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Forward-Escape Algorithm: A New Metaheuristic and Its Utilization to Handle Optimization Problem in Crab Precision Farming

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Abstract: There are a lot of optimization studies in the precision farming system including the farming process and the logistics process in the back front and the harvesting management in the fore front. On the other hand, metaheuristic is a popular stochastic optimization technique that has been utilized in wide range of optimization studies, especially in engineering field. Unfortunately, the optimization cases in smart farming in the introductions of new metaheuristics is still rare to find. Based on this problem, this work introduces a new metaheuristic called as forward escape algorithm (FEA). FEA is developed based on swarm intelligence. It employs three directed searches where the first two searches are the motion toward the target and the third search is the motion away from the target. The assessment of FEA is conducted by deploying FEA to solve 23 standard functions and crab seed order allocation problem in crab vertical farming system. During the assessment, FEA is benchmarked with potter optimization algorithm (POA), red panda optimization (RPO), total interaction algorithm (TIA), hiking optimization (HO), and dollmaker optimization algorithm (DOA). The result shows that FEA is better than POA, RPO, TIA, HO, and DOA in 19, 15, 15, 22, and 14 functions respectively. Meanwhile, FEA is competitive as it becomes the second best in solving crab seed order allocation problem after DOA.

Keywords: Optimization, Swarm intelligence, Crab farming, Order allocation problem.

1. Introduction

Aquafarming plays an important role in supplying and securing nutrient needs. Aquafarming or also known as aquaculture, is an effort to cultivate aquatic organisms such as fish, crustaceans, mollusks, plants, and so on under a controlled environment, such as pond, tank, cage, and so on. As the massive development of information technology, especially internet of things (IoT), the technique for aquafarming has been transforming into precision aquafarming to achieve high yield in production [1]. Many studies focused on the water monitoring system, especially to monitor or control the condition of the water, such as dissolve solid (DO) [1], temperature [1], water pollutant [2], salinity [3], and so on. Many studies in smart aquafarming also utilized machine learning methods, such as long short-term memory (LSTM) for water quality prediction [4], the combination of convolutional neural network (CNN) and gated recurrent unit (GRU) for fish feeding system [5], and so on.

Despite the massive deployment of machine learning techniques in precision farming, especially for monitoring and detection, metaheuristics play an important role in the support system for the smart, precision, or intelligent farming. Its role is especially in achieving operational excellence. There are many studies that utilizes metaheuristic in the farming system. Grey wolf optimization (GWO) has been utilized to optimize the path planning for agricultural robots in the complex vertical farms [6]. GWO also has been utilized to solve the optimization problem in the electrification for agricultural vehicles [7]. Particle swarm optimization (PSO) has been utilized to improve the efficiency of the crop reapers, especially for the small-scale farmers [8]. Genetic algorithm (GA) has been implemented to optimize the water resource allocation in the irrigation area with the additional objectives are preserving water conservation and reducing emission [9], the layout of the coastal cage for fish farming in Bali, Indonesia [10], and irrigation planning in India with constraints in water and storage limitations [11].

Unfortunately, although there have been optimization studies in the farming system or agricultural system in more common, the use of metaheuristics to optimize problem in this field is still insufficient compared to other fields, specially manufacture, logistics, transportation, power system, and so on. Metaheuristics have been used in an extensive manner in this field to achieve operational excellence. On the other hand, operational excellence is also important and critical in farming system to make this sector profitable and sustainable, moreover, because the uncertainty in agricultural sector is high. Moreover, efficiency becomes more important because of the low margin nature in the agricultural sector.

Meanwhile, there are a lot of metaheuristics have been introduced in the recent years. Many of these metaheuristics are metaphor-based metaheuristics, such as potter optimization algorithm (POA) [12], red panda optimization (RPO) [13], hiking optimization (HO) [14], dollmaker optimization algorithm (DOA) [15], sculptor optimization algorithm (SOA) [16], Komodo mlipir algorithm (KMA) [17], carpet weaver optimization (CWO) [18], deep sleep optimization (DSO) [19], language education optimization (LEO) [20], hippopotamus optimization (HO) [21], mutated leader optimization (MLO) [22], artificial protozoa optimization (APO) [23], pufferfish optimization algorithm (POA) [24], fossa optimization algorithm (FOA) [25], swarm magnetic optimizer (SMO) [26], and so on. On the other hand, some few other metaheuristics are metaphor free such as total interaction algorithm (TIA) [27], golden search optimization (GSO) [28], average subtraction-based optimization (ASBO) [29], multiple interaction optimizer (MIO) [30], and so on. Many of these metaheuristics used standard functions or engineering design problems as use cases in their first publication. Meanwhile, the use of optimization studies in the farming system as practical problem in the first introduction of new metaheuristics is hard to find.

Based on this unresolved problem, this paper introduces a new metaheuristic that is free from metaphor. This proposed metaheuristic is called as forward-escape algorithm (FEA). As its name suggests, FEA employs both forward motion and escape motion. The forward motion can be seen as the motion toward a target while the escape motion can be seen as a motion away from the target.

FEA is then implemented to solve both standard problems and practical problems in precision farming systems. Specifically, the crab seed order allocation problem for crab vertical farming is chosen as the practical use case. The reasoning for choosing this problem is as follows. First, crab is less popular than fish or shrimp in many studies regarding smart or precision farming although the economic value of crab is not inferior to fish, shrimp, or other water-based organisms, especially the soft-shell crab [31]. Second, seeding is a critical process besides feeding process or water treatment in achieving high yield farming [32].

Based on this explanation, FEA is designed as a general-purpose metaheuristic. Its advantage compared to other metaheuristics is the use of escape motion to avoid the worse circumstance. Meanwhile, as a practical optimization problem, the crab seed order allocation problem is a constrained problem that consists of the equality constraint and inequality constraint. In this context, this paper also investigates the advantage of this method to handle this practical constrained problem.

The scientific contributions of this paper are listed as follows.

- This work introduces a new metaheuristic called as forward-escape algorithm (FEA) that perform forward and escape motions in a dedicated manner.
- FEA is assessed to address 23 functions as a standard use case.
- FEA is assessed to address the crab seed order allocation problem for crab vertical farming as a practical use case.
- The performance of FEA is compared with five new metaheuristics.

Below is the organization of the remainder of this paper. Section two discusses the recent development of metaheuristics, especially the swarm-based ones and the recent studies in the precision farming. Section three provides the formal model of the proposed FEA and the seeding optimization problem for crab vertical farming. Section four provides the performance assessment of FEA in addressing both standard and practical problems. Section five discusses a comprehensive analysis regarding the results, findings, and limitations. Section six provides the conclusion and the baseline for future studies.

