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An Energy and Fuel-effective Solution for School Exploration of a Fishing Vessel Through Swarm Intelligence Approach

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Abstract

In recent years, energy and fuel efficiencies have been considered in scientific studies. These parameters become extremely important in maritime, especially for fishing vessel activities. In this study, an innovative approach is proposed to reduce the fuel consumed by fishing vessels and carbon emissions to the environment during the fish exploration process. Key elements of the proposed approach are autonomous underwater vehicles (AUVs) and the application of swarm intelligence. With this approach, which can be considered a pioneer in maritime, the AUVs released from the fishing vessel find the school through the swarm intelligence behavior of Grey Wolves. In this article, the method is modeled as a simulation, and its applicability in the future is also discussed. In the present studies, the conventional fish search method and the proposed method were modeled, and the results were examined. When the obtained results are examined, it is seen that the proposed method increases the successful voyage rate by 2.94 times compared to the conventional method, while the distance covered in the exploration activity decreases by 8.61 times. The results demonstrated that the proposed innovative approach is an energy-efficient, cost-effective, and environmentally friendly solution that is also applicable and usable in the future.

Keywords: Energy efficient, Carbon emission, AUVs, Grey Wolf Algorithm, Swarm intelligence

1. Introduction

The EU Marine Strategy Framework Directive states that the economy and energy efficiency in fisheries are critical components of the ecosystem-based approach to fisheries management [1]. It should be emphasized that energy efficiency, approaches, and studies that will protect the ecosystem have become of great importance [1-3]. Scientific awareness has also manifested itself in the institutional field; for example, International Maritime Organization (IMO) has enacted a new law that includes reducing carbon emissions from ships and providing energy efficiency technically and operationally [4].

This scientific study in this context examines the problem of fuel consumption, energy efficiency, and carbon emissions in the scope of fishing vessels. Researchers have significantly contributed to the fuel consumption and efficiency of fishing vessels. Individual voyage planning was studied by creating a decision tree model with the data obtained from fishing vessels [1], and statistical studies based on the product costs of fishing vessels were performed between specific dates [2]. The use of magnetic devices has been tried to provide energy efficiency [3], low-friction mesh technology is recommended [5], and fuel consumption is reduced by using a DC electric propulsion system [6]. As can be seen, studies are primarily focused on statistical approaches to improving existing equipment or approaches to reducing fuel consumption and increasing energy efficiency through weight reduction. In this study, the approach to solving the problem from a novel angle examines a different strategy for lowering fuel consumption and raising energy efficiency in fishing vessels.

For example, the search process of fishing vessels to find fish mass is one of the most important factors that increase fuel consumption and thus product cost [7,8]. Fishing vessels may need to scan fish for long periods to find the fish

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mass. One of the most important reasons is that the Sound Navigation and Ranging (SONAR) on board can observe a limited area. In scientific studies, effective SONAR distances are accepted between 100 and 1200 m bands [9-13]. Furthermore, it is necessary to consider that the SONAR device is positioned under the vessel and creates resistance during the vessel [14,15]. The resistance created has an additional direct effect on the increase in fuel consumption.

This scientific study, which includes a completely innovative method for reducing fuel consumption, presents unmanned vehicle technologies, which have become increasingly popular in recent years as an innovative solution for energy efficiency. The development of AUVs dates back to the 1960s. Over the years, hardware developments in this field (energy management, sensing technologies, etc.) have continued [16]. In recent years, studies and applications of autonomous underwater vehicles have become remarkable. Its use in polar regions, where obtaining data in ocean science and traveling with manned vehicles is extremely dangerous, is just one of the AUV applications [17,18]. Other applications include marine environment mapping applications [19,20], evaluation applications of dangerous situations that may arise at submarine oil and gas connection points [18], and military applications [20].

