.*, 2022). In aquaculture, some studies have applied these methods to balance fish growth, waste control, and resource consumption, although with limited integration of AI based water quality indicators. Furthermore, efforts have been made to analyze the costs associated with maintaining water quality in large scale ponds, including chemical treatments, filtration systems, aeration, and continuous monitoring (Garlock *et al.*, 2024).

Although the foundations of AI in aquaculture are well established, recent literature has begun to explore empirical applications in real farming systems. Studies such as (Vásquez-Quispesivana *et al.*, 2022) have provided a broad overview of the principles and potential of

AI for water quality prediction. Hybrid neural network-based systems have been developed for parameter prediction in Recirculating Aquaculture Systems (RAS), demonstrating their feasibility in operational environments. However, many of these cases focus on single parameter optimization of a specific chemical or biological process. In other words, there remains a significant gap in the development and validation of hybrid methodologies that integrate prediction and multi-objective decision making (through ANN and MOGA, respectively) to balance water quality and operational cost.

Finally, this article contributes a novel multi-objective optimization framework for tilapia aquaculture that integrates AI-based predictive modeling with Pareto-based decision-making. It is among the first to derive closed-form predictive equations from trained neural networks for cost–quality trade-offs in aquaculture environments.

MATERIALS AND METHODS

The methodology applied in this work is illustrated in Figure 1. First, it is necessary to construct the Database (DB) containing all input and output variables, considering the simulated data generated with SIMNET II[®] (Simulation Network v.2). This information serves as the input for generating mathematical models through Artificial Neural Networks (ANNs).

Once the mathematical models are obtained, Multi-Objective Genetic Algorithms (MOGA) can be used to optimize paired combinations on a Pareto front. The decision-maker will then be able to select the optimal result based on specific constraints, priorities, and preferences. Finally, feedback to the DB enables the continuation of the cycle and the improvement of expected outcomes.

RESULTS AND DISCUSSION

According to the proposed methodology, the results of each stage are presented below.

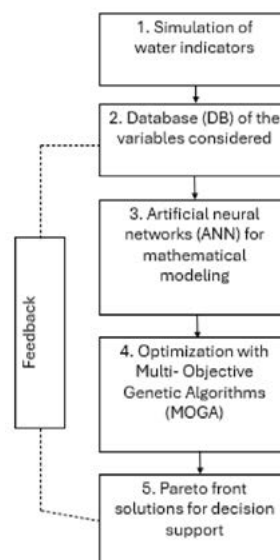


Figure 1. Decision support methodology using Artificial Intelligence (AI).

Simulation of water indicators

To achieve an accurate analysis and obtain reliable references in the field of aquaculture, it is essential to have a real and up-to-date farm database. In this case, since real system data were not available, simulation was used to generate the parameters of interest. In this context, a database was developed using the SIMNET II[®] simulator for the input variables and project objectives. At this stage, a review of both books and scientific articles focused on Tilapia farms was carried out to identify which variables can directly affect water quality. With the objective of identifying the indicators that directly influence water quality, the control elements that compose the water quality in tilapia farms were. Ten key water quality indicators were defined as fundamental to its assessment. These variables were compiled and presented in Table 1.

Next, the simulation of the water quality indicators was carried out. Using the SIMNET II[®] software, data was simulated based on the ranges established in Table 1. The use of a uniform distribution is justified as it represents the most conservative and least biased approach in the absence of real data, adhering to the principle that every value within a known range is equally probable. For the ten water quality indicators, a uniform distribution was selected. A sample size of 100 was deemed sufficient to invoke the validity of the Central Limit Theorem, ensuring that subsequent inferential methods would be appropriate. It is worth noting that in the Kolmogorov–Smirnov test of normality for WQ and TC, the following results were obtained (Table 2).

Figure 2 shows the node-based programming language used to generate the input data for the simulator.