2. Related works

In this section, the discussion is divided into two parts. The first part is about the recent development of metaheuristics. The second part is about the studies regarding crab farming. The objective of the first discussion is to find the potential or blank spot of the development of metaheuristics. On the other hand, the objective of the second discussion is to find the potential of implementing the metaheuristics to solve optimization problem in crab farming.

Many recent metaheuristics were developed based on swarm intelligence. As swarm-based technique, it contains several numbers of autonomous entities called as agents. Then, these agents work collectively without central command and control by constructing a population called swarm. Although there is not any central command, the collective intelligence within the swarm makes this group move by certain pattern where in the beginning, they are scattered within the space. Then, as iteration goes on, this swarm converges on the certain small area where the best agent usually becomes the final solution.

Most of metaheuristics perform forward motion during their directed search. This motion becomes the mainstream motion. This forward motion can be found in particle swarm optimization (PSO) as the early swarm-based metaheuristic where the agent moves toward the local best agent and the global best agent with certain composition and speed [33]. Then, the many popular swarm-based metaheuristics follow this path like grey wolf optimization (GWO) where the agent moves toward the middle among three best agents (alpha, beta, and gamma wolves) [34].

In some metaheuristics, the escape motion is conducted conditionally due to the relative quality between the target and the agent. When the target is worse than the agent then the escape motion is conducted. Otherwise, the forward motion is conducted. It happens because the target is a randomly picked agent or a randomized solution within space. So, there is not any guarantee that the target is better than the agent while moving toward the worse place is not wise as it gives lower opportunity for improvement.

This circumstance also occurs in recent swarm-based metaheuristics. Table 1 provides the list of some recent metaheuristics including their targets and the direction. The proposed metaheuristic is presented in the last row.

Table 1 shows that most of metaheuristics perform forward motion for their directed search. This circumstance becomes the consequence of the targets, which most of them are the finest or finer agents. Only a few of them perform escape motion or avoid the target. But this motion is performed conditionally only if this target is worse than the agent. This circumstance gives opportunity to develop a new swarm-based metaheuristic that does not perform forward motion only but also escape motion in a dedicated manner.

Table 1. Review of latest swarm-based metaheuristics

No	Metaheuristic	Target	Direction
1	POA [12]	mixture between the finest agent and the gap between the agent and the finest agent, the finest agent	forward for both targets
2	RPO [13]	a randomly picked finer agents plus the finest agent	forward
3	TIA [27]	all other agents	forward or escape conditionally
4	HO [14]	the finest agent	forward
5	DOA [15]	the finest agent	forward
6	DSO [19]	the finest agent	forward
7	FOA [25]	a randomly finer agent	forward
8	GSO [28]	global finest agent and local finest agent	forward
9	KMA [17]	the finest agent, the middle of finer high-quality agents, the middle of all high-quality agents	forward for all targets
10	this work	the finest agent, a randomly picked finer agent, and a randomly picked worse agent	forward for first and second targets, escape for third target

The second discussion is about crab farming. In general, crab farming is less popular than fish farming. This circumstance also affects the limited studies of crab farming compared to fish farming. Based on Scopus indexing web, there are only 284 crab farming related documents compared to 13,865 fish farming related documents. Most of these studies focused on the biological or ecological aspects.

Some studies explored the disease that attacks the crab, such as reovirus that can make mass mortality for crab [35], white spot syndrome virus [36], Vibrio alginolyticus [37], and so on. Some studies focused on the ecosystem or ecological aspects, for example the advantage of the mussel farm to the crustacean farming [38], mangrove ecosystem [39], microplastic contamination [40], and so on.

One popular crab framing is the soft-shell crab. Different from the common crab where the shell is hard so that it should be broken first to consume, people can consume its shell too. This advantage makes the price of the soft-shell crab higher than the common crab. Meanwhile, soft-shell crab is not a specific species of crab, but it is common crab.

(a)

(b)

Figure. 1 Vertical crab farming in Surabaya, Indonesia: (a) crab racks and (b) crab in the boxes

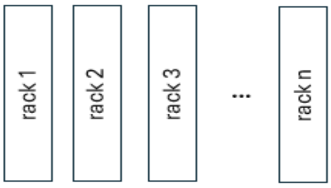
The soft shell comes from the molting process. The molting process can be defined as the replacement of the exoskeleton with the newer one through decalcification process [31]. Then, within hours the exoskeleton becomes harder, and it completes within 24 to 48 hours [41]. It makes the price of the crab decrease if these molted crabs are not harvested immediately [31].

There are several parameters that are commonly used for optimization in crab farming, especially the soft-shell crab. The first parameter is the survival rate which is the percentage of the number of crabs that survive compared to the number of initial crabs [31]. The second parameter is the molting percentage which is the percentage of the number of molted crabs compared to the number of initial crabs [31]. The third parameter is the final biomass which is the total crab weight [31]. Other studies added several other metrics including production per yield and conservation ratio [42].

Meanwhile, there is an innovative technique for crab farming known as vertical crab farming. This technique is also called as apartment system. This technique offers several benefits. First, it reduces space needed for farming so that in one way, it can reduce the land cost while in the other way, it solves the land limitation problem so that it is suitable for urban farming where the space availability is very limited. Second, it reduces the mortality rate as this system provides each crab in a private room so that cannibalistic behavior among crabs especially during the molting process in the high-density crab farming can be avoided [43]. The picture of vertical crab farming is provided in Fig. 1.

The vertical crab farming system can be seen as a three-dimensional matrix. In general, the system consists of a certain number of racks. Then, each rack has a certain number of floors while each floor contains a certain number of rooms. Each room contains one crab only. The illustration of this vertical system is provided in Fig. 2 where Fig. 2a illustrates the array of racks and Fig. 2b illustrates the array of floors and rooms. As a three-dimensional matrix, the location of each crab can be identified based on the rack index, floor index, and room index.

On the other hand, there are a lot of opportunities to implement metaheuristics to solve various optimization problems in the crab vertical farming, whether in the farming process, the upstream, and the downstream sides. In the upstream side, the relation with the supplier plays an important role as the success of the crab farming also depends highly on the suppliers. Farming needs good relationship with suppliers for the crab seed, food, and the water treatment system in appropriate quality and quantity.



