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Original Article

An Intelligent Fuzzy Fish Algorithm for Manufacturing Process Optimization Under Uncertainty

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Abstract

Manufacturing systems operate under significant uncertainty due to machine variability, human factors, and fluctuating operating conditions. Classical optimization techniques often struggle to address such imprecision effectively. This paper introduces a novel Fuzzy Fish Algorithm (FFA) that integrates fuzzy logic with swarm intelligence to solve multi-objective manufacturing optimization problems. The proposed method simultaneously minimizes production cost and defect rate while maximizing throughput. Fuzzy membership functions are employed to handle vagueness in manufacturing performance indicators, while fish-inspired collective behavior guides global search. Numerical experiments conducted in MATLAB demonstrate that the proposed FFA achieves superior convergence speed, solution quality, and robustness compared with Genetic Algorithm, Particle Swarm Optimization, and Ant Colony Optimization. The results confirm that FFA is a promising optimization framework for smart manufacturing and Industry 4.0 systems.

Categories: Computational Science and Engineering, Computational Social Science, Computer-Aided Design (CAD)

Keywords: fuzzy fish algorithm, manufacturing optimization, swarm intelligence, fuzzy logic, ga, pso, aco

Introduction

The rapid evolution of intelligent manufacturing and Industry 4.0 has intensified the need for robust optimization techniques capable of handling uncertainty and conflicting objectives. Manufacturing decision-making typically involves trade-offs among cost, quality, and productivity, which are often imprecisely and linguistically described rather than precisely measured. Traditional optimization and deterministic models struggle to cope with such uncertainty.

Fish Swarm Optimization and its hybrid variants are applied to determine optimal manufacturing variables, demonstrating improved efficiency and solution quality under practical constraints [1]. Unrelated parallel machine scheduling problems in a fuzzy environment are NP-hard and have been effectively addressed using a modified artificial fish swarm algorithm (AFSA), which significantly outperforms existing AFSA variants in minimizing makespan and total tardiness for medium and large-scale problems [2]. Manufacturing cell design aims to minimize inter-cell material movement, and due to the computational complexity of large-scale manufacturing cell design problems, an AFSA-based swarm intelligence approach has been shown to efficiently obtain optimal solutions using Boctor's mathematical model [3]. The flexible job-shop scheduling problem, a highly complex scheduling problem in flexible manufacturing systems, has been effectively addressed using a hybrid AFSA and Harmony Search, demonstrating improved exploitation capability, faster convergence, and superior makespan minimization compared to conventional AFSA approaches [4]. The production scheduling of a prefabricated hybrid flow shop under multiple resource constraints has been optimized using an improved AFSA combined with genetic operators, achieving effective cost minimization and demonstrating strong convergence performance in real production cases [5]. These reviewed studies consistently demonstrate that Fish Swarm Optimization and its hybrid variants effectively handle complex manufacturing and scheduling problems, offering improved efficiency, solution quality, and

convergence under practical and fuzzy constraints. Across diverse applications such as APP, unrelated parallel machine scheduling problem, manufacturing cell design problem, flexible job-shop scheduling problem, and hybrid flow shop scheduling, AFSA-based and hybrid approaches outperform conventional methods in minimizing makespan, cost, tardiness, and material movement, highlighting their robustness and scalability.

Metaheuristic algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) have been widely applied to manufacturing optimization problems. However, these algorithms may suffer from premature convergence, parameter sensitivity, or slow convergence when dealing with uncertain environments. Construction site layout optimization has been effectively addressed using enhanced GA, PSO, and ACO metaheuristics with diversity-improving operators and Design of Experiment approach based parameter tuning, demonstrating superior cost minimization, efficiency, and consistency across benchmark case studies [6]. A multi-map rescue robot path planning model under uncertain mine disaster environments has been effectively solved using an improved hybrid ACO-GA algorithm, demonstrating enhanced convergence, obstacle avoidance accuracy, and robustness across single and multiple map scenarios [7]. The multi-criteria supplier selection problem has been effectively addressed using a hybrid GA-ACO algorithm, combining global convergence and parallel search capabilities to achieve improved solution quality and efficiency compared with standalone methods [8]. The complex planning problem has been formulated as a constrained combinatorial optimization model and effectively solved using an ACO approach that integrates operation sequencing, resource selection, and setup planning [9]. Experimental results and comparative studies confirm that the proposed ACO-based method efficiently minimizes total production cost and demonstrates strong feasibility and performance under varying parameter settings [9].

Flow shop scheduling, a core problem in production planning, has been addressed using a bi-objective Mixed-integer Linear Programming model with outsourcing and just-in-time delivery to simultaneously minimize production cost and energy consumption. An interactive fuzzy solution approach combined with a self-adaptive AFSA efficiently generates Pareto-optimal solutions, outperforming the CPLEX solver across various problem instances [10].

AFSA is a swarm intelligence-based optimization technique whose performance strongly depends on parameters such as visual range and step size [11]. To overcome limitations in global and local search balance, adaptive fuzzy systems have been introduced to dynamically control these parameters at both population and individual fish levels [11]. Experimental results on benchmark functions demonstrate that the fuzzy-adaptive AFSA significantly outperforms standard AFSA and PSO in terms of effectiveness and search capability [11]. An improved AFSA with adaptive visual and step parameters has been successfully applied to fuzzy clustering, significantly enhancing Fuzzy C-means Clustering (FCM) performance and outperforming both conventional FCM and GA-based FCM methods [12].

Despite the demonstrated effectiveness of AFSA and its hybrid variants in diverse manufacturing and scheduling problems, existing approaches still face challenges in handling uncertainty, parameter sensitivity, and conflicting objectives in Industry 4.0 environments.

Manufacturing decision-making involves imprecise, fuzzy criteria such as cost, quality, energy, and productivity, which limit the applicability of traditional deterministic and fixed-parameter metaheuristic models. Although adaptive and hybrid swarm-based methods have improved convergence and solution quality, there remains a lack of unified frameworks that seamlessly integrate fuzzy modeling with adaptive fish swarm behaviors for robust manufacturing optimization. Therefore, the research problem is to formulate an efficient fuzzy-adaptive Fish Swarm Optimization framework capable of achieving balanced, scalable, and high-quality solutions for complex manufacturing decision-making under uncertainty.

