

# AI-driven optimization of the Particle Swarm reduces the mortality of Prawns

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**Abstract-** Even though the Prawn, Shrimp, and Lobster (PSL) fertility rate is rather high, but their birth and death rates is imbalanced. Most of the PSL died after hatching but the reason is unknown. PSL convert into Nauplius after hatching. Nauplius birth and death rate is relatively poor, and the reason is an enigma. This is why the indemnification redemption process calls for well-considered pertinent substantiated research. PSL lays 300,000 to 500,000 eggs on the ocean floor, but their survival rate is under 50%. This study uses the artificial intelligence algorithms Particle Swarm Optimization (PSO) and Fuzzy Analytical Hierarchical Process (FAHP) to address the early stage of PSL migration from egg hatching to Nauplius. The migration of (PSL) Nauplius from the seabed to the optimum feed, best position, and ideal velocity is the first stage of this investigation. Best feed and related (PSL) growth is the focus of the second phase of this study. To attain better outcomes in terms of PSL weight, four different diets, chemicals, and temperatures were fed in four distinct ponds. Particle (PSL) movement toward the objective or search space—in this case, a sea, river, or control-conditioned pond—is closely related to particle swarm optimization, which was applied in this study. These PSLs travel from their starting position to the ideal position for a higher quality of life at a predetermined speed. PSL movement decisions are influenced by cost, population, learning coefficients, and particle global, among other interrelated factors. The related factors that affect PSL movement choices are cost, population, learning coefficients, particle global position, particle current location, updated PSL location, and particle velocity. The particles learn the path, timing, and velocity once they have communicated and moved to their optimum location. Salinity, dissolved oxygen, nutritional food, and other factors come into play once the PSLs have reached their appropriate site. These two algorithms will display the birth and mortality rates in the PSL. They will cooperate in order to restore PSL growth.

**Index Terms-** Artificial Intelligence, Particle swarm optimization, Fuzzy Analytical Hierarchical Process.

## 1 Introduction

In order to achieve gigantic for powerful comprehension, intelligence represents diametric understanding based on considered environmental information. The Food and Agriculture Organization (FAO) and the Worldwide Fund

(WWF) are about to invest a significant sum of money in aquamarine rehabilitation, according to various unassailable facts that are having negative effects on the life of (PSL) in its early stages and that deprived aquamarine life by vexing exacerbation. Once enough time has passed, the PSL life cycle will be completely destroyed by the dreaded, disturbed forces. The following questions will be addressed by this study, and they are as follows:

(i) Is there a technique to track PSL growth round-the-clock or reduce PSL Nauplius mortality through research?

(ii) Is it possible to do pH sensing under control condition to ensure the purity of the water?

(iii) Is there an artificial intelligence (AI) model or prototype is available that can detect food, chemicals, dissolved oxygen, and water temperature of PSL ponds?

(iv) Is it possible to obtain real time results from AI? The PS optimization moves a particle through learning and communication from a general location to an optimum location while maintaining a constant speed. PSO will lead to an increase in the death and birth model of PSL, and FAHP will make sure that the aforementioned atmosphere is ideal for their growth rate. In conclusion, the farmers will profit financially, and both the environment and PSL will gain.

Any particle's main objective is to seek for and acquire the best space at a particular velocity to fulfil its purpose. FAHP is further broken into four primary categories. a) Formulation of the aforementioned issue, b) Accuracy of the facts utilizing mathematical comparison, c) vindication or consistency checks, and d) in-depth study employing unprovable connected facts from the beginning. The proposed system is something that carries out difficult logical labor based on thirteen non-cohort factors, such as nutrient food, water, a favorable environment, and appropriate chemicals, which improves PSL fecundity and lowers the mortality rate. However, if the proposed system is not implemented, it may cause adverse effects on PSL farmers.

### 1.1 PSL Taxonomy

The shrimp, or penaeus of the genus whose specie is penaeus mondon, belongs to the Malacostraca class, whose order is Decapoda and whose penaidae family includes penaid shrimps as well [1]. According to FAO statistics, PSL catches have been declining as a ratio of 5 to 1 for several years, and the causes of this malleability include automated fish trawlers and the

negative consequences of toxic waste and other factors which is still unknown. To put it another way, the aquamarine scientist has given up and they are searching for a novel solution to stop such limiting, crippling impacts [2].