(a)

room 1	room 2	room 3	...	room m	floor 1
room 1	room 2	room 3	...	room m	floor 2
room 1	room 2	room 3	...	room m	floor 3
...	...	...	...	...	...
room 1	room 2	room 3	...	room m	floor o

(b)

Figure. 2 Vertical crab farming as array: (a) array of racks, (b) array of floors and rooms

One of optimization problems that can be explored is the order allocation problem for the crab seed. In general, order allocation problems are commonly performed in various industries, such as manufacturing system of cement product [44], electronic commerce trading [45], and so on. Meanwhile, this problem is still rare to find in studies related to crab farming. This circumstance becomes a motivation to promote the crab seed optimization problem.

3. Model

3.1 Proposed FEA model

The idea of FEA comes from the basic motion of the directed search. In most cases, the agent moves toward the target. Meanwhile, in a few other cases, the agent moves away from the target. This idea is then implemented into three directed searches in FEA. Two searches perform the motion toward the target, or they are called forward motions. On the other hand, there is one search that performs the motion away from the target, or it is called escape motion.

The agent moves toward the target if the target is better than the agent. Meanwhile, the agent moves away from the target if the target is worse than the agent. In the first forward search, the agent moves toward the finest agent. In the second forward search, the agent moves away from a randomly chosen finer agent. In the escape search, the agent moves away from a randomly chosen worse agent.

This idea is then transformed into algorithm where algorithm 1 provides the formal presentation of FEA. Meanwhile, Eq. (1) to Eq. (14) formalizes the mathematical presentation of FEA. The notations that are used in the modeling of FEA are provided in Table 2.

The formalization of FEA begins with the presentation of FEA as a population-based metaheuristics. Eq. (1) formalizes that the system consists of a set of agents that constructs a swarm. Eq. (2) formalizes that a solution consists of certain values where the size equals the dimension of the problem.

Table 2. Notation list for FEA model

Notation	Description
x	agent
X	set of agents
x_s	selected agent
x_{ft}	the finest agent
X_{fr}	group of finer agents
X_{wr}	group of worse agents
ca	solution candidate
a	index for agent
b	index for dimension
d	dimension size
of	objective function
lb	lower boundary
ub	upper boundary for certain dimension
t	iteration
T	maximum iteration
u_1	uniform random between 0,1
u_2	uniform random between 1 or 2
u_3	uniform random within a population

algorithm 1: forward escape algorithm

```
start
  setup n(X), T, and of
  for all x in X
   initialize x_a
   update x_ft
  end for
  for t=1 to T
   for all x in X
    first forward search and update x_ft
    second forward search and update x_ft
    escape search and update x_ft
   end for
  end for
  return x_ft
stop
```

$$X = \{x_1, x_2, x_3, \dots, x_n\} \quad (1)$$

$$x_a = \{x_{a,1}, x_{a,2}, \dots, x_{a,d}\} \quad (2)$$

The initialization phase consists of two processes. The first process is generating an initial solution within the space by following the uniform distribution as provided in Eq. (3). Then, the finest agent is updated each time a solution is initialized as provided in Eq. (4).

$$x_{a,b} = lb_b + u_1(ub_b - lb_b) \tag{3}$$

$$x'_{ft} = \begin{cases} x_a, of(x_a) < of(x_{ft}) \\ x_{ft}, else \end{cases} \tag{4}$$

There are three searches in every iteration that are performed by every agent. Each search consists of three processes: (1) performing the motion to generate a solution candidate, (2) updating the agent based on the solution candidate, and (3) updating the finest agent based on the new value of the agent. The updating of the finest agent is formalized using Eq. (4).

The first search is formalized using Eq. (5) and Eq. (6). Eq. (5) generates the first solution candidate by moving toward the finest agent. Then, Eq. (6) is used to update the agent based on the first solution candidate.

$$c_{1,a,b} = x_{a,b} + u_1\left(x_{ft,b} - u_2 x_{a,b}\right) \tag{5}$$

$$x'_a = \begin{cases} c_{1,a}, of\left(c_{1,a}\right) < of(x_a) \\ x_a, else \end{cases} \tag{6}$$

The second search is formalized using Eq. (7) to Eq. (10). Eq. (7) formalizes the construction of a set that contains all finer agents compared to the related agent plus the finest agent. Then, Eq. (8) formalizes the picking of an agent from this set to be the target for the second search. Eq. (9) formalizes the motion toward this target to generate the second solution candidate. Eq. (10) formalizes the updating of the agent by using the second solution candidate.

$$X_{fr,a} = \{\forall x \in X \wedge of(x) < of(x_a)\} \cup x_{fr} \tag{7}$$

$$x_{s1,a} = u_3\left(X_{fr,a}\right) \tag{8}$$

$$c_{2,a,b} = x_{a,b} + u_1\left(x_{s1,a,b} - u_2 x_{a,b}\right) \tag{9}$$

$$x'_a = \begin{cases} c_{2,a}, of\left(c_{2,a}\right) < of(x_a) \\ x_a, else \end{cases} \tag{10}$$

The third search is formalized using Eq. (11) to Eq. (14). Eq. (11) formalizes the construction of a set that contains all worse agents compared to the related agent. Eq. (12) formalizes the randomly picking agent from this set. Eq. (13) formalizes the escape motion which is escaping from the target to generate the third solution candidate. Eq. (14) formalizes the updating process of the agent by using the third solution candidate.

$$X_{wr,a} = \{\forall x \in X \wedge of(x) > of(x_a)\} \tag{11}$$

$$x_{s3,a} = u_3\left(X_{Wr,a}\right) \tag{12}$$

$$c_{3,a,b} = x_{a,b} + u_1\left(x_{s3,a,b} - u_2 x_{a,b}\right) \tag{13}$$

$$x'_a = \begin{cases} c_{3,a}, of\left(c_{3,a}\right) < of(x_a) \\ x_a, else \end{cases} \tag{14}$$

The computational complexity of FEA is explained below. The complexity during the initialization phase is presented as $O(n(X).d)$ as there is a nested loop that contains two loops. Meanwhile, the complexity during the iteration phase is presented as $O(T.n(X)(n(X)+d))$ as there is nested loop that contains four loops. The outer loop is the looping from the first iteration to the maximum iteration. The middle loop is the looping for all agents to perform the searching process. The inner loop is the looping to construct the finer agent set and worse agent set, and the looping for whole dimension during the motion process.

3.2 Crab seed order allocation problem model

This sub section presents the model of the crab seed order allocation problem. The system is a crab farmer that has a certain number of crab boxes. Then, this farmer should purchase crab seeds from a certain number of suppliers. Each supplier has its selling price. Each supplier has its own capacity to provide the seed. The total number of seeds that farmer should purchase is equal to the number of his crab boxes. Meanwhile, the objective of this optimization problem is to minimize the total purchasing cost. Based on this explanation, the mathematical model of this problem is provided in Eq. (15) to Eq. (21). The system is illustrated in Fig. 3. The notations that are used in this model are listed in Table 3.