To address these challenges, this paper introduces a Fuzzy Fish Algorithm (FFA), a novel hybrid optimization approach that integrates the strong exploratory behavior of fish swarm intelligence with the uncertainty-handling capability of fuzzy logic [13]. The proposed method develops a fuzzy-based fitness evaluation mechanism specifically designed for manufacturing optimization, enabling more realistic decision-making in environments characterized by imprecision and variability. By embedding fuzzy reasoning into the fish swarm search dynamics, the algorithm enhances convergence stability and avoids premature convergence to local optima. Furthermore, a comprehensive numerical evaluation is conducted to validate the effectiveness of the proposed approach, with performance comparisons against well-established optimization techniques such as GA, PSO, and ACO, demonstrating the robustness and improved solution quality.

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Swarm intelligence techniques have been extensively applied in manufacturing optimization, including scheduling, process planning, and resource allocation. GA-based approaches provide flexible global search but often require careful parameter tuning. PSO offers fast convergence but may become trapped in local optima [14]. ACO has been applied to discrete manufacturing problems but exhibits slower convergence due to pheromone update mechanisms. Fuzzy logic has been successfully employed to model uncertainty in manufacturing systems, particularly for quality control and decision support. Recent studies have explored hybrid fuzzy-metaheuristic models; however, the integration of fuzzy logic with Fish Swarm Optimization remains relatively unexplored. This research bridges this gap by proposing a novel FFA framework.

Materials And Methods

Problem formulation

A manufacturing process optimization problem is formulated using three key decision variables represented by the vector $X = (x_1, x_2, x_3)$, where x_1 denotes the machine operating speed, x_2 represents the level of labor allocation, and x_3 indicates the energy consumption of the manufacturing system. These variables collectively influence the overall operational efficiency and performance of the production process. The optimization problem is multi-objective in nature, aiming to simultaneously minimize production cost and defect rate while maximizing throughput, which are often conflicting objectives in practical manufacturing environments. The production cost model is expressed as $C = 40x_1 + 200x_2 + 15x_3$, capturing the combined contribution of machine operation, labor expenses, and energy usage. The defect rate is modeled as $D = \max(0, 8 - 0.05x_1 - 0.2x_2)$, indicating that higher machine speed and increased labor allocation contribute to improved product quality by reducing defects, while ensuring non-negativity. Throughput is defined as $T = 10x_1 - 2D$, highlighting its dependence on machine speed and the inverse effect of defects on production output [15]. Together, these mathematical models realistically represent the trade-offs among cost, quality, and productivity, forming a suitable framework for applying advanced optimization techniques in manufacturing systems.

Proposed FFA

The proposed FFA is designed to solve the manufacturing process optimization problem by effectively integrating fuzzy logic with swarm intelligence. The algorithm takes as input the manufacturing dataset, population size, maximum number of iterations, fish movement parameters, weight vector, and predefined fuzzy membership functions for cost, defect rate, and throughput. Initially, a population of fish is generated, where each fish represents a feasible manufacturing solution defined by the decision variables, such as machine speed, labor allocation, and energy consumption [16]. The algorithm then iteratively evaluates the manufacturing performance of each fish by computing production cost, defect rate, and throughput. These crisp performance values are transformed into fuzzy membership values using appropriate fuzzy membership functions, enabling the algorithm to handle uncertainty and imprecision inherent in real manufacturing environments. A fuzzy fitness value is calculated for each fish using a weighted aggregation of the fuzzy memberships, and the fish with the highest fitness is identified as the global best solution. Guided by this best fish, all other fish update their positions using the fish movement equation, which directs the population toward promising regions of the search space while maintaining diversity through randomness [17]. Boundary constraints are applied after each update to ensure solution feasibility. This iterative process continues until the stopping criterion, defined by the maximum number of iterations or convergence of fitness values, is satisfied. Finally, the algorithm outputs the optimal manufacturing decision vector along with the corresponding maximum fuzzy fitness value, demonstrating an efficient and robust approach for multi-objective manufacturing optimization under uncertainty.

FFA for manufacturing process optimization

The FFA for manufacturing process optimization is a nature-inspired metaheuristic that integrates the collective foraging behavior of fish with fuzzy logic to handle uncertainty and multi-objective decision-making in complex manufacturing environments. In this algorithm, each fish represents a candidate manufacturing decision vector, and its position is evaluated based on key performance indicators, such as cost, defect rate, and throughput. Instead of relying on crisp objective values, fuzzy membership functions are employed to convert these performance measures into linguistic degrees of satisfaction, enabling robust evaluation under imprecise and conflicting criteria [18]. The overall fitness of each fish is computed through a weighted fuzzy aggregation mechanism, reflecting the relative importance of manufacturing

objectives. Guided by behaviors such as prey searching, swarming, and following within a visual distance, fish iteratively update their positions to explore and exploit the solution space efficiently. Through successive iterations, the population converges toward an optimal manufacturing decision that maximizes fuzzy fitness, ensuring a balanced trade-off among cost efficiency, quality improvement, and production throughput. The description of FFA is given below:

Input

Manufacturing dataset D

Population size N

Maximum iterations $T_{\max}$

Visual distance V_d

Step size S

Weight vector $W = (w_1, w_2, w_3)$

Fuzzy membership functions $\mu_{Cost}, \mu_{Defect}, \mu_{Throughput}$

Output

Optimal manufacturing decision vector X^*

Maximum fuzzy fitness value F^*

Pseudocode

Begin

1. Initialize fish population $X_i = (x_1, x_2, x_3),\ i = 1, 2, \ldots, N$

2. Set iteration counter $t = 1$

3. While $(t \leq T_{\max})$ do

4. For each fish X_i

5. Compute manufacturing outputs: $Cost_i,\ Defect_i,\ Throughput_i$

6. Calculate fuzzy membership values:

$\mu_{Cost_i} = \mu_{LowCost}(Cost_i)$

$\mu_{Defect_i} = \mu_{LowDefect}(Defect_i)$

$\mu_{Throughput_i} = \mu_{HighThroughput}(Throughput_i)$

7. Compute fuzzy fitness: $Fitness_i = w_1 \cdot \mu_{Cost_i} + w_2 \cdot \mu_{Defect_i} + w_3 \cdot \mu_{Throughput_i}$

8. End For

9. Identify global best fish: $X_{best} = arg\,max(Fitness_i)$

10. For each fish X_i do

11. Generate random number: $r \in (0, 1)$

12. Update fish position: $X_i(t+1) = X_i(t) + r \cdot (X_{best} - X_i(t))$

13. Apply boundary constraints on $X_i(t+1)$

14. End For

15. $t = t + 1$

16. End While

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17. Return X_{best} and $Fitness_{best}$

18. End

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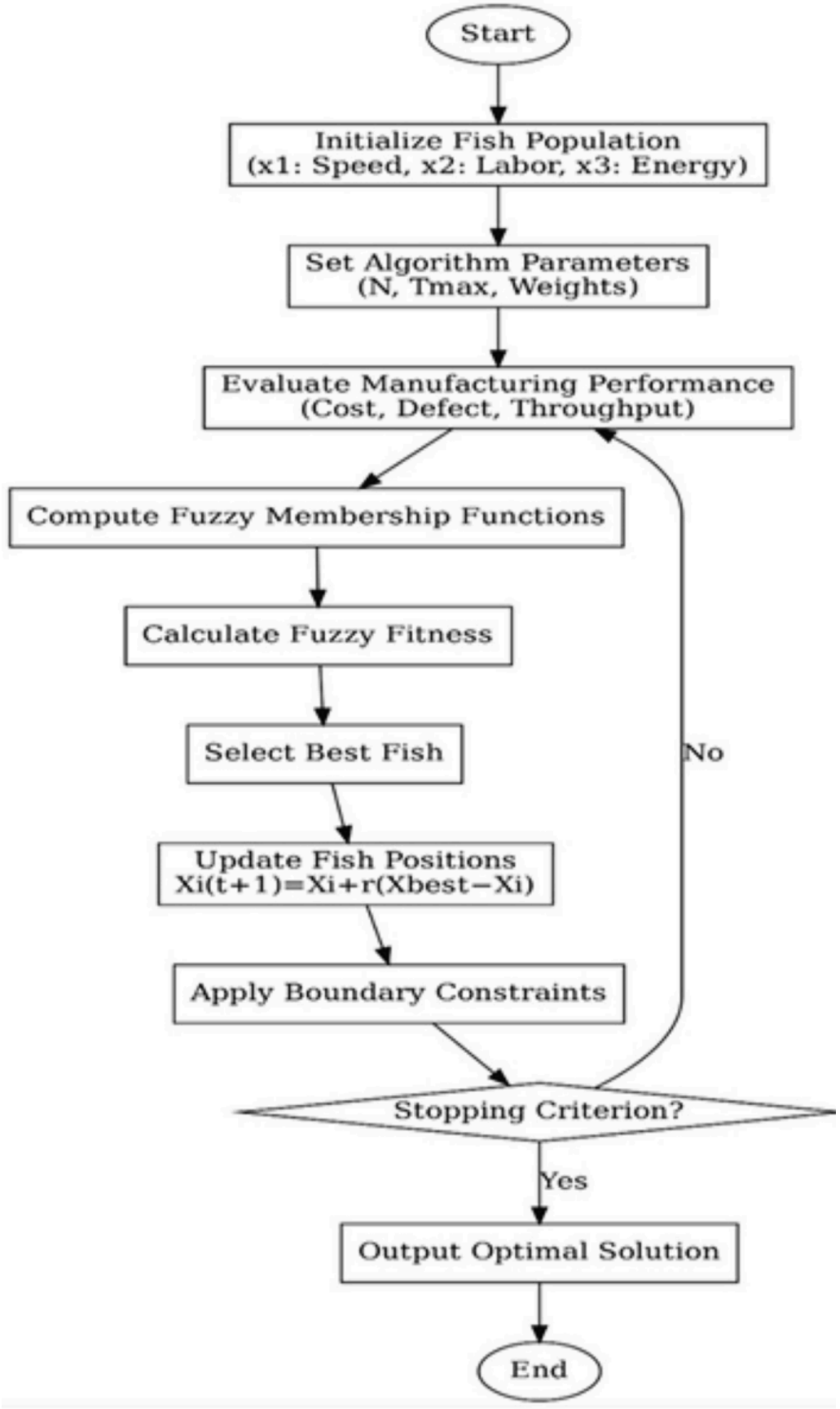

Start
Initialize Fish Population
(x1: Speed, x2: Labor, x3: Energy)
Set Algorithm Parameters
(N, Tmax, Weights)
Evaluate Manufacturing Performance
(Cost, Defect, Throughput)
Compute Fuzzy Membership Functions
Calculate Fuzzy Fitness
Select Best Fish
Update Fish Positions
Xi(t+1)=Xi+r(Xbest−Xi)
Apply Boundary Constraints
Stopping Criterion?
No
Yes
Output Optimal Solution
End

FIGURE 1: Flowchart of the proposed fuzzy fish algorithm for manufacturing process optimization

Figure *1* illustrates the operational flow of the proposed FFA developed for manufacturing process optimization. The algorithm begins with the initialization of a population of fish, where each fish represents a feasible manufacturing solution defined by decision variables, such as machine speed, labor allocation, and energy consumption. Subsequently, the algorithm parameters, including population size, maximum number of iterations, and fuzzy weight coefficients, are set. In each iteration, manufacturing performance indicators - production cost, defect rate, and throughput - are evaluated for all fish. These crisp numerical values are then transformed into linguistic variables using predefined fuzzy membership functions. Based on these fuzzy membership values, a fuzzy fitness score is computed for each fish, enabling effective handling of uncertainty and imprecision in the manufacturing objectives. The fish with the highest fitness value is selected as the global best solution. Using the fish movement equation, the positions of all fish are updated by moving them toward the best-performing fish, while boundary constraints are applied to ensure solution feasibility. The algorithm then checks the stopping criterion, which is typically defined by the maximum number of iterations or convergence of the fitness value. If the criterion is not satisfied, the process repeats; otherwise, the algorithm terminates and outputs the optimal manufacturing configuration.