### 1.2 PSL Life Cycle

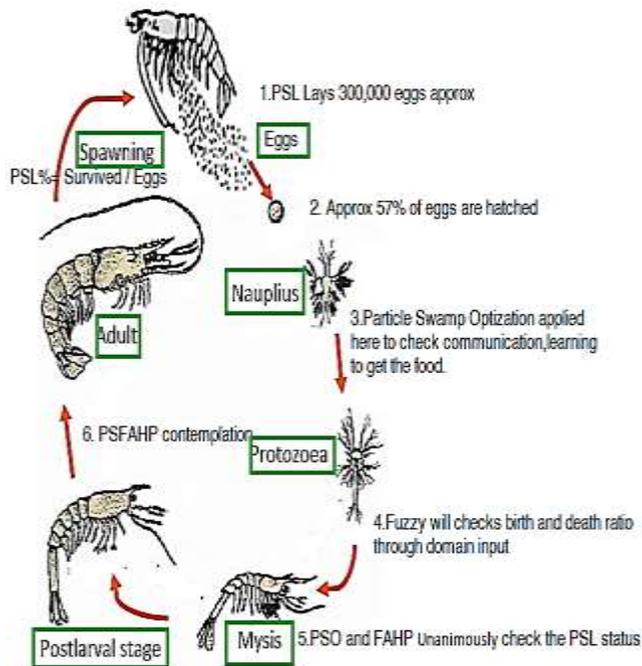


Fig. 1 Prawn, Shrimp, lobster life cycle from egg to adult.

### 1.3 Literature Review

One of the nutrients necessary for PSL growth is carbon ("C"), hence sugarcane or sweet potato molasses or a combination of rice bran and cassava is beneficial for healthy growth. The aforementioned bio-floc, in particular, is crucial for PSL survival and robust development [3]. Famous scientist Ngoc Hai conducted some experiments and came to the conclusion that PSL population growth is related to genetic diversity, which refers to differences and similarities in PSL genes. In other words, his study showed how variations in DNA, RNA, and chromosomes will affect the population of PSL. A favorable environment for PSL, such as one with balanced aquamarine diversity, is also crucial [4][5][6]. The sea substrate is packed with all the necessary elements for PSL, such as healthy nutrients like seaweed [7][8][9]. Other factors for restoring normal PSL growth include feeding frequency, nutrient content of the food, water temperature, and monitoring of PSL growth patterns [10][11][12]. Once the government reduced catches, processed industrial waste, and took appropriate action against the timber mafia that was responsible for cutting down mangrove trees, there was no longer a threat to PSL [13][14]. Thomas Malthus, a famous scientist who created a population and food supply chain graph, suggested that reproduction should be reduced [15][16][17]. Additionally, only 58 percent of PSL eggs are hatching, necessitating the

researcher's improvement of the hatchery rate by taking the appropriate action at the appropriate time [18][19][20]. The following questions are the focus of this study, and they are as follows:

- Is it possible to lower the mortality rate of Nauplius (PSL)?
- Is continuous PSL growth feasible?
- Is it possible to keep pH sensing going?
- Is there an Artificial Intelligence (AI) based model that can detect food, chemical, dissolved oxygen, and water temperature?

Can farmers use AI to view real-time (PSL) growth results?

The answers of aforementioned questions are provided through this research. Our prototype does, in fact, deliver real-time spectacular, fascinating results by succinctly evaluating voluminous data. The PSL-validated solution's sensors are shown in the following diagram. The worst part of the analytical hierarchical process is input data increasing time complexity will also increase with deep reflection offered by enormous computation. The analytical hierarchical process is rather straightforward, following multi-criteria for gigantic findings based on ranking data. According to the study, the complexity is approximately  $O[(mn^2, m^2n)]$ , where 'm' represents the nine alternates and 'n' represents the given criteria [29]. Any system needs the best sensor for incredible outcomes; this study is using different sensors, and its job is to handle the following issues: Because they are straightforward and give farmers complex information, the following results are given to FAHP for consideration: a) pH b) salinity c) temperature d) algae e) clear water f) dissolved oxygen. Less time spent on FAHP and sensors results in a smart system that can make decisions on its own more quickly [23].