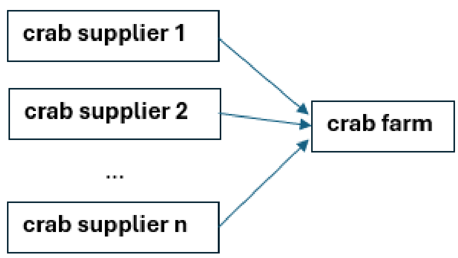


Figure. 3 Illustration of relation in crab seed order allocation problem

Table 3. Notation list for seed order allocation problem

Notation	Description
s	crab seed supplier
S	set of crab seed suppliers
q	quantity
q_{min}	minimum quantity
q_{max}	maximum quantity
q_{tot}	total order quantity
of	objective function of crab seed order allocation problem
p	price
p_{tot}	total purchasing cost

$$S = \{s_1, s_2, \ldots, s_n\} \tag{16}$$

$$q_{min,i} \leq q_i \leq q_{max,i} \tag{17}$$

$$q_{tot} = n_{box} \tag{18}$$

$$q_{tot} = \sum_n q_i \tag{19}$$

$$of = min(p_{tot}) \tag{20}$$

$$p_{tot} = \sum_n p_i q_i \tag{21}$$

The explanation of Eq. (16) to Eq. (21) is as follows. Eq. (16) shows that the system consists of a set of crab suppliers where n is the number of crab seed suppliers. Eq. (17) shows the inequality constraints where the order allocation for each supplier should be within its range. Eq. (18) shows the equality constraint where the total order should be equal to the number of crab boxes. Eq. (19) shows that the total order quantity is obtained by accumulating order quantity of all suppliers. Eq. (20) shows that the objective is to minimize the total purchasing cost. Eq. (21) shows that total purchasing cost is obtained by accumulating purchasing from all suppliers where the purchasing cost from each supplier is obtained by multiplying the order quantity with the purchasing price p.

4. Experiment and result

This section provides the performance assessment of FEA in handling the optimization problems. There are two use cases in this work. The first use case is a set of 23 standard functions. The second use case is seed supplier optimization in crab farming. In both cases, FEA is benchmarked with five metaheuristics including POA, RPO, TIA, HO, and DOA.

The reasoning for choosing these five techniques among a lot of other available techniques is as follows. First, these five metaheuristics are chosen as they are new which some of them were first introduced in 2023 while the others were firstly introduced in 2024. Comparing the proposed technique with older methods may fall into obsoleteness.

Table 4. Result on handling HDUFs

F	Parameter	POA [12]	RPO [13]	TIA [27]	HO [14]	DOA [15]	FEA
1	mean	3.0103×10^1	1.7156×10^2	9.6224	1.7018×10^2	2.1437×10^2	0.0023
	range	5.0411×10^1	5.1227×10^2	1.6605×10^1	4.6588×10^2	4.7234×10^2	0.0072
	mean rank	3	5	2	4	6	1
2	mean	0.0000	0.0000	0.0000	9.0197×10^3	0.0000	0.0000
	range	0.0000	0.0000	0.0000	1.4365×10^5	0.0000	0.0000
	mean rank	1	1	1	6	1	1
3	mean	2.1611×10^3	6.5664×10^3	1.0767×10^3	4.1038×10^3	7.5492×10^3	1.5829×10^2
	range	1.3674×10^4	1.6383×10^4	2.3069×10^3	1.1772×10^4	2.2022×10^4	2.1091×10^3
	mean rank	3	5	2	4	6	1
4	mean	4.6966	1.3159×10^1	2.6926	6.2103	1.3806×10^1	0.1118
	range	4.9177	2.1336×10^1	2.7033	8.0630	1.3863×10^1	0.1958
	mean rank	3	5	2	4	6	1
5	mean	8.5441×10^2	9.3472×10^3	1.9969×10^2	1.4477×10^5	1.7195×10^4	5.7563
	range	3.1008×10^3	4.2607×10^4	3.8175×10^2	5.9960×10^5	7.3759×10^4	1.5072
	mean rank	3	4	2	6	5	1
6	mean	5.5234×10^1	1.6231×10^2	1.3799×10^1	1.8979×10^2	2.3783×10^2	5.7563
	range	2.1843×10^2	2.6204×10^2	1.9671×10^1	3.5575×10^2	2.6227×10^2	1.5072
	mean rank	3	4	2	5	6	1
7	mean	0.0609	0.1560	0.0844	2.7402×10^2	0.1218	0.0211
	range	0.1283	0.3148	0.1777	6.0987×10^2	0.3411	0.0621
	mean rank	2	3	4	6	5	1

Table 5. Result on handling HDMFs

F	Parameter	POA [12]	RPO [13]	TIA [27]	HO [14]	DOA [15]	FEA
8	mean	-2.0305×10^3	-2.4251×10^3	-1.7165×10^3	-1.7042×10^2	-2.4218×10^3	-2.1162×10^3
	range	1.6955×10^3	1.5475×10^3	1.4788×10^3	3.5552×10^2	2.0433×10^3	1.4379×10^3
	mean rank	4	1	5	6	2	3
9	mean	8.5535×10^1	1.1440×10^2	7.5639×10^1	3.3360×10^2	1.0702×10^2	2.5551
	range	1.6790×10^2	1.4620×10^2	1.8212×10^2	1.8841×10^2	2.1948×10^2	4.6378×10^1
	mean rank	3	5	2	6	4	1
10	mean	2.3972	4.2597	1.6445	6.9728	4.4756	0.0113
	range	2.2442	3.7912	1.5259	5.3052	3.8929	0.0195
	mean rank	3	4	2	6	5	1
11	mean	1.3000	2.2329	1.0419	1.2173	3.0235	0.0452
	range	0.6475	1.7893	0.4512	0.7217	3.4765	0.2945
	mean rank	4	5	2	3	6	1
12	mean	1.7222	4.2002	0.9545	9.3972	5.0262	0.9355
	range	2.6842	4.7313	0.8813	1.4328×10^1	1.0241×10^1	0.7348
	mean rank	3	4	2	6	5	1
13	mean	6.0083	5.5585×10^1	4.2009	3.6079×10^2	1.0767×10^2	3.0590
	range	4.8896	6.1680×10^2	3.5514	4.1665×10^3	9.8612×10^2	0.5896
	mean rank	3	4	2	6	5	1