It is clear that the perspectives on the solution to the problem discussed in this study are limited. For this reason, it is exciting that the study fills the gap in this field and contributes to the literature. The proposed method aims to detect the fish mass of a group of AUVs that the fishing vessel will release into the sea in a particular area in a short time, with a collaborative approach focused on swarm intelligence that mimics the hunting behavior of the grey wolf pack. Sharing the detected location information with the fishing vessel via AUVs enables the fishing vessel to achieve less fuel consumption, carbon emissions, and energy efficiency.

The flow order of the article is planned as follows. Section 2 discusses the contributions of the article to the literature. Section 3 explains the method, Section 4 evaluates the studies and findings, and the results are discussed in Section 5.

2. Contributions to the Literature

It is possible to list the contributions of this scientific study to the literature as follows:

• A system model has been proposed that will make fishing vessels cost-effectively and emit less carbon in a shorter time.

• In the proposed system model, one of the maritime applications is integrated through autonomous vehicle technologies, one of the popular technologies of recent years.

• The application of school detecting through a collaborative approach with AUVs, current technology in the maritime field, is proposed for the first time.

• It was achieved that the AUV group reached a solution using a model inspired by nature. It has been a pioneer study in this area.

3. Material and Methodology

The school search process is analyzed with a focus on swarm intelligence, which proposes a solution that will provide cost-effective and less carbon emission. A simulation model was developed for the solution. The swarm is made up of AUVs, and each AUV is a member of the swarm. Swarm intelligence was created by mimicking the natural herd behavior and hunting methods of grey wolves. Mirjalili et al. [21] proposed and used grey wolf pack hunting behavior for the first time to solve an optimization problem. An objective function is needed in conventional optimization problems to reach the solution. In this approach, the objective function is nothing more than the instantaneous distance of the AUVs, defined as the wolf pack, to the school. In the simulation studies, the wolf pack leadership hierarchy and hunting behavior were modeled and integrated into each individual, and an artificial wolf pack consisting of underwater AUVs was obtained. AUVs released from the fishing vessel have been enabled to find the fish school in a cost-effective and eco-friendly way. Figure 1 depicts the applied scenario.

In this section, the method of the scientific study is explained. Figure 1 shows the main elements used in the study: AUVs representing swarm individuals, the grey wolf algorithm used for swarm intelligence, evaluations in terms of applicability, assumptions for simulations, constraints, and conditions.

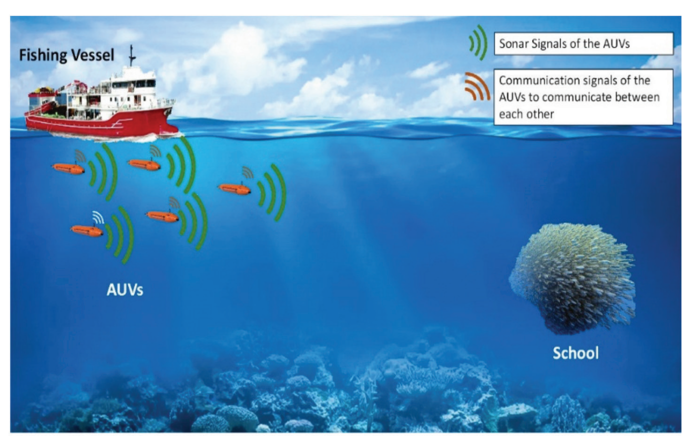

Figure 1. *Applied scenario for the study*

3.1. Autonomous Underwater Vehicles

AUVs have started to be used in most maritime applications as developing technology in recent years. AUVs are equipped with high-resolution cameras, pressure, temperature, proximity, and chemical sensors to collect data while performing tasks [17-20]. They obtain the necessary information using the sensor fusion they have. The figure below shows an AUV used in these studies (Figure 2).

Figure 2. *ABE autonomous vehicle [19]*

Designs for AUVs in scientific studies and applications are being developed and made available in various mobility, size, and speed configurations. Designed and developed AUVs used in scientific studies can have length values between 0.92-10.44 m and speed values in the range of 0.2-41.67 m/s. The length of AUV designs, similar to biological creatures, ranges from 0.09-2.5 m and the maximum rotation angle per second varies in the range of 6.84-670 deg/s [22]. Considering the designs, developments, and scientific studies, it appears that AUV applications resemble biological creatures and can move like them in the near future. This circumstance suggests that the proposed method and the simulated studies will be applicable soon. Another aspect to investigate is the communication between AUVs with swarm intelligence and the management of detection processes for fish school detection. Thus, the feasibility of this simulated study should be discussed.