In West Bengal, Pallavi Dutta carried out a menial task in which her study supported the Bio-floc system because it is a successful industry there. Later, this study projected the facts using the Non-linear Auto-Regressive (NAR) model after performing data curation; the input data was of 36 years, and the study then aggregated the harmful effect and Morbidity which will result in 2050 as a dreaded blow for all of us [24]. Although Vietnam is well-known for its seafood, three diseases, including white spot syndrome and acute hepatopancreatic necrosis, are currently plaguing the Mekong Delta. The GIS system identified this illness spread and afterwards combined (ML) Machine learning for precise prediction. This study uses GIS technology to limit the horrific exacerbates of the shrimp sickness along the Mekong delta, which may lead to a decline in Vietnam exports [25][26]. In order to solve the power problem and give humans with round-the-clock support that can lessen farmers' efforts, researcher Umar Farouk has developed a new concept. It makes use of contemporary instruments such as robotics, sensors, drones, macro, and micro-sensors. CIA technology supports cloud-based computation through Internet of Things (IoT) and artificial intelligence, according to this study [27]. Australian researchers have made outstanding efforts to reduce disparities. Three

factors—salinity, dissolved oxygen, and water temperature—were applied in 2021 by a researcher by the name of Mashud to a combination of machine learning algorithms, including the (SVM) Support vector machine, (NN) Neural Network, (KNN) K-nearest mean neighbors, (RA) Regression Analysis, (DT) Decision Tree, (GNB) Gaussian Nave Bayes, and (RF) Random Forest. AdaBoost provided the impetus [28][29]. In contrast, the goal of this study is to lower the Nauplius mortality rate. Particle Swamp Optimization (PSO) is linked to the mortality of Nauplius; primarily, Nauplius didn't receive nutrient-rich food, the best position with ideal direction, nominal velocity because of unfavorable environmental circumstances. The distracted Nauplius fails to get the ideal position and lost all their energy and ultimately died due to less conducive environmental condition. This research has filled the gap by giving PSL necessary components [30][31]. The mortality rate has decreased as a result. This is the novelty of this research.

## II MATERIALS AND METHODS

2.1 For financially rewarding purposes, artificial intelligence algorithms can reduce inequalities and morbidities in the aquamarine industry, particularly in PSL-controlled ponds. To do this, two key monitoring algorithms—the Particle Swamp Optimization (PSO) and the Fuzzy Analytical Hierarchical Process—are used to obtain the indemnified, vindicated findings (FAHP). The first algorithm determines Nauplius' rate of distraction within a particular time. The second method shows the rate of growth of (PSL). The outcome depends on how heavily the following variables are weighed: a balanced or nutrient-rich diet, an ideal water temperature, pure hydrogen (pH), the presence of salinity, crucial amounts of calcium and magnesium, etc. When the pH exceeds 10, the PSL mortality rate will increase, and the size of the PSL is determined by the aforementioned parameters. Farmers will get remarkable outcomes if they adhere to the following rules.

Factor 1: The water tank's bottom must be covered with grains and tiny sea stones or pebbles, and the tank's depth must be two meters.

Factor 2: In order to provide a continuous supply of oxygen, oxygen pumping motors must be placed in the tanks.

Factor 3. Two meals each day of nutrient-rich food must be provided.

Factor 4: A water temperature sensor has been installed.

Factor 5: Prescribed factors reduce the Nauplius distraction rate, resulting in ultimately greater PSL.

The PSFAHP divides the analysis process into three primary sections out of five steps: the first is the discrepancy or looking received a problem for rational analysis; the second part gives the considered eclectic; and the third section is a sharp contrast to the voluminous mathematics. There are built-in checks and balances for the PSFAHP technique.

Step 1: Pertinent Alternate

There are fourteen parameters that the fuzzy AHP process is examining here, including apparent conditions ("AC"), pond milieu ("PM"), pond thermal condition ("PTC"), dissolved calcium and magnesium salts in the pond ("CAM"), dissolved hard salts ("DHS"), dissolved soft salts ("DSS"), nitrogen-based wastes of aquatic organisms ("NW"), and dissolved oxygen ("OX"). It is purely a byproduct. The outcome is only based on rudimentary environmental components that have been internalized for a successful outcome.