Table 6. Result on handling FDMFs

F	Parameter	POA [12]	RPO [13]	TIA [27]	HO [14]	DOA [15]	FEA
14	mean	1.7258×10^1	1.0765×10^1	1.1178×10^1	7.3343×10^1	1.0396×10^1	9.3556
	range	8.7332×10^1	2.1315×10^1	1.3196×10^1	4.7415×10^2	1.9156×10^1	1.3458×10^1
	mean rank	5	3	4	6	2	1
15	mean	0.0383	0.0203	0.0060	0.2992	0.0158	0.0085
	range	0.1128	0.0835	0.0440	2.1051	0.0631	0.0589
	mean rank	4	5	1	6	3	2
16	mean	-0.8608	-0.9968	-0.9898	1.1483×10^1	-0.9487	-0.9285
	range	0.7811	0.2064	0.2197	1.3581×10^2	0.5621	0.7019
	mean rank	5	1	2	6	3	4
17	mean	8.6719	0.4650	2.9830	2.1251	0.4945	4.8508
	range	4.1415×10^1	0.6847	1.9767×10^1	6.7398	0.7328	2.0809×10^1
	mean rank	6	1	4	3	2	5
18	mean	3.5395×10^1	1.4318×10^1	1.6045×10^1	9.8703×10^2	1.1493×10^1	5.0855×10^1
	range	2.2750×10^2	8.9832×10^1	8.6890×10^1	5.8165×10^3	8.8697×10^1	1.7636×10^2
	mean rank	4	2	3	6	1	5
19	mean	-0.0495	-0.0495	-0.0495	-0.0317	-0.0495	-0.0495
	range	0.0000	0.0000	0.0000	0.0495	0.0000	0.0000
	mean rank	1	1	1	6	1	1
20	mean	-2.2012	-2.7129	-2.2264	-0.5359	-2.8080	-2.0730
	range	1.9737	1.1602	2.4383	1.6211	1.0347	1.6712
	mean rank	4	2	3	6	1	5
21	mean	-1.5810	-1.3612	-1.3983	-0.6975	-1.6474	-2.1265
	range	4.9750	1.8216	2.2283	1.3839	3.2605	3.9358
	mean rank	3	5	4	6	2	1
22	mean	-1.5963	-1.6752	-1.9534	-1.2177	-2.1933	-1.6752
	range	3.6031	5.0178	4.2295	4.6087	7.3793	2.8556
	mean rank	4	3	2	6	1	3
23	mean	-1.6032	-1.9657	-1.5508	-0.9620	-2.4926	-2.3177
	range	3.2431	2.8363	2.5815	1.4746	4.4996	3.8882
	mean rank	4	3	5	6	1	2

Second, these five techniques provide a wide variety of searching methods. HO is the technique that do not employ stringent acceptance [14]. TIA is the only technique that does not utilize the best or better agents [27]. RPO [13] and DOA [15] represent techniques that employ neighborhood search. DOA

[15] and POA [12] are techniques that utilize the best agent as target but in a different manner. RPO is the technique that utilizes a randomly selected better agent [13].

The 23 standard functions are chosen as they cover a wide range of circumstances. This set of functions contains seven high dimension unimodal functions (HDU) which each of these functions have single optimal solution. It also contains 17 multimodal functions where each of these functions contains multiple optimal solutions but only one global optimal while the rest are local optimal solutions. These high multimodal functions can be split into six high dimension functions (HDM) and ten fixed dimension functions (FDM). In this work, the dimension for high dimension functions is set to 30. The result is provided in Table 4 to Table 7.

Table 4 shows the supremacy of FEA in handling all functions in HDUs as it performs the best of all HDUs. Meanwhile, there are other metaheuristics that also achieve the best result including POA, RPO, TIA, and DOA in F2. In these functions, TIA becomes the second best as it achieves the second best in five functions (F1, F3, F4, F5, and F6) and the fourth best in handling F7. DOA becomes the worst technique as it becomes the worst in four functions (F1, F3, F4, and F6) while HO becomes the second worst as it becomes the worst in three functions (F2, F5, and F7). The performance disparity between the best and the worst is wide in all seven functions.

Table 5 shows the supremacy of FEA in handling most functions in HDMs. It achieves the best result in five functions (F9 to F13). It became the third best in F8. HO becomes the worst performer in five functions (F8, F9, F10, F12, and F13). The performance disparity between the best and the worst is narrow in F8 and F12 and wide in other functions.

Table 6 reveals the competitiveness of FEA in handling FDMs. It becomes the best in three functions (F14, F19, and F21), second best in two functions (F15 and F23), third best in F22, fourth best in F16, and sixth best in three functions (F17, F18, and F20). In this group, HO becomes the worst technique as its result in on the sixth rank in 9 functions (F14 to F16 and F18 to F23).

Table 7 reveals the supremacy of FEA compared to all functions. FEA is superior to POA, RPO, TIA, HO, and DOA in 19, 15, 15, 22, and 14 functions. This result also shows that FEA is superior to HO in almost all functions. Meanwhile, FEA is superior to all five techniques in handling high dimension functions. On the other hand, though competition occurs in FDMs where FEA is superior to TIA and DOA in three functions.

Table 7. Superiority of FEA in 23 functions

Cluster	POA [12]	RPO [13]	TIA [27]	HO [14]	DOA [15]
1	6	6	6	7	6
2	6	5	6	6	5
3	7	4	3	9	3
Total	19	15	15	22	14

The second use case is the seed supplier optimization problems in crab precision farming which is the crab seed order allocation problem. The price and the weight of the crab are obtained from Tokopedia and Shopee which both are the online marketplace in Indonesia. Meanwhile, the scenario of the farming system, including the number of crab boxes is based on the crab farmer in Surabaya, Indonesia. The use case is a crab farm whose objective is crab fattening. This farm operates 1,500 crab boxes. In the beginning, all boxes are empty so that the farmer should orders 1,500 crab seeds. The weight of the seed is 250 gram each. There are five suppliers that provide crab seeds for this farm. The price of each seed is provided in Table 8.

There are two scenarios for the quantity range. The first scenario is that the range of each crab seed supplier is from 10 percent to 30 percent from total order. The second scenario is the range is from 10 percent to 40 percent from total order. The result for the first scenario is provided in Table 9 while the result for the second scenario is provided in Table 10.

The result shows that FEA is competitive in handling crab seed order allocation problem. FEA becomes the second best in both scenarios. Meanwhile, DOA becomes the best performer in handling this problem in both scenarios.