When the detection and verification of fish swarms are examined, conventionally utilized SONAR can be seen as a natural solution. Image recognition can also be accomplished by equipping AUVs with high-resolution cameras and using image processing and deep learning applications [23]. Another issue is the communication of AUVs with each other. In detecting a school of fish, AUVs must constantly communicate with each other and determine their distance from each other. There are three different methods used for AUV communication in the literature. These are radio frequency (RF), acoustic, and optical wireless communication [24,25]. The channel model in water is unlike the channel model in the air for RF signals. In water, the signal becomes weaker, so the communication distance decreases. The distance can be increased by extending the wavelength, but then the communication speed will decrease [24]. Studies have been conducted on Underwater Wireless Sensor Networks using RF signals [26,27]. Conversely, acoustic communication provides a low data rate (around kbps) over long distances (around 20 km), and they have a high cost and bulky transceiver [25]. Furthermore, optical wireless communication offers the advantages of low cost, a small volume of transceiver hardware, a fast communication speed, and the ability to establish a medium distance connection (at the level of 10 m).

Working with RF signals for the proposed scenario can be an obstacle. In contrast, factors such as the cost-effectiveness of acoustic communication and the need for bulky transceivers may create disadvantages. But optical wireless communication has a cost-effective structure, small volume of transceiver equipment that can reduce energy consumption, fast communication speed, and ability to establish a medium-distance connection. Thus, it can be considered a viable solution for AUV to AUV and AUV to vessel communication.

This analysis showed that the simulated work is applicable in the future.

3.2. Grey Wolf Algorithm for Swarm Intelligence

In the applied scenario, each of the AUVs released from the fishing vessel is considered an individual with swarm intelligence. Grey wolf pack hunting behavior was chosen as swarm behavior. This is because it converges easier and faster in optimization problems [28]. It is assumed that the AUVs have the necessary sensor hardware to mimic the wolf pack hunting behavior.

Grey wolves are predators at the top of the food chain in nature. They live in groups of 5-12 wolves and have a strict leadership hierarchy among themselves, as shown in Figure 3 below. The first layer is the α layer, which is formed by male and female wolves with the highest leadership degree; they are responsible for decisions such as deciding to hunt, sleep, and get up. In the second layer, the β layer, individuals are responsible for helping other wolf pack members and other tasks. The third layer is the δ layer. Members of this layer are responsible for protecting the packing area, warning the wolf pack of any danger, and caring for injured pack members. The last layer of hierarchy is ω, whose members must submit to all other wolf pack members [21,29].

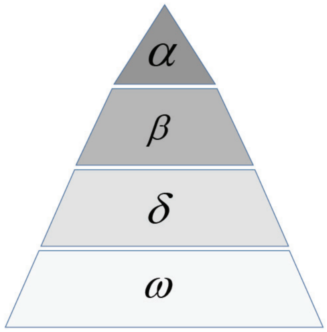

Figure 3. *Hierarchy of the grey wolves*

The hierarchical model mentioned acts a crucial role in the hunting behavior of the grey wolf pack. Primarily, grey wolves seek and track their prey. Then the α wolves direct the other wolves to surround the prey. After that, α wolves order the β and δ wolves to attack. When prey tends to flee, wolves that feed from the rear of the prey continue to attack and capture their prey. The behavior of grey wolves in this hunt has been mathematically modeled [21,29].

If the number of members of the grey wolf pack is K, the search area is d, and i^{th} wolf's position can be defined as: $P_i = (P_{i1}, P_{i2}, P_{i3}, \ldots, P_{id})$. According to the mathematical model, the best solution is considered the solution of the α wolves. The second and third best solutions are β and δ wolves, respectively. The remaining candidate solutions are the solution of ω wolves.