The database generation strategy using SIMNET II[®] enabled the reproduction of credible operational scenarios in the absence of historical records, relying on reference ranges described by Kemmer and on the simulator's internal (Dblp: Simulation with SIMNET II., n.d.; Manual Del Agua: Su Naturaleza, Tratamiento y Aplicaciones - Frank N. Kemmer, Nalco Chemical Company - Google Libros, n.d.). The adoption of a uniform distribution was chosen as a conservative criterion to represent uncertainty without prior bias (*Libro: Beyond Lean - Simulación En La Práctica (Standridge) - LibreTexts Español, n.d.*), the statistical justification of the sample size (n=100) and the application of the Central

Table 1. Summary of water quality indicators.

Water indicators	Range
Temperature	18 °C - 30 °C
Dissolved Oxygen	4 - 10 mg/l
pH	6.5 - 8.5
TAN	0.5 mg/l
Nitrite	1.64 mg/l
Nitrate	180 mg/l
Transparency	40 - 45 cm
Hardness	40 - 100 mg/l
Alkalinity	50 - 120 mg/l
Carbon Dioxide	20 mg/l

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$END:
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Figure 2. Node-based programming language for the simulation of water quality indicators using SIMNET II®.

Table 2. The Kolmogorov-Smirnov Test of Normality for WQ and TC.

	(D)	p-value	Results
WQ	0.07428	0.61249	The data do not differ significantly from those that follow a normal distribution.
TC	0.07428	0.6125	The data do not differ significantly from those that follow a normal distribution.

Limit Theorem for subsequent analyses were based on classical sampling and inference principles (Anderson & Gerbing, 1984).

Variables considered

Databases (DBs) are fundamental in information management due to their accessibility and availability for analysis. After performing the simulations of the water quality indicators, the information was consolidated into the database. Table 3 presents detailed information from the simulation for each water quality indicator.

Using the database of water quality indicators, the Rank and Rating of water quality (WQ) were conceptually quantified using Equation 1. For TC, minimum and maximum monthly cost values were established for the water quality indicators of an earthen pond with a capacity of 500 m³ (approximately equivalent, in proportional terms, to the annual cost of a 50 m³ recirculation pond), without considering factors such as electricity, specialized personnel, automation, and others.

$$QW = \sum_{n=1}^i X_i \tag{1}$$

These estimated parameters for both key objectives are summarized in Table 4, whose importance lies in the fact that the WQ and TC values defined here (as the cost range) represent the performance targets that the ANNs will model and the MOGA will optimize.

Table 3. Simulation results for water quality indicators.

BD	Temperature	Dissolved oxygen	pH	TAN (Total Ammonia Nitrogen)	Nitrite	Nitrate	Transparency	Hardness	Alkalinity	Carbon dioxide
no	18 - 30 °C	4 - 10 mg/l	6.5 - 8.5	<0.5 mg/l	<1.64 mg/l	<180 mg/l	40 - 45 cm	40 - 100 mg/l	50 - 120 mg/l	Up to 20 mg/l
1	22.7708	6.3854	7.2951	0.1988	0.6520	71.5612	41.9878	63.8537	77.8294	7.9512
2	27.9339	8.9669	8.1556	0.4139	1.3576	149.0083	44.1391	89.6694	107.9477	16.5565
3	20.7888	5.3944	6.9648	0.1162	0.3811	41.8318	41.1620	53.9439	66.2679	4.6480
4	29.1199	9.5600	8.3533	0.4633	1.5197	166.7985	44.6333	95.5995	114.8661	18.5332
5	22.1621	6.0811	7.1937	0.1734	0.5688	62.4315	41.7342	60.8105	74.2789	6.9368
6	22.4094	6.2047	7.2349	0.1837	0.6026	66.1412	41.8373	62.0471	75.7216	7.3490
7	27.0514	8.5257	8.0086	0.3771	1.2370	135.7708	43.7714	85.2569	102.7998	15.0857
8	20.6647	5.3323	6.9441	0.1110	0.3642	39.9702	41.1103	53.3234	65.5440	4.4411
9	19.2910	4.6455	6.7152	0.0538	0.1764	19.3650	40.5379	46.4550	57.5308	2.1517
10	19.8399	4.9200	6.8067	0.0767	0.2515	27.5986	40.7666	49.1996	60.7328	3.0665