Step 2: Analyzing the presented disparity with discernment.

Making a problem into relevant smaller ones is another callous move in this regard. How in-depth this method will be for reflection or where this study will produce favorable results will be limited.

Step 3: Juxtaposing priorities for thorough thought.

Contrasting priorities to encourage thoughtful consideration.

As a result, a matrix is established in pairs, and one element may create a link evenly with other factors at lower levels

Step 4: Careful Consistency.

This step exalts liquidity with appreciation; in confine, it is twice as significant as another element that provides protection against decline (PFD), and (PFD) and appreciation are related one after the other.

Step 5: Make a decision based on the encircled massive Weights.

The FAHP provides contemplated results. This can be done by doing in-depth analysis of vast amounts of data to produce conclusive, concise results. It is, in essence, a meticulous tool that outperformed other AI systems.

PSL is searching for best feed. Distance covered by PSL 950 μm or 0.95 m.m towards feed [32].

Step1. Initialize the process:

Loop

Initial positions of PSL = $X_i$

Initial velocity of PSL = $V_i$

Find first PSL initial velocity= ?

$$V(X_{11}) = [0.95 * 7] \quad V(X_{12}) = [0.95 * 3] \quad V(X_{13}) = [0.95 * 9]$$

$$V(X_{21}) = [0.95 * 2] \quad V(X_{22}) = [0.95 * 8] \quad V(X_{23}) = [0.95 * 10]$$

$$V(X_{31}) = [0.95 * 3] \quad V(X_{32}) = [0.95 * 4] \quad V(X_{33}) = [0.95 * 1]$$

$$V(X_{41}) = [0.95 * 9] \quad V(X_{42}) = [0.95 * 2] \quad V(X_{43}) = [0.95 * 5]$$

$$V(X_{51}) = [0.95 * 2] \quad V(X_{52}) = [0.95 * 9] \quad V(X_{53}) = [0.95 * 1]$$

Velocity Matrix =

$$\begin{bmatrix} 6.65 & 2.85 & 8.55 \\ 1.9 & 7.6 & 9.5 \\ 2.85 & 3.8 & 0.95 \\ 8.55 & 1.9 & 4.75 \\ 1.9 & 8.55 & 0.95 \end{bmatrix}$$

Updated PSL velocity=

$$\begin{bmatrix} 7+6.65 & 3+2.85 & 9+8.55 \\ 2+1.9 & 8+7.6 & 10+9.5 \\ 3+2.85 & 4+3.8 & 1+0.95 \\ 9+8.55 & 2+1.9 & 5+4.75 \\ 2+1.9 & 9+1.9 & 1+0.95 \end{bmatrix} = \begin{bmatrix} 13.65 & 5.85 & 17.55 \\ 3.9 & 15.6 & 19.5 \\ 5.85 & 7.8 & 1.95 \\ 17.55 & 3.9 & 9.75 \\ 3.9 & 10.9 & 1.95 \end{bmatrix}$$

Step2. Fitness formulation of PSL  $f(x_i^t)$ :

Loop

Nominal Fitness values > Best Fitness value ( $g_{Best}$ )

Then

Update ( $g_{Best}$ ) value with new value

Else

No change

$$F(X) = 10*(X_1-1)^2 + 20*(X_2-2)^2 + 30*(X_3-3)^2$$

$$f(x_1^0) = 10*(13.65-1)^2 + 20*(5.85-2)^2 + 30*(17.55-3)^2 = 8247.8$$

$$f(x_2^0) = 10*(3.9-1)^2 + 20*(15.6-2)^2 + 30*(19.5-3)^2 = 11950.80$$

$$f(x_3^0) = 10*(5.85-1)^2 + 20*(7.8-2)^2 + 30*(1.95-3)^2 = \mathbf{941.10}$$

$$f(x_4^0) = 10*(17.55-1)^2 + 20*(3.9-2)^2 + 30*(9.75-3)^2 = 4178.1$$

$$f(x_5^0) = 10*(3.9-1)^2 + 20*(10.9-2)^2 + 30*(1.95-3)^2 = 1701.4$$

$(g_{Best}) = 941.10$  PSL location which is nearest to the quality food

Step3. Locate and follow the PSL which is nearest to best feed:

Find velocity and position of successor PSL.

$$\text{Location of Successor (PSL)} = (x_i^{t+1}) = x_i^t + t * v_i^t$$

Velocity of Successor (PSL)=

$$(v_{k+1}^i) = wv_k^i + c_1 r_1 (x_{Best}^t - x_i^t) + c_2 r_2 (g_{Best}^t - x_i^t)$$

Whereas:  $a = 0$ ;  $b = 1$ ;  $r_1 = (b-a) * \text{rand}(1,1) + a$ ;

$$r_2 = (b-a) * \text{rand}(1,1) + a$$

$$v_1^1 = 0.9 * 6.65 + 2 * r_1 * (13.65 - 13.65) + 2 * r_2 * (5.85 - 13.65) = -8.3385$$

Initial Velocity

Initial Position

X <sub>1</sub>	X <sub>2</sub>	X <sub>3</sub>	X <sub>1</sub>	X <sub>2</sub>	X <sub>3</sub>
6.65	2.85	8.55	13.65	5.85	17.55
1.9	7.6	9.5	3.9	15.6	19.5
2.85	3.8	0.95	5.85	7.8	1.95
8.55	1.9	4.75	17.55	3.9	9.75
1.9	8.55	0.95	3.9	10.9	1.95

$$\text{Velocity} = 0.9 * V_i + 2 * (0 < \text{Random} < 1) * (x_{Best_i} - x_i) + 2 * (0 < \text{Random} < 1) * (g_{Best_i} - x_i)$$

	X <sub>1</sub>	X <sub>2</sub>	X <sub>3</sub>
V(P1)	4.33	9.64	8.7
V(P2)	4.31	0.067	-13.66
V(P3)	25.03	-0.633	15.84
V(P4)	-18.63	8.65	1.71
V(P5)	-4.87	-4.08	0.002

Updated Prawn Velocity and position  $x_i^{t+1}$

	X <sub>1</sub>	X <sub>2</sub>	X <sub>3</sub>
VP(P1)	17.98	15.49	26.25
VP(P2)	8.21	15.667	5.84
VP(P3)	30.88	7.167	17.79
VP(P4)	-1.08	12.55	11.46
VP(P5)	-0.97	6.82	1.952

Step 4 Calculate New fitness value

The new PSL fitness is based on the relationship below. The global best-ranked first particle or prawn minus one, second particle or prawn minus two, and third particle or prawn position minus three all have a power of two, and multiple of 10, 20, and 30 respectively.

$$F(x) = 10*(X_1-1)^2 + 20*(X_2-2)^2 + 30*(X_3-3)^2$$

The value of the prawn or particle after computing the minimal value is the ( $g_{Best}$ ), and it is 536.40.

1. First Prawn 22739.681
2. Second Prawn 4497.54678
3. Third Prawn 16024.42478
4. Forth Prawn 4416.462
5. **Fifth Prawn 536.40612 . This is ( $g_{Best}$ ).**

The second phase involves updating the ( $g_{BEST}$ ) value, also known as the current global best position. No one is exactly sure how many particles will have their positions altered in the current ( $g_{BEST}$ ). This algorithm selects the least value by comparing the old ( $g_{BEST}$ ) position with the current ( $g_{BEST}$ ) position. All of these values will be referred to as being in the current ( $g_{BEST}$ ) position. The following is the contemplation:

Find the current  $g_{BEST}$

$$\text{If } f(x_1^1) < f(g_{BEST}) \text{ then } g_{BEST} = x_i^t$$

Evaluate Fitness ( $g_{BEST}$ ) New ( $g_{BEST}$ )

$$\text{First Prawn } \underline{8247.8} < 22739.68$$

$$\text{Second Prawn } 11950.8 > \underline{4497.547}$$

$$\text{Third Prawn } \underline{941.1} > 16024.42$$

$$\text{Forth Prawn } \underline{4178.1} < 4416.462$$

$$\text{Fifth Prawn } 1701.4 > \underline{536.4061}$$

Choose smallest values for current best ( $g_{BEST}$ )

$$\text{First Prawn } 8247.8$$

$$\text{Second Prawn } 4497.54678$$

$$\text{Third Prawn } 941.1$$

$$\text{Forth Prawn } 4178.1$$

$$\text{Fifth Prawn } \mathbf{536.40612}$$

Two new values are produced as a result.