The mathematical model of grey wolves' siege behavior of prey is as follows (equations 1 and 2 as below):

$$\vec{D} = \left|\vec{C}.\vec{P}_p(t) - \vec{P}(t)\right| \tag{1}$$

$$\vec{P}_p(t+1) = \vec{P}_p(t) - \vec{A}.\vec{D} \tag{2}$$

Where t refers to the current iteration; $\vec{A}$ and $\vec{C}$ are the coefficient vectors; $\vec{P}_p$ is the position vector of the prey; $\vec{P}$ denotes the position vector of the wolf pack. The c oefficient vectors $\vec{A}$ and $\vec{C}$ can be calculated as follows (equations 3 and 4 as below):

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \tag{3}$$

$$\vec{C} = 2.\vec{r}_2 \tag{4}$$

Where $\vec{r}_1$ and $\vec{r}_2$ are random vectors $\in [0, 1]$; $\vec{a}$ is a linearly decreasing value from 2 to 0 depending on the iteration number and is calculated as follows (equation 5 as below):

$$\vec{a} = 2\left(1 - \frac{t}{T_{\max}}\right) \tag{5}$$

Where $T_{\max}$ denotes the determined maximum iteration number. After the wolf pack has caught the prey, the other wolves surround the prey at the command of the α wolf. Then the α, β, and δ wolves start to approach the prey, and their position with the prey is calculated. The mathematical model of this situation is defined in the equations below:

$$\vec{D}_\alpha = \left|\vec{C}_1.\vec{P}_\alpha - \vec{P}\right| \tag{6}$$

$$\vec{D}_\beta = \left|\vec{C}_2.\vec{P}_\beta - \vec{P}\right| \tag{7}$$

$$\vec{D}_\delta = \left|\vec{C}_3.\vec{P}_\delta - \vec{P}\right| \tag{8}$$

$$\vec{P}_1 = \vec{P}_\alpha - \vec{A}_1.(\vec{D}_\alpha) \tag{9}$$

$$\vec{P}_2 = \vec{P}_\beta - \vec{A}_2.(\vec{D}_\beta) \tag{10}$$

$$\vec{P}_3 = \vec{P}_\delta - \vec{A}_3.(\vec{D}_\delta) \tag{11}$$

$$\vec{P}(t+1) = \frac{\vec{P}_1 + \vec{P}_2 + \vec{P}_3}{3} \tag{12}$$

$\vec{P}_1, \vec{P}_2, \vec{P}_3$ positions of the α, β, and δ wolves can be calculated using equations (6-11). Then next position of the wolf pack $\vec{P}(t+1)$ is obtained by averaging, as shown in equation (12). Pseudo codes of the grey wolf algorithm can be seen in Algorithm 1.

In terms of applicability, to transfer swarm intelligence to individuals, each individual must be able to determine the distance between itself and the other individuals as well as the distance between itself and the school of fish. For the distance detection process between individuals, Underwater Optical Wireless Communication can be used for AUV2AUV communication, considering the underwater optical channel model [25,30]. Conversely, SONAR, image processing, and deep learning techniques can detect the fish school, including the distance between the fish school and AUVs. After these hardware features are equipped for individuals, the relevant algorithms with swarm intelligence are transferred to the individuals, and an artificial grey wolf pack that acts with swarm intelligence is obtained. In optimization problems, the best result is searched until a maximum number of iterations is reached. In the applied scenario, the best result is to provide the desired and predetermined distance of individuals to the school of fish. Therefore, the best distance is constantly updated during the search process to reach the desired value.

Algorithm 1. Grey Wolf Algorithm [21]

```
Initialize: TheP i (i = 1,2,...,K)grey wolf population
P i (i = 1,2,...,K)
Initialize: a, A, t=0, and C
Calculate the fitness of each search agent
Xα=the best search agent
Xβ=the second best search agent
Xδ=the third best search agent
While (t<MaxIteration) do
For each search agent
Calculate the position of the current search agent by using
Equation (12)
end for
Update the a, A, and C
Calculate the fitness of all search agents
Update the Xα , Xβ and Xδ
t= t+1
end while
Return Xα
```

3.3. Assumptions, Constraints, and Conditions for Simulation Domain

While various parameter values were selected in the simulation studies, other scientific studies were referenced, and some assumptions, rules, and constraints were created for the applied scenarios.