96	25.2266	7.6133	7.7044	0.3011	0.9876	108.3988	43.0111	76.1329	92.1551	12.0443
97	23.2163	6.6082	7.3694	0.2173	0.7129	78.2449	42.1735	66.0816	80.4286	8.6939
98	28.7625	9.3812	8.2937	0.4484	1.4709	161.4372	44.4844	93.8124	112.7811	17.9375
99	27.0207	8.5104	8.0035	0.3759	1.2328	135.3109	43.7586	85.1037	102.6209	15.0346
100	21.3919	5.6960	7.0653	0.1413	0.4636	50.8785	41.4133	56.9595	69.7861	5.6532

Table 4. Estimation of WQ and TC objective parameters.

WQ	
Range	Rating
160.67 - 249.07	Acceptable
249.08 - 337.48	Medium
337.49 - 425.89	Fair
425.90 - 514.30	Bad
TC	
Minimum	\$ 98,689.16
Maximum	\$ 453,800.86

The definition of the variables and the objectives WQ and TC facilitated the construction of robust objective functions for subsequent modeling; this approach aligns with studies on forecasting and data preparation for neural networks and other predictive

techniques (Zhang *et al.*, 1998). Likewise, the partitioning of data into training, validation, and test sets adheres to methodological recommendations to ensure reproducibility and reduce overfitting (Aggarwal, 2023).

Artificial Neural Networks (ANNs) for Mathematical Modeling

Artificial Neural Networks (ANNs) act as nonlinear mathematical models that learn from data. The input function, network architecture, and training process — using algorithms such as backpropagation— allow the network to adjust its weights to approximate complex functions and nonlinear relationships within the data (Ian Goodfellow, Yoshua Bengio *et al.*, 2016). The applications of ANNs in mathematical modeling are extensive. In engineering, they are used for modeling dynamic systems, process control, and prediction (Zhang *et al.*, 1998) Current research focuses on improving training algorithms, developing more efficient architectures, and advancing model interpretation techniques (Samek *et al.*, 2017).

The Mean Square Error (MSE) was selected as the performance function for supervised training. When each input is applied to the network, its output is compared to the target value. The goal is to minimize the average sum of these errors. The MSE algorithm adjusts the weights and biases of the linear network to minimize this mean squared error. The error is calculated as the difference between the target values and the outputs generated by the network. The error function corresponds to the MSE, and the learning error ($e(k)$) is defined as:

$$MSE = \frac{1}{Q} \sum_{k=1}^Q e(k)^2 \quad (2)$$

$$e(k) = y_i(k) - g_i(k) \quad (3)$$

where Q refers to the number of inputs-output example patterns used in training, i is the index of the example pattern (vector), and $y_i(k)$ and $g_i(k)$ represent the desired (target) and ANN-predicted values of output node k , respectively.

The minimization of MSE does not guarantee complete training of the network. Overfitting may occur when the network is trained excessively or when its architecture contains more hidden neurons than necessary (over-parameterization). Several procedures exist for defining ANN architecture (Elsken *et al.*, 2018); in this study, a two-phase procedure was applied. The MATLAB[®] online platform was selected, as it includes a dedicated module for ANN development (*MATLAB - El Lenguaje Del Cálculo Técnico*, n.d.).

Phase 1: Configuration of the ANN parameters, including all elements required for learning, as shown in Table 5. It is of utmost importance to divide the 100 data samples into three groups: Training, Validation, and Testing. For this study, proportions of 75%, 15%, and 15%, respectively, were used. Splitting the data into these three sets helps build more

Table 5. Configuration of parameters for the ANNs.

Training parameters	
Network Type	Backpropagation (RP)
Input	Input variable matrices
Target 1	Variable vector: WQ
Target 2	Variable vector: TC
Training Function	Lenberg-Marquardt algorithm
Adaptation Function for Learning	Gradient descent with momentum
Performance Function	Mean square error
Number of Hidden Layers	1
Number of Hidden Neurons	4
Hidden Layer Transfer Function	Hyperbolic tangent
Output Layer Transfer Function	Linear
Number of Iterations	1000

accurate and reliable models (Aggarwal *et al.*, 2023) preventing overfitting and ensure that the model can generalize to new and real data. This architecture and division are essential for the reproducibility of the mathematical model.