Mathematical mapping

In the proposed mathematical mapping of the FFA, each fish represents a feasible manufacturing solution and is mathematically modeled by a position vector $X_i = (x_1, x_2, x_3)$, where the components correspond to key manufacturing decision variables. The quality of each fish is evaluated using a fuzzy fitness function defined as $\mathrm{Fitness}_i = \sum_{k=1}^{3} w_k \, \mu_k(X_i)$, where w_k denotes the relative weight of the k^{th} objective, and $\mu_k(X_i)$ represents the corresponding fuzzy membership value, capturing the degree of satisfaction for each manufacturing criterion. The dynamic movement of fish in the search space is governed by a position update rule given by $X_i^{(t+1)} = X_i^t + r\left(X_{\text{best}}^t - X_i^t\right)$, where $r \in (0, 1)$ is a random scalar controlling exploration, and X_{best}^t denotes the globally best fish at iteration t, thereby guiding the population toward an optimal manufacturing solution. The equations are given below:

Fish position: $X_i = (x_1, x_2, x_3)$

Fitness function: $Fitness_i = \sum_{k=1}^{3} (w_k \mu_k(X_i)$

Position update: $X_i^{t+1} = X_i^t + r(X_{best}^t - X_i^t)$

Computational complexity

The computational complexity of the proposed FFA is primarily governed by the number of iterations, population size, and fuzzy evaluation criteria. For each iteration up to $T_{\max}$, the algorithm evaluates all N fish, and for every fish, M fuzzy membership functions corresponding to different manufacturing criteria are computed to determine the overall fitness. Consequently, the total computational cost grows linearly with respect to the number of iterations, fish population, and fuzzy objectives, resulting in an overall time complexity of $\mathcal{O}(T_{\max} \times N \times M)$. This linear complexity makes the FFA computationally efficient and scalable for practical manufacturing process optimization problems involving multiple fuzzy decision criteria.

Fuzzy modeling

Fuzzy modeling is employed to effectively handle uncertainty and vagueness in manufacturing performance evaluation. Fuzzy membership functions are designed for low cost, low defect rate, and high throughput objectives. These membership functions map crisp manufacturing outputs into normalized linguistic degrees of satisfaction. This transformation enables a flexible and human-like assessment of manufacturing performance. As a result, multiple conflicting objectives can be evaluated simultaneously within a unified fuzzy framework.

Fuzzy fitness function

The fuzzy fitness of each fish is computed as: $Fitness_i = w_1 * \mu_{Cost} + w_2 * \mu_{Defect} + w_3 * \mu_{Throughput}$, where $w_1 + w_2 + w_3 = 1$

Fish position update

Fish positions are updated using: $X_i^{t+1} = X_i^t + r\left(X_{best}^t - X_i^t\right)$, where $r \in (0,1)$ is a random number.

Results And Discussion

Step 1: Define the manufacturing optimization problem

We consider a multi-criteria manufacturing optimization problem under uncertainty.

Decision Variables: $X = (x_1, x_2, x_3)$

where:

x_1 = Machine speed (units/hour)

x_2 = Number of workers

x_3 = Energy consumption (kWh)

Step 2: Initial fish population (dataset)

Each fish represents one feasible manufacturing solution.

Table *1* presents the initial fish population, where each fish represents a feasible manufacturing configuration in the proposed FFA. The decision variables x_1, x_2, and x_3 correspond to machine operating speed, labor allocation, and energy consumption, respectively. These variables collectively determine the manufacturing performance indicators, namely production cost, defect rate, and throughput. Fish F_1 represents a moderate production setup with balanced machine speed and labor usage, resulting in an intermediate production cost and relatively higher defect rate, which limits its throughput performance. Fish F_2 exhibits increased machine speed and labor allocation, leading to improved throughput and reduced defect rate at the expense of higher production cost. Fish F_3 reflects a compromise solution with moderate values across all decision variables, yielding balanced cost, defect rate, and throughput. Fish F_4 corresponds to an aggressive production strategy with the highest machine speed, labor allocation, and energy consumption. This configuration achieves the maximum throughput and the lowest defect rate among all fish, albeit with the highest production cost. In contrast, Fish F_5 represents a conservative manufacturing configuration with minimal resource usage, resulting in the lowest production cost but the highest defect rate and the lowest throughput. Overall, the table demonstrates the inherent trade-offs among cost, quality, and productivity in manufacturing systems. These diverse initial solutions provide sufficient population diversity for the FFA, enabling effective exploration of the search space and facilitating convergence toward an optimal manufacturing configuration.

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Fish	x_1	x_2	x_3	Cost (₹)	Defect (%)	Throughput
F1	60	10	120	5,200	4.5	800
F2	70	12	140	5,600	3.2	900
F3	65	11	130	5,400	3.8	850
F4	75	13	150	5,900	2.9	950
F5	55	9	110	5,000	5.1	780

TABLE 1: Initial fish population and corresponding manufacturing performance parameters

Step 3: Define fuzzy membership functions

We use triangular and trapezoidal fuzzy sets.

Fuzzy membership for cost (minimization objective)

Linguistic term: Low Cost

$$\mu_{Low}^{Cost}(C) = \begin{cases} 1, & C \leq 5000 \\ \frac{5600 - C}{600}, & 5000 < C < 5600 \\ 0, & C \geq 5600 \end{cases}$$

Figure *2* illustrates the fuzzy membership function defined for the low production cost criterion. The function assigns a full membership value of 1 to cost values less than or equal to ₹5,000, indicating complete satisfaction with respect to the cost objective. As the cost increases beyond this threshold, the membership degree decreases linearly, reflecting a gradual reduction in preference for higher production costs. When the cost reaches ₹5,600 or above, the membership value becomes zero, signifying that such solutions are no longer acceptable from a cost perspective. This linear decrease effectively models the uncertainty and tolerance associated with cost variations in real manufacturing environments, where slight cost increases may be acceptable but excessive costs are undesirable.