The simulation environment created for the scenarios assumes that the search and scanning activity is carried out in an area of 20x20 NM^2. The movement of the fish school and the fishing vessel within this area is allowed in the applied scenarios. The speed of fishing vessel was determined as 14.2 knots [31], and horse mackerel was taken into account for the speed of the school. The maximum speed of a horse mackerel is about 6 m/s [22]. In the simulation studies, the school speed was accepted as 6 m/s. Two scenarios were used in simulations. The first scenario is the fishing vessel surveying the school of fish in the designated area, and the second is the proposed approach. However, in the simulations, a search upper limit has been set for the fishing vessel; if the fishing vessel cannot find a school of fish within 100 NM, the search for fish for that voyage is terminated. This was referred to as a failed voyage because any search activity beyond the specified limit would be illogical and inefficient.

4. Simulation Studies and Results

Simulation studies are performed using MATLAB® and a computer with Intel® Core™ i7-6500U CPU @ 2.5 GHz and 8 GB RAM. In the study for the first scenario, the effective SONAR distance of the fishing vessel was determined as 800 m [10]. The fishing vessel is assumed to maneuver by randomly changing one direction at 0.5, 1, 2, and 5 NM, and the fish shoal is assumed to maneuver by randomly changing one direction at 0.15, 0.3, 0.6, and 1.5 NM, respectively. Running the scenario 5000 times yielded the average distance values of the fishing vessel until it found the fish school, including the histograms it produced. Figure 4 depicts the simulations run.

The Figure 4 shows the random displacement behavior of the fishing vessel and the school of fish and the point at which the vessel detects the school of fish. Some movements change direction randomly at 5 NM intervals of the fishing vessel and 1.5 NM intervals of the school. It is seen that the two elements encounter each other under the radar distance determined as 0.43 NM within the defined area.