Phase 2: Using the previously obtained information, the training of the ANNs was carried out. The objective was to find the best MSE and R regression results (for Training, Validation, and Testing). The Training data are used to adjust the weights and parameters of the neural network during the learning process. They allow the network to learn patterns and relationships within the data, optimizing its predictive capability. The Validation data are used to tune hyperparameters, prevent overfitting, and determine when to stop training. They help assess how well the model is generalizing during training, allowing adjustments to the structure or parameters, which prevents bias and overfitting. The Testing data are completely new and unseen by the network during training or validation. They serve to objectively and conclusively evaluate the model's ability to generalize to unseen data, ensuring that the model is robust and reliable for real-world applications. The results are presented in Table 6 for WQ and TC.

As can be observed in both results, a single hidden layer was considered sufficient to represent the behavior of the objectives. Likewise, architecture with four hidden neurons was determined to be optimal due to the lowest MSE value obtained for both WQ and TC objectives. These results highlight the strong agreement between the calculated and measured values, and therefore, the effectiveness of the ANNs in modeling these objectives.

These ANN-based models can now be integrated into a mathematical modeling procedure to determine the WQ and TC functions. To generate the mathematical models through equations, the following data were extracted from the trained networks: initial weights (IW), first-layer bias (b1), final weights (LW), and final-layer bias (b2). Using these values, two functions were created from the ANN one for each objective —as shown below:

Table 6. Tests of network properties and training parameters of the WQ and TC network.

Tests of network properties and training parameters of the WQ network									
Config. Number	Network propieties		Training parametres			Networks results			
	Layers	Neurons	Epochs	Goal	Max fail	Training	Test	Validation	MSE
1	2	1,1	40	0	6	0.99475	0.99631	0.99444	80.164
2	2	2,1	16	0	6	0.98551	0.97856	0.99203	174.862
3	2	3,1	10	0	6	0.99911	0.99891	0.99992	0.645
4	2	4,1	66	0	6	0.99999	0.99999	0.99999	0.0001
5	2	5,1	840	0	6	0.99998	0.99997	0.99996	0.044
6	2	6,1	46	0	6	0.9996	0.9995	0.99971	5.984
7	2	7,1	54	0	6	0.9998	0.99992	0.99997	0.794
Tests of network properties and training parameters of the TC network									
1	2	1,1	28	0	6	0.99522	0.99236	0.99367	111.1055
2	2	2,1	20	0	6	0.99277	0.99713	0.98831	179.1784
3	2	3,1	64	0	6	0.99993	0.99992	0.99994	183.7075
4	2	4,1	1000	0	6	0.99999	0.99999	0.99999	0.8445
5	2	5,1	16	0	6	0.99999	0.99999	0.99999	1.412
6	2	6,1	15	0	6	0.90436	0.90488	0.92486	512.7797
7	2	7,1	31	0	6	0.9999	0.99993	0.99995	174.1735