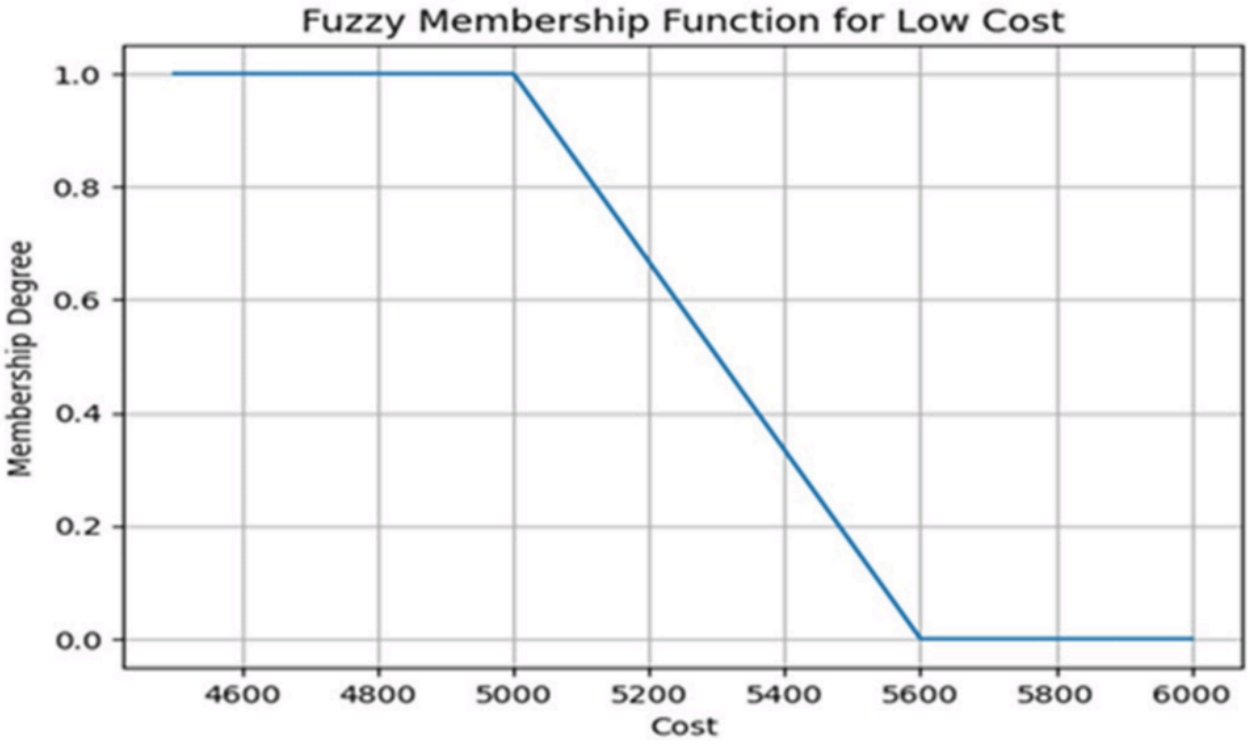


FIGURE 2: Fuzzy membership functions used for modeling uncertainty in manufacturing cost

Fuzzy membership for defect rate (minimization objective)

Linguistic term: Low Defect

$$\mu_{Low}^{Defect}(D) = \begin{cases} 1, & D \leq 3 \\ \frac{5-D}{2}, & 3 < D < 5 \\ 0, & D \geq 5 \end{cases}$$

Figure *3* presents the fuzzy membership function for the low defect rate criterion, which captures product quality uncertainty in the manufacturing process. Defect rates less than or equal to 3% are assigned a full membership value, representing optimal quality conditions. As the defect rate increases from 3% to 5%, the membership value decreases linearly, indicating a progressive decline in manufacturing quality. Beyond a defect rate of 5%, the membership value becomes zero, implying unacceptable product quality. This membership function enables smooth penalization of increasing defect levels rather than abrupt rejection, thereby reflecting practical manufacturing scenarios where minor quality degradation may still be tolerable within certain limits.