1. New ( $g_{BEST}$ )=941.1
2. New ( $p_{BEST}$ ) position=536.40612

Step 5 Update the counter

$$t = t + 1$$

$$t = 2$$

Step 6 Output ( $g_{BEST}$ ) &  $x_i^{t+1}$

$$\text{Fifth Prawn } \begin{matrix} X_1 & X_2 & X_3 \\ 3.9 & 10.9 & 1.95 \end{matrix} = 536.40612$$

$$(g_{Best}) = 941.1$$

$$x_i^t = 536.40612$$

End Loop

This action will keep going until the halting criterion is satisfied.

III. EXPERIMENT

3.1 Fuzzy Analytical Hierarchical Process FAHP

Step 1: Relevant Substitutions

There are fourteen parameters that the fuzzy AHP process is examining here, including apparent conditions ("AC"), pond milieu ("PM"), pond thermal condition ("PTC"), dissolved calcium and magnesium salts in the pond ("CAM"), dissolved hard salts ("DHS"), dissolved soft salts ("DSS"), nitrogen-based wastes of aquatic organisms ("NW"), and dissolved oxygen ("O<sub>x</sub>"). The outcome is only based on rudimentary environmental components that have been internalized for a successful outcome.

Step 2: Analyzing the presented disparity with discernment.

Making a problem into relevant smaller ones is another callous move in this regard. How in-depth this method will be for reflection or where this study will produce favorable results will be limited.

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Step Four: Careful Consistency

This step exalts liquidity with appreciation; in confine, it is twice as significant as another element that provides protection against decline (PFD), and (PFD) and appreciation are related one after the other.

Step 5: Make a decision based on the encircled massive Weights.

The FAHP holds the user's attention by doing in-depth analysis of vast amounts of data to produce conclusive, concise results. It is, in essence, a meticulous tool that outperformed other AI systems. Figure 2 above shows the general outline of the entire procedure.

For clarity's sake, the Fuzzy AHP Triangular Scale is equal to the AHP scale.

$$FAHP=AHP$$

1. Equally Important (E\_Imp) = (1,1,1)=1
2. Weakly Important (W\_Imp) = (2,3,4)=3
3. Fairly Important (F\_Imp) = (4,5,6)=5
4. Strongly Important (S\_Imp) = (6,7,8)=7
5. Absolute Important (A\_Imp) = (9,9,9)=9

List of intermediate values

1. (1,2,3)=2
2. (3,4,5)=4
3. (5,6,7)=6
4. (7,8,9)=8

For Reciprocal conversion following relationship is used

$$\tilde{A}^{-1} = \left( \frac{1}{u}, \frac{1}{m}, \frac{1}{l} \right)$$

Furthermore rule of multiplication is as follows:

$$\tilde{A}_1 \otimes \tilde{A}_2 = (l_1, m_1, u_1) \otimes (l_2, m_2, u_2)$$

Table 1 FOUR DIFFERENT PSL PONDS' FUZZY WEIGHTS

Fuzzy AHP	Fuzzy Geometric mean Value $\tilde{r}_i$	$\tilde{A}^{-1} = (l, m, u)^{-1}$	$\tilde{w}_i = (\tilde{r}_1 \otimes \tilde{r}_2 \oplus \tilde{r}_3 \oplus \dots \oplus \tilde{r}_n)^{-1}$
Pure Hydrogen (pH)	(3.301, 3.946, 4.529)	(3.301, 3.946, 4.529) $\otimes$ (0.0931, 0.1124, 0.13894)	(0.307558763, 0.443652437, 0.62941518)
Dissolved Calcium and Magnesium	(1.513, 2.030, 2.569)	(1.513, 2.030, 2.569) $\otimes$ (0.0931, 0.1124, 0.1389)	(0.140936716, 0.22819734, 0.35706751)
Dissolved Hard & Soft salts	(1.157, 1.435, 1.781)	(1.157, 1.435, 1.781) $\otimes$ (0.09314, 0.1124, 0.1389)	(0.10777775, 0.161359887, 0.24757678)
Dissolved O <sub>2</sub>	(0.617, 0.764, 0.953)	(0.617, 0.764, 0.953) $\otimes$ (0.09314, 0.1124, 0.1389)	(0.057537173, 0.08596056, 0.13244283)
Apparent Conditions C <sup>0</sup>	(0.416, 0.507, 0.660)	(0.416, 0.507, 0.660) $\otimes$ (0.09314, 0.1124, 0.1389)	(0.038780232, 0.05700304, 0.09183073)
Nitrogen based wastes of aquamarine creatures	(0.190, 0.212, 0.240)	(0.190, 0.212, 0.240) $\otimes$ (0.09314, 0.1124, 0.1389)	(0.017770778, 0.023826732, 0.03339956)
Fuzzy Weight :	<b>(7.196, 8.896, 10.735)</b>	<b>(1/7.196, 1/8.896, 1/10.735)</b>	

Table 2 AHP RESULT FOR 4 DIFFERENT PSL PONDS

Domain	AHP provided Weights	Norms	Control condition Pond	Approval
Pure Hydrogen (pH)	<b>0.336</b>	0.216	A	Approved
Dissolved Calcium and Magnesium	0.063	0.283	B	
Dissolved Hard & Soft salts	0.328	0.258	C	
Dissolved O <sub>2</sub>	0.033	0.243	D	
Apparent Conditions C <sup>0</sup>	0.11	0	None	
Nitrogen based wastes of aquamarine creatures	0.129	0	None	

4 RESULT AND DISCUSSION

For this study, particle swarm optimization (PSO) was used. The PSL follow the another particle or Prawn which is nearest to quality food and learns how to do the task by keeping a constant velocity in dimension D. Another algorithm FAHP starts by figuring out the cost and population (X). The findings demonstrate that PSL fitness is based on nutrients in three-dimensional space according to the formula  $H(t) = F(t) + N$ . (3D). With a population of 57 percent inertia, a W damp of 0.9, and two learning coefficients C1 and C2 with values of 2, and 2, Part B initializes the parameters for the first iteration. Further discussion is given to particle characteristics such position, velocity, cost, ideal position, and optimal cost position. The particle velocity equation  $V_{k+1}^i = wV_k^i + C_1r_1(xBest_i^t - X_i^t) + C_2r_2(gBest_i^t - X_i^t)$  shows the relationship between particle velocity and the best cost of nature. Position and velocity updates happen later in 3D space. The main finding of this study is the death rate, which is at an all-time high. The causes include that Nauplius lost their bearings because of drain water at the seashore, which has a lower reflection rate than white foamy sea water. Nauplius is drawn to this foamy water, which also reveals the area's low salinity level. Nauplius has a single red eye that it uses to see the white colour of the seashore's white frothy water reflection. In summary, this research shows that ( $pBest$ ) and ( $gBest$ ) represent the best position and best global value of (PSL) to date, but these results can only be obtained when the Nauplius observes the white light emanating from white, foamy sea water. Furthermore, this study used the Fuzzy Analytical Hierarchical Process to test the Hypothesis in four PSL ponds under control conditions (FAHP). According to this study, if Nauplius is lost and does not see the white light signal, it will die. Once it notices the light, it goes in that direction, increasing its chances of surviving or perishing. The primary cause of PSL death is low white-colored foamy sea water; Nauplius' red eye failed to see the white light and thus sidetracked from its optimal position. The Nauplius red eye missed the white light and became distracted, losing its optimal position ( $pBest$ ), which is the primary cause of PSL mortality rate. Low white color foamy sea water is also a contributing factor ( $LPosition$ ). Through FAHP, further research has identified the optimal nutrient pond for PSL. The criteria are founded on the points listed below: Aquamarine waste, pH, dissolved  $Ca^{++}$ ,  $Mg^{++}$ ,  $O_2$ , soft and hard salts, and perceived conditions. Here Pond "A" was able to adapt the right pH, chemical, nutrient, and temperature levels thanks to data generated by smart sensors. The system has rejected other ponds and notified the farmers since they are not operating as intended. Table 1 demonstrates how Fuzzy AHP is applied to fulfil the given requirements. For optimum PSL growth, farmers must regulate temperature, pH, and other variables in the pond after adding nitrogen-