Mathematical Model for Objective 1: WQ

$$\begin{aligned}
 & ((\tanh(((x(1)*0.0049968)+(x(2)*0.034285)+(x(3)*-0.019807)+(x(4)*-0.0017199)+(x(5)*-0.028447)+(x(6)*0.21671)+(x(7)*0.0026845)+(x(8)*0.65055)+(x(9)*-0.54799) \\
 &)+(x(10)*0.29388))-1.2197*(0.98079))+(\tanh(((x(1)*0.023596)+(x(2)*-0.023796)+(x(3)*0.017018)+(x(4)*-0.0017697)+(x(5)*0.01408)+(x(6)*0.19465)+(x(7)*0.0088156) \\
 &)+(x(8)*0.0022432)+(x(9)*0.2251)+(x(10)*-0.054291))+0.35684*(2.5357))+(\tanh(((x(1)*0.51644)+(x(2)*-0.67643)+(x(3)*0.42876)+(x(4)*-0.050383)+(x(5)*0.33247)+(x(6)*-0.40687)+(x(7)*0.23169)+(x(8)*0.62352)+(x(9)*-0.1063)+(x(10)*0.10346))+ \\
 & 0.44275)*(-0.098809))+(\tanh(((x(1)*0.18712)+(x(2)*0.22074)+(x(3)*-0.34564)+(x(4)*0.11958)+(x(5)*0.8441)+(x(6)*0.91911)+(x(7)*0.35738)+(x(8)*-0.32313)+(x(9)*-0.57589)+(x(10)*0.70755))+1.7017)*(-0.0066347)))+(0.0024435)
 \end{aligned}$$

Mathematical Model for Objective 2: TC

$$\begin{aligned}
 & ((\tanh(((x(1)*-0.12296)+(x(2)*-0.023867)+(x(3)*0.0034111)+(x(4)*-0.0035701)+(x(5)*0.0053158)+(x(6)*0.060386)+(x(7)*0.0081848)+(x(8)*0.057618)+(x(9)*-0.57626)+(x(10)*0.1538))-1.0877)*(-0.93585))+(\tanh(((x(1)*-0.010018)+(x(2)*-0.00054628)+(x(3)*0.00012626)+(x(4)*-0.00034296)+(x(5)*0.00065472)+(x(6)*0.18945)+(x(7)*0.0013192)+(x(8)*-0.00048837)+(x(9)*0.0041064)+(x(10)*0.013708))-0.3333*(4.7887))+(\tanh(((x(1)*0.16722)+(x(2)*-0.054691)+(x(3)*1.4496)+(x(4)*1.9163)+(x(5)*-1.1945)+(x(6)*-0.69915)+(x(7)*-0.40534)+(x(8)*-1.2844)+(x(9)*-0.73376)+(x(10)*-1.0179))+1.265)*(0.0013304))+(\tanh(((x(1)*-0.95432)+(x(2)*-0.8476)+(x(3)*-0.02556)+(x(4)*1.3022)+(x(5)*-0.90819)+(x(6)*-0.78808)+(x(7)*-0.31321)+(x(8)*0.47276)+(x(9)*0.18617)+(x(10)*-0.34263))-0.73638)*(-0.00036176)))+(0.79315)
 \end{aligned}$$

Finally, thanks to the strong capacity of ANNs to interpolate and extrapolate, it is possible at this stage to employ the mathematical models obtained to predict both the present and future behavior of the system for the two objectives. This capability supports identifying optimal operational decisions for the aquaculture enterprise.

The configuration and training procedure of the ANNs, implemented in the MATLAB environment, enables the development of models with high interpolation capability and low uncertainty (Ian Goodfellow, Yoshua Bengio & Courville, 2016; *MATLAB - El Lenguaje Del Cálculo Técnico*, n.d.). The topology selection based on automated criteria and the discussion on overparameterization risk follow the literature on architecture search and selection (Elsken *et al.*, 2018), while the interpretation techniques and model robustness evaluation are grounded in applicability-focused AI approaches (Samek *et al.*, 2017).

Optimization with Multi-Objective Genetic Algorithms (MOGA)

In optimization based on genetic algorithms, the initial population constitutes a fundamental starting point of the search, as the subsequent efficiency of the algorithm is closely related to the quality of the first generation of individuals. A genetic algorithm operates with numerical chromosomes to calculate fitness for the execution of genetic operators. The encoding procedure aims to represent chromosomes as bit strings containing all the necessary information (Ray *et al.*, 2022).

The ANNs are used to calculate fitness according to the various performance objectives to be optimized. For this purpose, it is necessary to use the limits of the water quality indicators (see Table 1). The main objective of this study is to simultaneously consider the performance criteria involved, taken in pairs.

For the MOGA optimization of the WQ and TC objectives, typical genetic operators were used to modify the composition of the offspring in the next generation, based on the predefined probability values presented in Table 7.