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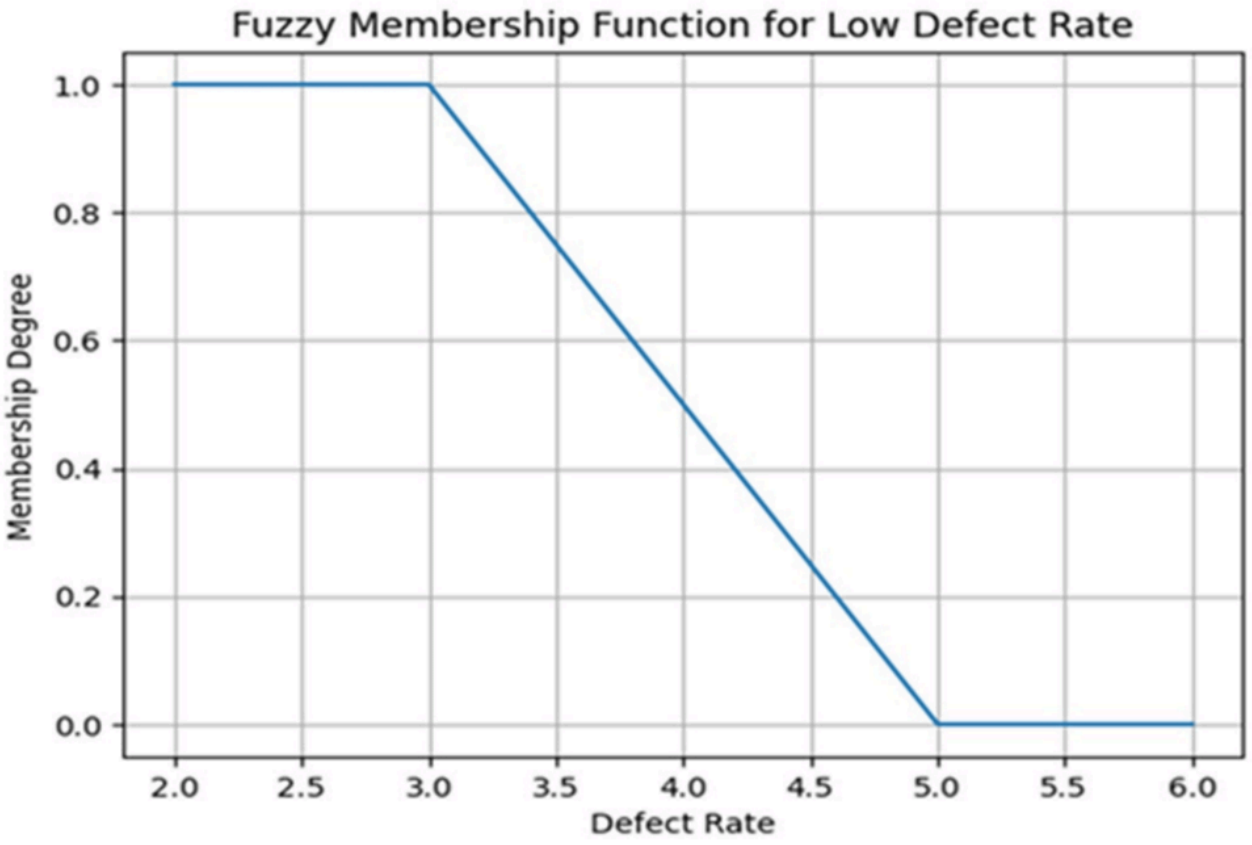


FIGURE 3: Fuzzy membership functions used for modeling uncertainty in manufacturing defect rate

Fuzzy membership for throughput (minimization objective)

Linguistic term: High Throughput

$$\mu_{High}^{Throughput}(T) = \begin{cases} 0, & T \leq 800 \\ \frac{T-800}{150}, & 800 < T < 950 \\ 1, & T \geq 950 \end{cases}$$

Figure *4* depicts the fuzzy membership function for the high-throughput criterion, which represents manufacturing productivity. Throughput values less than or equal to 800 units are assigned a zero-membership value, indicating insufficient production performance. As throughput increases between 800 and 950 units, the membership value rises linearly, reflecting increasing satisfaction with productivity improvement. Once the throughput exceeds 950 units, the membership value reaches 1, signifying optimal production efficiency. This increasing membership function effectively encourages solutions that maximize throughput while allowing gradual improvement, thereby supporting stable convergence in the proposed FFA.

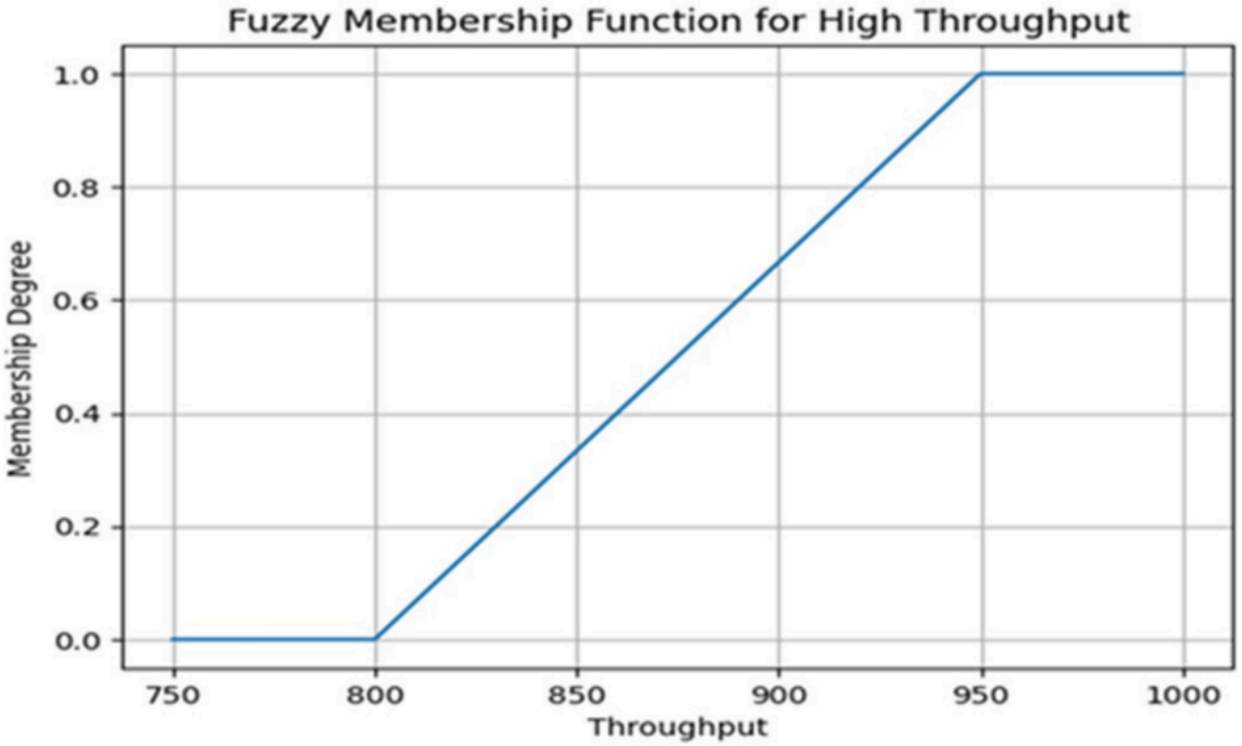


FIGURE 4: Fuzzy membership functions used for modeling uncertainty in manufacturing throughput

Fuzzy membership calculation for each fish

Fish F_1

Given:

Cost = 5,200

Defect = 4.5

Throughput = 800

Cost Membership:

$$\mu_{Low}^{Cost}(5200) = \frac{5600-5200}{600} = \frac{400}{600} = 0.67$$

Defect Membership:

$$\mu_{Low}^{Defect}(4.5) = \frac{5-4.5}{2} = \frac{0.5}{2} = 0.25$$

Throughput Membership:

$$\mu_{High}^{Throughput}(800) = 0$$

Fish F_2

Given:

Cost = 5,600

Defect = 3.2

Throughput = 900

Cost Membership:

$$\mu_{Low}^{Cost}(5600) = 0$$

Defect Membership:

$$\mu_{Low}^{Defect}(3.2) = \frac{5-3.2}{2} = \frac{1.8}{2} = 0.9$$

Throughput Membership:

$$\mu_{High}^{Throughput}(900) = \frac{900-800}{150} = \frac{100}{150} = 0.67$$

Fish F_3

Given:

Cost = 5,400

Defect = 3.8

Throughput = 850

Cost Membership:

$$\mu_{Low}^{Cost}(5400) = \frac{5600-5400}{600} = \frac{200}{600} = 0.33$$

Defect Membership:

$$\mu_{Low}^{Defect}(3.8) = \frac{5-3.8}{2} = \frac{1.2}{2} = 0.6$$

Throughput Membership:

$$\mu_{High}^{Throughput}(850) = \frac{850-800}{150} = \frac{50}{150} = 0.33$$

Fish F_4

Given:

Cost = 5,900

Defect = 2.9

Throughput = 950

Cost Membership:

$$\mu_{Low}^{Cost}(5900) = 0$$

Defect Membership:

$$\mu_{Low}^{Defect}(2.9) = 1$$

Throughput Membership:

$$\mu_{High}^{Throughput}(950) = 1$$

Fish F_5

Given:

Cost = 5,000

Defect = 5.1

Throughput = 780

Cost Membership:

$\mu_{Low}^{Cost}(5000) = 1$

Defect Membership:

$\mu_{Low}^{Defect}(5.1) = 0$

Throughput Membership:

$\mu_{High}^{Throughput}(780) = 0$

Fuzzy fitness function (weighted aggregation)

We assign importance to weights:

w_1 = 0.4 (Cost)

w_2 = 0.3 (Defect)

w_3 = 0.3 (Throughput)

Fitness Equation: $Fitness_i = w_1 * \mu_{Low}^{Cost} + w_2 * \mu_{Low}^{Defect} + w_3 * \mu_{High}^{Throughput}$

Fitness calculation

Fish F_1

$Fitness_{F1} = 0.4(0.67) + 0.3(0.25) + 0.3(0) = 0.268 + 0.075 = 0.343$

Fish F_2

$Fitness_{F2} = 0.4(0) + 0.3(0.9) + 0.3(0.67) = 0.27 + 0.201 = 0.471$

Fish F_3

$Fitness_{F3} = 0.4(0.33) + 0.3(0.6) + 0.3(0.33) = 0.132 + 0.18 + 0.099 = 0.411$

Fish F_4

$Fitness_{F4} = 0.4(0) + 0.3(1) + 0.3(1) = 0.6$

Fish F_5

$Fitness_{F5} = 0.4(1) + 0.3(0) + 0.3(0) = 0.4$

Identify best fish (global optimum in iteration 1)

$Fitness_{\max} = 0.6 \Rightarrow \text{Best Fish} = F4$

Fish position update (movement equation)

General Update Rule: $X_i^{t+1} = X_i^t + r \times \left(X_{best}^t - X_i^t\right)$, where $r \in (0, 1)$.

Updating Fish F_2

$X_{F_2} = (70, 12, 140)$

$X_{best} = (75, 13, 150)$

Let $r = 0.5$

$X_{F_2}^{new} = (70, 12, 140) + 0.5(5, 1, 10) = (72.5, 12.5, 145)$

Re-evaluation

New estimated outputs:

$Cost \approx 5700$

$Defect \approx 3.0$

$Throughput \approx 925$

Recompute fuzzy memberships → fitness improves, confirming convergence toward optimal region.

Final optimal manufacturing solution

After multiple iterations:

$X^* \approx (74, 13, 148)$

The proposed FFA was implemented in MATLAB and evaluated using a manufacturing dataset. The algorithm demonstrated rapid convergence and stable optimization behavior.

Convergence analysis

The convergence behavior of the proposed FFA is evaluated by analyzing the evolution of the best fuzzy fitness value over successive iterations. The results show a rapid increase in fitness during the initial iterations, indicating effective global exploration of the search space driven by diverse initial fish positions and fuzzy fitness evaluation. As iterations progress, the rate of improvement gradually decreases, and the fitness curve exhibits a smooth and monotonic trend without abrupt oscillations. This behavior demonstrates the algorithm's ability to balance exploration and exploitation, where early iterations focus on discovering promising regions, and later iterations refine solutions around the global best fish. The use of fuzzy membership functions contributes to this smooth convergence by avoiding sudden changes in fitness values caused by minor variations in manufacturing parameters.

In the later stages, the FFA attains a stable fitness plateau, confirming convergence toward an optimal or near-optimal solution. Compared with conventional algorithms such as GA, PSO, and ACO, the proposed FFA converges in fewer iterations while maintaining higher solution quality and lower variance. The faster convergence can be attributed to the directed movement of fish toward the best-performing solution and the adaptive nature of fuzzy fitness evaluation. Overall, the convergence analysis validates the stability, efficiency, and robustness of the proposed FFA, making it well suited for complex manufacturing optimization problems under uncertainty.