based aquatic waste. Then, the following formula is used to get the Fuzzy Geometric Mean Value  $\tilde{r}_i, \tilde{w}_i = \tilde{r}_i \otimes (\tilde{r}_i \oplus \tilde{r}_2 \oplus \dots \oplus \tilde{r}_n)$  Similar to that, fuzzy weight was calculated using the formula  $\tilde{w}_i = \tilde{r}_1 \otimes (\tilde{r}_2 \oplus \tilde{r}_3 \oplus \dots \oplus \tilde{r}_n)$ . A healthy pond must have an acceptable pH, dissolved calcium and magnesium, soft and hard salts, and finally the center of the area of the normalized weight, according to this study's findings after De-Fuzzification and the center of the normalized weight area. In comparison, AHP accuracy is inferior to Fuzzy AHP, but it correctly predicted the identical data in Tables 1 and 2, and the FAHP calculated pH score was 0.336 which is the best among all ponds.

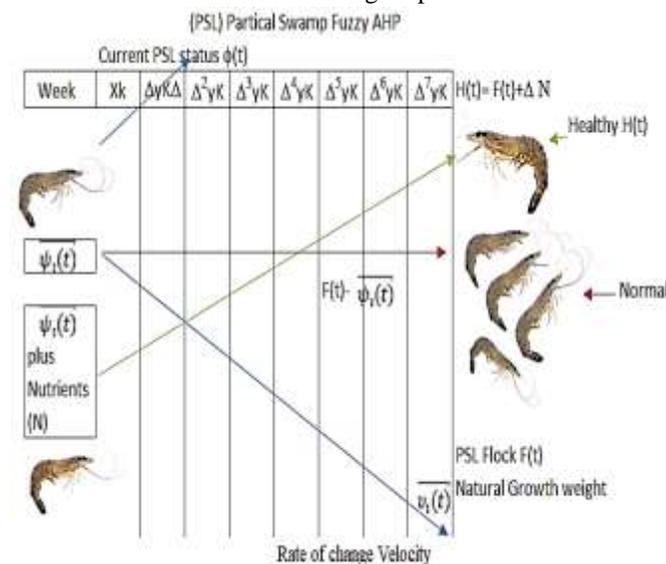


Fig 2. Particle Swamp FAHP for PSL growth

5. CONCLUSION AND FUTURE WORK

This study looked into the causes of (PSL) mortality. The first reason is that the lack of white foamy sea water and the deteriorated sea water quality at the shore distracted Nauplius. Nauplius is drawn to this foam, which it observes through a crimson eye on the rear. The likelihood of survival has increased as the rate of distraction decreases. Artificial intelligence research carries it out (PSO). The PSL's quality of life, which includes the right temperature, dissolved oxygen, nutrient-rich food, salinity, and other chemicals, is the second crucial component. Fuzzy Analytical Hierarchical Process, another artificial intelligence method, was used in this study since it offers the best PSL growth combinations.

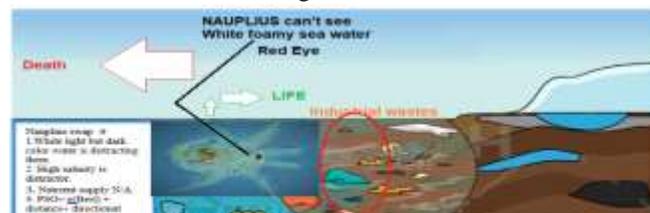


Fig 3. Distracted Prawn Nauplius (Source: <https://mindthegraph.com/>)

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## DATA AVAILABILITY

Initial curative PSL data is collected by the PSL farmers.

## CONFLICT OF INTEREST

Since only farmers will gain from this research, there is no conflict of interest.

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Following Figure developed in <https://mindthegraph.com/>