The integration of the functions derived from the ANNs into a MOGA framework enables efficient exploration of the solution space and the identification of Pareto fronts that represent the relationship between WQ and TC. The design of evolutionary operators and the ranking strategies employed are grounded in recent studies on evolutionary algorithms and hybrid frameworks for multi-objective optimization (Mandal *et al.*, 2018; Ray *et al.*, 2022). This combination facilitates the identification of nondominated solutions that can be operationally validated.

Table 7. MOGA optimization of WQ and TC.

MOGA parameters	
Population	200
Size number of generations	1000
Mutation	0.2
Crossover	Intermediate

Pareto Front Solutions for Decision Support

Pareto front solutions for decision support. It is important to recall that a Pareto optimal solution corresponds to a solution in which no improvement can be achieved in any of the objectives without causing a simultaneous deterioration in another (Mandal *et al.*, 2018). A Pareto optimal solution is also referred to as a non-dominated solution. Therefore, the best solution is the intersection point that presents the shortest distance to the ideal vector within the objective space, as shown in Figure 3.

This tool is considered important not only in engineering; its main advantage lies in providing a more representative visualization of all possible combinations, allowing decisions to be made based on the priorities, preferences, or specific constraints of the decision-maker. Figure 4 highlights a contradictory behavior between the two considered objectives, WQ and TC, as expected.

The presented results correspond to those obtained after the final Pareto sorting, applied to all optimal and feasible solutions found during the search to identify possible conflicting behaviors. In general, there may not exist a single optimal solution for a multi-objective problem, since one objective function can only improve at the expense of deteriorating

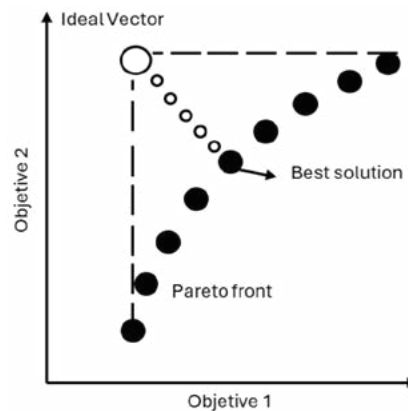


Figure 3. Conceptual representation of the Pareto front and the ideal solution.

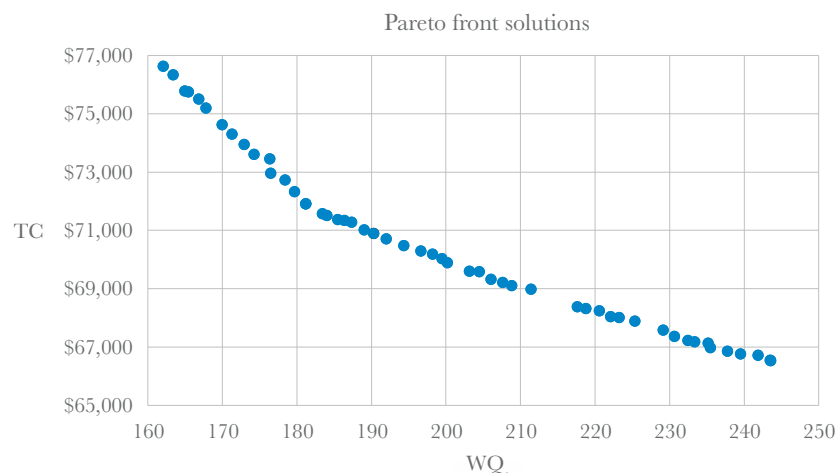


Figure 4. Pareto front with optimized solutions for water quality (WQ) and total cost (TC).

others due to their conflicting nature. Therefore, optimality becomes an illusion when the objectives are in conflict.

These criteria are of utmost importance to prevent any excess or deficiency in their final values. The hybrid methodology for solving multi-objective optimization problems is based on MOGA, coupling ANNs as evaluation functions. The reduction of TC contributes to lowering the maintenance costs of water quality indicators; however, maintaining the WQ standard represents a significant conflicting force. In Table 8, ten of the fifty-two results generated from the Pareto front are presented. WQ shows the minimum and maximum values associated with TC investment to ensure that water quality remains within acceptable standards.