Table 8. Price of crab seeds

Vendor	Price (IDR/seed)
1	76,000
2	42,500
3	69,250
4	77,750
5	65,000

Table 9. Result of the first scenario of crab seed order allocation problem

Metaheuristic	Total Purchasing Cost	Rank
POA [12]	92,878,090	4
RPO [13]	92,893,047	5
TIA [27]	92,595,952	3
HO [14]	95,245,693	6
DOA [15]	92,435,950	1
FEA	92,581,416	2

Table 10. Result of the second scenario of crab seed order allocation problem

Metaheuristic	Total Purchasing Cost	Rank
POA [12]	89,181,421	4
RPO [13]	89,201,937	5
TIA [27]	88,959,047	3
HO [14]	94,399,943	6
DOA [15]	88,514,875	1
FEA	88,892,812	2

The result also reveals the fierce competition among metaheuristics that employ stringent acceptance approach in handling crab seed order allocation problem. The gap among five metaheuristics (POA, RPO, TIA, DOA, and FEA) is very narrow. Meanwhile, the gap between these five metaheuristics and HO is little moderate.

5. Discussion

Overall, the result shows that FEA is proven superior and competitive in handling the optimization problems. FEA is proven superior in handling the high dimension functions whether they are unimodal or multimodal. Meanwhile, FEA is still superior in handling fixed dimension multimodal functions when it is compared to POA and HO. On the other hand, FEA is competitive in handling fixed dimension multimodal functions when it is compared to RPO, TIA, and DOA. Meanwhile, FEA is also competitive in handling crab seed order allocation problem as it is on the second best after DOA. It means FEA is better than POA, RPO, TIA, and HO in handling this practical use case.

The result also reveals the poor performance of HO in handling both use cases compared to other metaheuristics. This circumstance can be traced to the acceptance approach that is employed in the metaheuristics. HO employs loose acceptance so that worse solution is still accepted. Meanwhile, POA, RPO, TIA, HO, DOA, and FEA employs stringent acceptance approach.

Besides the excellence of FEA on handling standard 23 functions and the crab seed order allocation problem for crab vertical farming system, there are two limitations regarding this work. The first limitation is regarding the metaheuristic. The second limitation is regarding the practical use case in the crab farming system.

Regarding the metaheuristic technique, FEA exploits only the finest agent, a randomly chosen finer agent, and a randomly chosen worse agent. Meanwhile, there are a lot of other entities that can be chosen as the target. Meanwhile, FEA does not employ swarm split mechanism or conditional action like in other metaheuristics, such as KMA [17]. Besides, FEA also does not employ iteration-controlled strategy such as in marine predator algorithm (MPA) that shifts exploration to exploitation as iteration goes on [46].

Regarding the practical use case, this paper explores the order allocation problem only. Meanwhile, there are a lot of optimization problems that can be explored whether in the farming system, the upstream, and the downstream. In the upstream, as the relationship between the farmer and the suppliers, there are a lot of optimization problems, such as supplier or vendor selection, order scheduling, and so on. In the downstream, there are also a lot of optimization problems, such as customer selection and allocation, inventory or warehousing, to the transportation of the harvested products. In the farming system, there are also a lot of optimization problems, such as the electrification, water treatment system, employee management, and so on. The ultimate objective is to achieve the operational excellence to keep the crab farming still profitable and sustainable.

6. Conclusion

A new metaheuristic called as forward escape algorithm (FEA) has been introduced in this work. The presentation of FEA includes the concept, model formalization, assessment, and the comprehensive analysis of FEA. The result on handling 23 standard functions reveals the supremacy of FEA in handling high dimension functions and its competitiveness in handling fixed dimension multimodal functions. FEA is better than POA, RPO, TIA, HO, and DOA in 19, 15, 15, 22, and 14 functions. Moreover, FEA is also competitive on handling crab seed order allocation problem where the scenario is elaborated from the actual condition in Indonesia as it becomes the second best after DOA.

The exploration and implementation of FEA in specific manner and metaheuristics in a more general manner in handling optimization problem in modern aquaculture system is challenging. This consideration can be exploited in future studies. This exploration can be performed whether in the upstream as a relation with suppliers, downstream as a relation with customers, and within the farming system to achieve operational excellence as it is important for the profitability and sustainability of the modern aquaculture.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization: Kusuma and Akbar; methodology: Kusuma and Adiputra; software: Akbar and Kusuma, Data: Hendrarini, Ema, Putra, and Saputra; formal analysis: Soegiarto; writing-original paper draft: Kusuma; writing-review and editing: Kusuma; funding acquisition: Kusuma, Putra, and Saputra.

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References

[1] R. P. Shete, A. M. Bongale, and D. Dharrao, "IoT-Enabled Effective Real-Time Water Quality Monitoring Method for Aquaculture", *MethodsX*, Vol. 13, Art. 102906, 2024.

[2] M. A. Soares, R. Singh, S. Kumar, R. Jha, J. Nedoma, R. Martinek, and C. Marques, "The role of smart optical biosensors and devices on predictive analytics for the future of aquaculture systems", *Optics and Laser Technology*, Vol. 177, Art. 111049, 2024.

[3] F. Ahmed, M. H. I. Bijoy, H. R. Hemal, and S. R. H. Noori, "Smart Aquaculture Analytics: Enhancing Shrimp Farming in Bangladesh Through Real-Time IoT Monitoring and Predictive Machine Learning Analysis", *Heliyon*, Vol. 10, No. 17, Art. e37330, 2024.

[4] D. R. Gandh, V. P. Harigovindan, K. P. R. A. Haq, and A. Bhide, "Attention-Driven LSTM and GRU Deep Learning Techniques for Precise Water Quality Prediction in Smart Aquaculture", *Aquaculture International*, Vol. 32, No. 6, pp. 8455-8478, 2024.

[5] S. Son, and Y. Jeong, "An Automated Fish-Feeding System Based on CNN and GRU Neural Networks", *Sustainability*, Vol. 16, No. 9, Art. 3675, 2024.

[6] J. Shen, T. S. Hong, L. Fan, R. Zhao, M. K. A. M. Arifin, and A. As'arry, "Development of an Improved GWO Algorithm for Solving Optimal Paths in Complex Vertical Farms with Multi-Robot Multi-Tasking", *Agriculture*, Vol. 14, No. 8, Art. 1372, 2024.

[7] A. Ghobadpour, A. Cardenas, G. Monsalve, and H. Mousazadeh, "Optimal Design of Energy Sources for a Photovoltaic/Fuel Cell Extended-Range Agricultural Mobile Robot", *Robotics*, Vol. 12, No. 1, Art. 13, 2023.