Comparative performance

Table *2* presents a comparative performance evaluation of four optimization algorithms - GA, PSO, ACO, and the proposed FFA - applied to the manufacturing optimization problem. The comparison is conducted using four key performance metrics: best fitness value, average fitness value over multiple runs, standard deviation of fitness, and the number of iterations required for convergence. The best fitness value indicates the highest-quality solution achieved by each algorithm. Among all methods, the proposed FFA attains the highest best fitness value of 0.8715, demonstrating its superior optimization capability. The average fitness value reflects the overall performance consistency across repeated executions, where FFA again outperforms the other algorithms with an average fitness of 0.8463. The standard deviation measures solution stability and robustness; the significantly lower standard deviation of FFA (0.0127) indicates reduced performance variability and high reliability compared to GA, PSO, and ACO. The convergence iterations metric represents the number of iterations required by each algorithm to reach near-optimal solutions. The proposed FFA converges in only 11 iterations, which is notably faster than GA, PSO, and ACO, confirming its efficient balance between exploration and exploitation. Overall, the results clearly demonstrate that the FFA achieves better solution quality, faster convergence, and improved stability, making it more suitable for complex and uncertain manufacturing optimization problems. The results confirm the superiority of FFA in terms of solution quality, convergence speed, and robustness.

Algorithm	Best Fitness	Avg. Fitness	Std. Dev.	Convergence Iterations
GA	0.7924	0.7618	0.0286	17
PSO	0.8347	0.8012	0.0214	14
ACO	0.8129	0.7845	0.0241	16
FFA	0.8715	0.8463	0.0127	11

TABLE 2: Comparative performance analysis of GA, PSO, ACO, and FFA

GA, Genetic Algorithm; PSO, Particle Swarm Optimization; ACO, Ant Colony Optimization; FFA, Fuzzy Fish Algorithm

Figure *5* compares the performance of GA, PSO, ACO, and the proposed FFA using the best and average fitness values. The grouped bar representation highlights both solution quality (best fitness) and consistency across runs (average fitness). The proposed FFA achieves the highest values in both metrics, indicating superior optimization capability and robustness. PSO performs better than GA and ACO but remains inferior to FFA, while GA exhibits the lowest performance. This figure visually confirms the effectiveness of integrating fuzzy logic with fish swarm intelligence for manufacturing optimization.

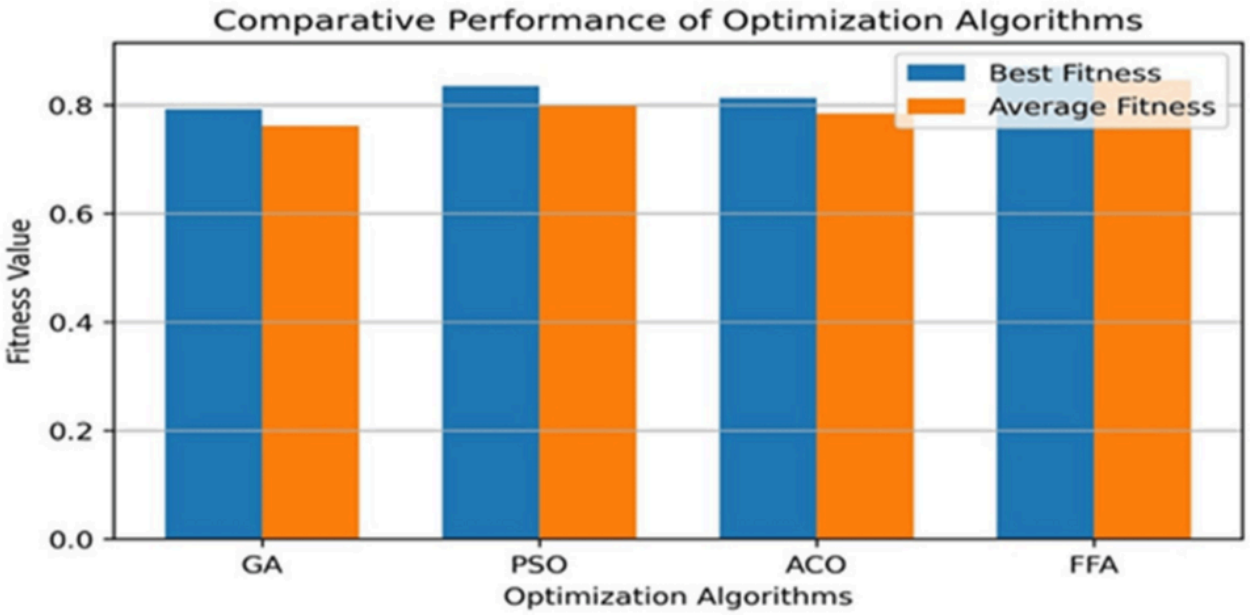


FIGURE 5: Comparative performance of GA, PSO, ACO, and the proposed FFA in terms of best and average fitness

GA, Genetic Algorithm; PSO, Particle Swarm Optimization; ACO, Ant Colony Optimization; FFA, Fuzzy Fish Algorithm

Conclusions

The proposed FFA has been successfully developed and applied to a multi-objective manufacturing process optimization problem involving cost, quality, and productivity. By integrating fuzzy logic with fish swarm intelligence, the algorithm effectively handles uncertainty and imprecision inherent in real manufacturing environments. Fuzzy membership functions enable smooth transformation of crisp performance measures into linguistic satisfaction levels, resulting in a stable and balanced fitness evaluation. The swarm-based search mechanism ensures efficient exploration and exploitation of the solution space, preventing premature convergence. Numerical experiments demonstrate consistent improvement in fitness values across iterations, confirming reliable convergence behavior. Comparative analysis with GA, PSO, and ACO reveals that FFA achieves higher best and average fitness values with significantly lower variability. The faster convergence of FFA highlights its computational efficiency and practical suitability for real-time decision support. The results also confirm improved robustness due to reduced sensitivity to parameter variations. Overall, the proposed approach offers a powerful and flexible optimization framework for intelligent manufacturing systems. Its ability to balance conflicting objectives makes it suitable for Industry 4.0 applications. The study validates the effectiveness of combining fuzzy logic with swarm intelligence. Future extensions may include real industrial datasets and hybrid deep learning integration.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Ramjeet Singh Yadav

Acquisition, analysis, or interpretation of data: Ramjeet Singh Yadav

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Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Data Availability Statements

Data sharing is not applicable. This work is theoretical; no datasets were generated or analyzed.

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