Finally, as this cycle is repeated, AI tools will be able to strengthen their computations for greater accuracy and efficiency through continuous feedback and the contribution of a permanently updated database.

The Pareto front obtained clearly illustrates the trade-off between maximizing water quality and minimizing operational costs; this contradiction is consistent with previous findings in aquaculture management and sustainability indicators, highlighting the practical value of providing a set of solutions from which the decision-maker or management team can choose. Consequently, the proposed ANN–MOGA framework contributes a methodological tool that, although developed using simulated data, establishes a foundation for future implementations with real-time data and subsequent validation (Mandal *et al.*, 2018; Ray *et al.*, 2022; Samek *et al.*, 2017).

Table 8. Solutions for WQ y TC.

WQ	TC	Temperature	Dissolved Oxygen	pH	TAN	Nitrite	Nitrate	Transparency	Hardness	Alkalinity	Carbon Dioxide
162.1	\$ 76,614.47	19.818	5.905	7.061	0.31	1.205	0.768	41.426	65.343	50.253	19.241
163.4	\$ 76,329.68	19.757	5.847	7.046	0.31	1.202	0.764	41.418	65.999	50.274	19.216
166.85	\$ 75,485.84	19.61	5.698	7.009	0.308	1.199	0.739	41.394	67.685	50.313	19.2
196.67	\$ 70,279.92	19.414	5.052	6.905	0.288	1.264	0.49	41.247	79.198	50.368	19.471
199.47	\$ 70,028.27	19.434	5.02	6.904	0.286	1.274	0.453	41.237	80.084	50.428	19.523
200.23	\$ 69,882.39	19.453	5.017	6.906	0.286	1.277	0.483	41.235	80.315	50.375	19.53
203.16	\$ 69,590.12	19.49	4.989	6.907	0.284	1.287	0.528	41.225	81.208	50.353	19.561
239.57	\$ 66,748.62	19.861	4.673	6.922	0.259	1.406	0.534	41.106	91.427	50.591	19.933
241.87	\$ 66,713.21	19.877	4.651	6.922	0.257	1.412	0.571	41.101	92.017	50.642	19.956
243.61	\$ 66,525.09	19.894	4.636	6.923	0.256	1.418	0.543	41.095	92.481	50.644	19.972

CONCLUSIONS

The study demonstrated that the combination of Multi-Objective Genetic Algorithms (MOGA) and Artificial Neural Networks (ANN) is an effective tool to simultaneously

optimize water quality (WQ) and total cost (TC) in intensive aquaculture systems. MOGA calculated the best possible solution for water quality while respecting the cost constraint, which should remain between \$66,525 and \$76,615 per month for a 500 m³ earthen pond. The optimal ANN topology, configured with four hidden neurons, achieved a prediction accuracy greater than 99% for both objectives, confirming its reliability. Altogether, these results establish a methodological framework for decision support based on artificial intelligence, applicable to the efficient and sustainable management of tilapia farming systems.