[8] D. Mishra and S. Satapathy, "Modified Reaper for Small-Scale Farmers: An Approach for Sustainable Agriculture", *Environment, Development and Sustainability*, Vol. 26, No. 1, pp. 1451-1480, 2024.

[9] S. Cui, J. F. Adamowski, R. Albano, M. Wu, and X. Cao, "Optimal Resource Reallocation Can Achieve Water Conservation, Emissions Reduction, and Improve Irrigated Agricultural Systems", *Agricultural Systems*, Vol. 221, Art. 104106, 2024.

[10] R. Roberto, J. M. F. Jaramillo, K. Sugama, Poerbandono, and K. Orhan, "Method for Layout Optimization of Coastal Cage Aquaculture Systems in Southeast Asia", *Aquacultural Engineering*, Vol. 106, Art. 102438, 2024.

[11] S. A. Choudari, M. A. Kumbhalkar, M. M. Sardeshmukh, and S. V. Bhise, "Irrigation Planning for Development of An Effective Cropping Pattern Using Genetic Algorithm", *Multidisciplinary Science Journal*, Vol. 6, No. 7, Art. e2024083, 2024.

[12] T. Hamadneh, B. Batiha, O. Alsayyed, G. Bektemyssova, Z. Montazeri, M. Dehghani, and K. Eguchi, "On the Application of Potter Optimization Algorithm for Solving Supply Chain Management Application", *International Journal of Intelligent Engineering and Systems*, Vol. 17, No. 5, pp. 88-99, 2024, doi: 10.22266/ijies2024.1031.09.

[13] H. Givi, M. Dehghani, and S. Hubalovsky, "Red Panda Optimization Algorithm: An Effective Bio-Inspired Metaheuristic Algorithm for Solving Engineering Optimization Problems", *IEEE Access*, Vol. 11, pp. 57203-57227, 2023.

[14] S. O. Oladejo, S. O. Ekwe, and S. Mirjalili, "The Hiking Optimization Algorithm: A Novel Human-Based Metaheuristic Approach", *Knowledge-Based Systems*, Vol. 296, Art. 111880, 2024.

[15] S. A. Omari, K. Kaabneh, I. A. Falahah, K. Eguchi, S. Gochhait, I. Leonova, Z. Montazeri, M. Dehghani, "Dollmaker Optimization Algorithm: A Novel Human-Inspired Optimizer for Solving Optimization Problems", *International Journal of Intelligent Engineering and Systems*, Vol. 17, No. 3, pp. 816-828, 2024, doi: 10.22266/ijies2024.0630.63.

[16] T. Hamadneh, K. Kaabneh, O. Al-Sayed, G. Bektemyssova, Z. Montazeri, M. Dehghani,

and K. Eguchi, “Sculptor Optimization Algorithm: A New Human-Inspired Metaheuristic Algorithm for Solving Optimization Problems”, *International Journal of Intelligent Engineering and Systems*, Vol.17, No.4, pp. 564-575, 2024, doi: 10.22266/ijies2024.0831.43.

[17] Suyanto, A. A. Ariyanto, and A. F. Ariyanto, “Komodo Mlipir Algorithm”, *Applied Soft Computing*, Vol. 114, Art. 108043, 2022.

[18] S. Alomari, K. Kaabneh, I. A. Falahah, S. Gochhait, I. Leonova, Z. Montazeri, M. Dehghani, and K. Eguchi, “Carpet Weaver Optimization: A Novel Simple and Effective Human-Inspired Metaheuristic Algorithm”, *International Journal of Intelligent Engineering and Systems*, Vol.17, No.4, pp. 230-242, 2024, doi: 10.22266/ijies2024.0831.18.

[19] S. O. Oladejo, S. O. Ekwe, L. A. Akinyemi, and S. A. Mirjalili, "The Deep Sleep Optimizer: A Human-Based Metaheuristic Approach," *IEEE Access*, vol. 11, pp. 83639-83665, 2023.

[20] P. Trojovsky, M. Dehghani, E. Trojovska, and E. Milkova, “Language Education Optimization: A New Human-Based Metaheuristic Algorithm for Solving Optimization Problems”, *Computer Modeling in Engineering and Sciences*, Vol. 136, No. 2, pp. 1527-1573, 2023.

[21] M. H. Amiri, N. M. Hashjin, M. Montazeri, S. Mirjalili, and N. Khodadadi, “Hippopotamus Optimization Algorithm: A Novel Nature-Inspired Optimization Algorithm”, *Scientific Reports*, Vol. 14, Art. 5032, 2024.

[22] F. A. Zeidabadi, S. A. Doumari, M. Dehghani, Z. Montazeri, P. Trojovsky, and G. Dhiman, “MLA: A New Mutated Leader Algorithm for Solving Optimization Problems”, *Computers, Materials & Continua*, Vol. 70, No. 3, pp. 5632-5649, 2022.

[23] X. Wang, V. Snasel, S. Mirjalili, J. -S. Pan, L. Kong, and H. A. Shehadeh, “Artificial Protozoa Optimizer (APO): A Novel Bio-Inspired Metaheuristic Algorithm for Engineering Optimization”, *Knowledge Based Systems*, Vol. 295, Art. 111737, 2024.

[24] O. Al-Baik, S. Alomari, O. Alssayed, S. Gochhait, I. Leonova, U. Dutta, O. P. Malik, Z. Montazeri, and M. Dehghani, “Pufferfish Optimization Algorithm: A New Bio-Inspired Metaheuristic Algorithm for Solving Optimization Problems”, *Biomimetics*, Vol. 9, Art. 65, 2024.

[25] T. Hamadneh, B. Batiha, F. Werner, Z. Montazeri, M. Dehghani, G. Bektemyssova, and K. Eguchi, “Fossa Optimization Algorithm: A New Bio-Inspired Metaheuristic Algorithm for Engineering Applications”, *International Journal of Intelligent Engineering and Systems*, Vol.17, No.5, pp. 1038-1047, 2024, doi: 10.22266/ijies2024.1031.78.

[26] P. D. Kusuma and F. C. Hasibuan, “Swarm Magnetic Optimizer: A New Optimizer that Adopts Magnetic Behaviour”, *International Journal of Intelligent Engineering and Systems*, Vol. 16, No. 4, pp. 264-275, 2023, doi: 10.22266/ijies2023.0831.22.