REFERENCES

- Aggarwal, C. C. (2023). *Neural Networks and Deep Learning: A Textbook*. In *Neural Networks and Deep Learning: A Textbook*. Springer International Publishing. <https://doi.org/10.1007/978-3-031-29642-0/COVER>
- Anderson, J. C., & Gerbing, D. W. (1984). The Effects of Sampling Error on Convergence, Improper Solutions, and Goodness-of-Fit Indices for Maximum Likelihood Confirmatory Factor Analysis. *Psychometrika*, *49*(2), 155-173.
- Comité de Pesca. 36o período de sesiones, 8-12 de julio de 2024. Directrices para la acuicultura sostenible. (2024). FAO ; <https://openknowledge.fao.org/handle/20.500.14283/np423es>
- dblp: Simulation with SIMNET II. (n.d.). Retrieved October 9, 2025, from <https://dblp.org/rec/conf/wsc/Taha91.html>
- Elsken, T., Metzger, J. H., & Hutter, F. (2018). Neural Architecture Search: A Survey. *Journal of Machine Learning Research*, *20*, 1-21. <https://arxiv.org/pdf/1808.05377>
- Garlock, T. M., Asche, F., Anderson, J. L., Eggert, H., Anderson, T. M., Che, B., Chávez, C. A., Chu, J., Chukwuone, N., Dey, M. M., Fitzsimmons, K., Flores, J., Guillen, J., Kumar, G., Liu, L., Llorente, I., Nguyen, L., Nielsen, R., Pincinato, R. B. M., ... Tveteras, R. (2024). Environmental, economic, and social sustainability in aquaculture: the aquaculture performance indicators. *Nature Communications*, *15*(1), 5274. <https://doi.org/10.1038/S41467-024-49556-8>
- Ian Goodfellow, Yoshua Bengio, and A., & Courville. (2016). Deep learning. *Nature*, *22*, No.4 (pISSN 2093-3681 • eISSN 2093-369X), Number of pages: 800.
- Libro: Beyond Lean - Simulación en la Práctica (Standridge) - LibreTexts Español. (n.d.). Retrieved November 3, 2025, from [https://espanol.libretexts.org/Bookshelves/Ingenieria/Ingenieria_Industrial_y_de_Sistemas/Libro%3A_Beyond_Lean_-_Simulaci%C3%B3n_en_la_Pr%C3%A1ctica_\(Standridge\)](https://espanol.libretexts.org/Bookshelves/Ingenieria/Ingenieria_Industrial_y_de_Sistemas/Libro%3A_Beyond_Lean_-_Simulaci%C3%B3n_en_la_Pr%C3%A1ctica_(Standridge))
- Mandal, J. Kumar., Mukhopadhyay, Somnath., & Dutta, Paramartha. (2018). Multi-objective optimization : evolutionary to hybrid framework. Springer.
- Manual del agua: su naturaleza, tratamiento y aplicaciones - Frank N. Kemmer, Nalco Chemical Company - Google Libros. (n.d.). Retrieved October 9, 2025, from https://books.google.com.mx/books/about/Manual_del_agua.html?id=jbZ7NAAACAAJ&redir_esc=y
- MATLAB - El lenguaje del cálculo técnico. (n.d.). Retrieved October 9, 2025, from <https://la.mathworks.com/products/matlab.html>
- Ray, T., Mamun, M. M., & Singh, H. K. (2022). A Simple Evolutionary Algorithm for Multi-modal Multi-objective Optimization. 2022 IEEE Congress on Evolutionary Computation, CEC 2022 - Conference Proceedings. <https://doi.org/10.1109/CEC55065.2022.9870274>
- Samek, W., Wiegand, T., & Müller, K.-R. (2017). Explainable Artificial Intelligence: Understanding, Visualizing and Interpreting Deep Learning Models. <https://arxiv.org/pdf/1708.08296>
- Vásquez-Quispesivana, W., Inga, M., Betalleluz-Pallardel, I., La, A., Molina, M. A. La, Molina, L., & Perú, L. (2022). Inteligencia artificial en acuicultura: fundamentos, aplicaciones y perspectivas futuras. *Scientia Agropecuaria*, *13*(1), 79-96. <https://doi.org/10.17268/sci.agropecu.2022.008>
- Yang, J., Jia, L., Guo, Z., Shen, Y., Li, X., Mou, Z., Yu, K., & Lin, J. C. W. (2023). Prediction and control of water quality in Recirculating Aquaculture System based on hybrid neural network. *Engineering Applications of Artificial Intelligence*, *121*, 106002. <https://doi.org/10.1016/J.ENGAPPAL.2023.106002>
- Zhang, G., Eddy Patuwo, B., & Y. Hu, M. (1998). Forecasting with artificial neural networks:: The state of the art. *International Journal of Forecasting*, *14*(1), 35-62. [https://doi.org/10.1016/S0169-2070\(97\)00044-7](https://doi.org/10.1016/S0169-2070(97)00044-7)