[27] P. D. Kusuma and A. Novianty, "Total Interaction Algorithm: A Metaheuristic in Which Each Agent Interacts with All Other Agents", *International Journal of Intelligent Engineering and Systems*, Vol. 16, No. 1, pp. 224-234, 2023, doi: 10.22266/ijies2023.0228.20.

[28] M. Noroozi, H. Mohammadi, E. Efatinasab, A. Lashgari, M. Eslami, and B. Khan, “Golden Search Optimization Algorithm”, *IEEE Access*, Vol. 10, pp. 37515-37532, 2022.

[29] M. Dehghani, S. Hubalovsky, and P. Trojovsky, “A New Optimization Algorithm based on Average and Subtraction of the Best and Worst Members of the Population for Solving Various Optimization Problems”, *PeerJ Computer Science*, Vol. 8, Art. e910, 2022.

[30] P. D. Kusuma and A. Novianty, “Multiple Interaction Optimizer: A Novel Metaheuristic and Its Application to Solve Order Allocation Problem”, *International Journal of Intelligent Engineering and Systems*, Vol. 16, No. 2, pp. 440-453, 2023, doi: 10.22266/ijies2023.0430.35.

[31] C. Agustiyana, Y. Hadiroseyani, I. Irzal, and I. Effendi, “Optimization of the Production of Soft Shell Crab (Scylla sp.) Cultivation Using The Apartment System”, *Egyptian Journal of Aquatic Research*, 2024, in press.

[32] S. Alamsyah, Y. Fujaya, N. Rukminasari, A. A. Hidayani, M. Darwis, and M. Achdiat, “Utilization of Feed and Growth Performance of Mud Crabs: The Effect of Herbal Extracts as Functional Feed Additives”, *The Israeli Journal of Agriculture*, Vol. 74, Art. 1551973, 2022.

[33] A. G. Gad, “Particle Swarm Optimization Algorithm and Its Applications: A Systematic Review”, *Archives of Computational Methods in Engineering*, Vol. 29, pp. 2531-2561, 2022.

[34] Y. Liu, A. As’arry, M. K. Hassan, A. A. Hairuddin, and H. Mohamad, “Review of The Grey Wolf Optimization Algorithm: Variants

and Applications”, *Neural Computing and Applications*, Vol. 36, pp. 2713-2735, 2024.

[35] S. Sravani, A. Gopalakrishnan, A. S. John, R. Ramasubramanian, G. Kesavaperumal, N. M. Prabhu, B. Dhasarathan, and S. B. Natarajan, "Incidence of Mud Crab Reovirus (MCRV) Outbreak in Polyculture Ponds of Andhra Pradesh, South East Coast of India", *Journal of Invertebrate Pathology*, Vol. 204, Art. 108092, 2024.

[36] C. Lee, H. J. Jeon, B. Kim, S. Suh, P. Piamsomboon, J. H. Kim, and J. E. Han, “Cultured Penaeus Vannamei in Korea Co-Infected with White Spot Syndrome Virus and Decapod Hepanhamaparvovirus”, *Journal of the World Aquaculture Society*, Vol. 55, No. 1, pp. 373-385, 2024.

[37] C. T. -K. Kwok, R. C. -W. Yu, P. -T. Hau, K. Y. -C. Cheung, I. C. -F. Ng, J. Fung, I. T. -F. Wong, M. C. -Y. Yau, W. -M. Liu, H. -K. Kong, G. K. -H. Siu, F. W. -N. Chow, and S. -W. Seto, “Characteristics And Pathogenicity of Vibrio Alginolyticus SWS Causing High Mortality in Mud Crab (Scylla serrata) Aquaculture In Hong Kong”, *Frontiers in Cellular and Infection Microbiology*, Vol. 14, Art. 1425104, 2024.

[38] T. Stamp, S. J. Pittman, L. A. Holmes, A. Rees, B. J. Ciotti, H. Thatcher, P. Davies, A. Hall, G. Wells, A. Olczak, and E. V. Sheehan, “Restorative Function of Offshore Longline Mussel Farms with Ecological Benefits for Commercial Crustacean Species”, *Science of the Total Environment*, Vol. 95115, Art. 174987, 2024.

[39] C. Humber, M.W. Bulbert, J. Chavez, I. N. Y. Parawangsa, K. Majerus, and M. Campera, “Resource Availability and Use in Restored, Unmanaged, and Aquaculture Mangrove Ecosystems in Indonesia”, *Resources*, Vol. 13, No. 9, Art. 117, 2024.

[40] J. -N. Huang, L. Xu, B. Wen, J. -Z. Gao, and Z. -Z. Chen, “Characteristics and risks of microplastic contamination in aquaculture ponds near the Yangtze Estuary, China”, *Environmental Pollution*, Vol. 34315, Art. 123288, 2024.

[41] Y. Fujaya, N. Rukminasari, N. Alam, M. Rusdi, H. Fazhan, and K. Waiho, “Is Limb Autotomy Really Efficient Compared to Traditional Rearing in Soft-Shell Crab (Scylla Olivacea) Production?”, *Aquaculture Reports*, Vol. 18, Art. 100432, 2020.

[42] M. M. Rahman, M. R. M. Ranju, and M. L. Islam, "Study on Growth, Survival and Intactness of Sub-Adult to Adult Mud Crab Aquaculture under Low Saline Earthen Ponds in The Coastal Areas of Bangladesh", *Bangladesh Journal of Fisheries*, Vol. 34, No. 1, pp. 19–26, 2022.

[43] X. Zi, Y. Li, G. Li, B. Jia, E. Jeppesen, Q. Zeng, and X. Gu, “A Molting Chemical Cue (N-acetylglucosamine-6-phosphate) Contributes to Cannibalism of Chinese Mitten Crab Eriocheir sinensis”, *Aquatic Toxicology*, Vol. 263, Art. 106666, 2023.

[44] A. T. Wibowo, N. I. Arvitrida, and E. Widodo, “Raw Material Order Allocation Problem Using Mixed Integer Linear Programming and Simulation”, *Operations and Supply Chain Management*, Vol. 14, No. 4, pp. 444-455, 2021.

[45] Y. Zhou, M. Liu, F. Ma, N. Luo, and M. Yin, “Modelling and Solving the Supply Marketing Order Allocation Problem with Time Consistency and Bundle Discounts”, *Journal of The Operational Research Society*, Vol. 73, No. 8, pp. 1682-1691, 2022.

[46] A. Faramarzi, M. Heidarinejad, S. Mirjalili, and A. H. Gandomi, “Marine Predators Algorithm: A Nature-inspired Metaheuristic”, *Expert System with Applications*, Vol. 152, Art. 113377, 2020.