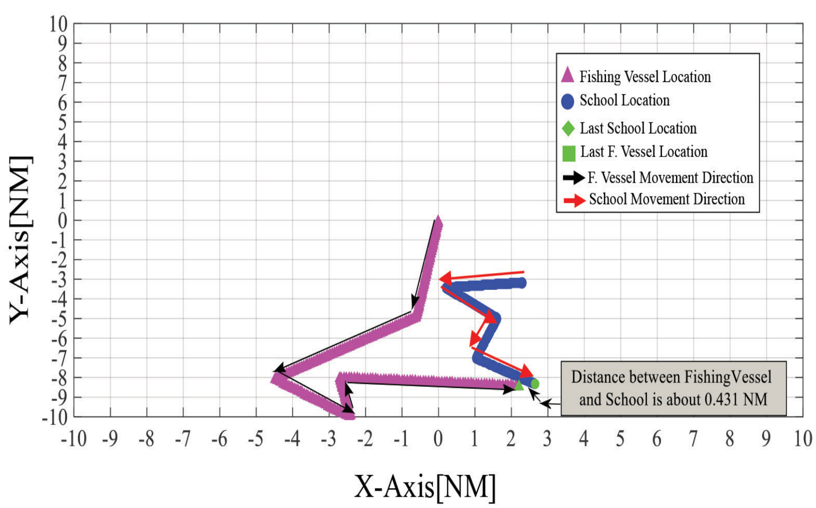

Figure 4. *One of the performed simulations belongs to 1st scenario*

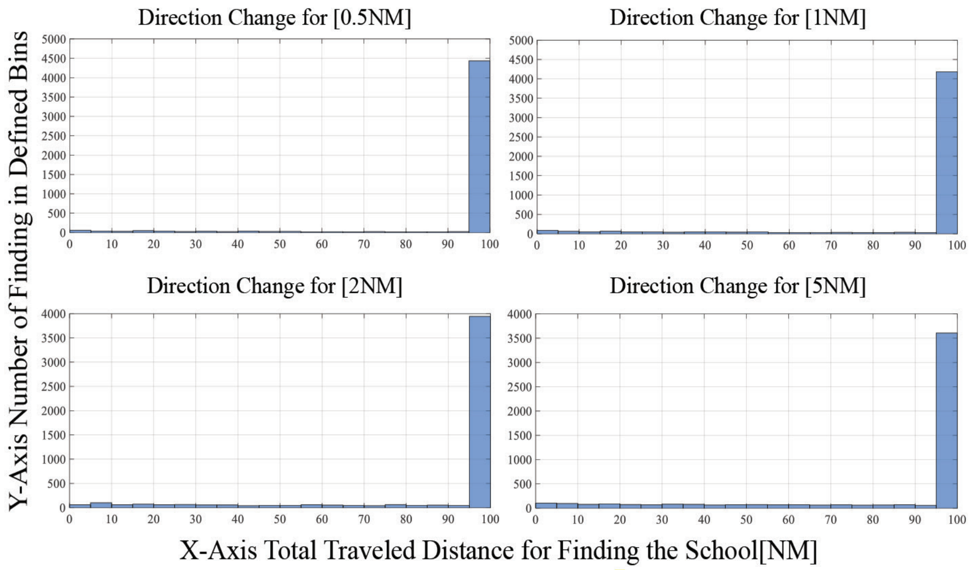

Figure 5. *Histograms for different direction change range in the 1st scenario*

Figure 5 depicts the histograms of the results obtained from 5000 runs for the case where the fishing vessel maneuvers at 0.5, 1, 2, and 5 NM and the school at 0.15, 0.3, 0.6, and 1.5 NM, respectively, by changing direction. When the histograms are examined, there is clear clustering in the 80-100 NM range for each random change of direction distance, indicating that similar results were obtained in most of the simulations run on each graph. The main reason for clustering 80-100 NM is that a certain NM constraint is given to the simulation. The search has been called off if a school of fish is not found after 100 NM of exploration. Table 1 presents the number of the successful voyage and giving up of the school within the determined distance constraint (100 NM) as a result of 5000 runs for each random change of direction distance.

Table 1. *School finding distances under different change of direction range for 1st scenario*

Direction changing range of fishing vessel (FV) and school	Average finding distance [NM]	Number of giving up	Number of successful voyages	Success rate [%]
FV (5NM), School (1.5NM)	84.62	3542	1458	29.16
FV (2NM), School (0.6NM)	88.08	3899	1101	22.02
FV (1NM), School (0.3NM)	90.21	4156	844	16.88
FV (0.5NM), School (0.15NM)	93.16	4410	580	11.60

According to Table 1, as the distance to change direction decreases, the number of successful voyages decreases, and the average distance traveled increases. While evaluating the conventional method, the best result obtained with this method was considered, i.e., it was assumed that the fishing vessel traveled an average of 84.62 NM at a time. Therefore, under the determined constraint, the success rate of the conventional method is 29.16%.

The second scenario, i.e., the primary proposed method in this study, is detecting school through AUVs. Like the first scenario, this scenario is modeled in the MATLAB® environment. The number of individuals is selected between 5 and 12 in the Grey Wolf Algorithm. In this simulation, the number of individuals was kept to a minimum in terms of cost-effectiveness and was determined as 5. The search space boundaries, school speed, and the number of simulation runs remain unchanged from the first scenario.

In the second scenario, in any running process, the voyage is considered unsuccessful if any of the AUV individuals perform a search activity over 100 NM. After the unsuccessful voyage number is obtained, it is subtracted from the total number of runs, and the successful voyage number is calculated. Figure 6 presents the results of four different successful sample search activities based on simulation studies. It was initially assumed that an average school of fish moves at a speed of 6 m/s. The swarm intelligence approach designed for AUV individuals was revised under this condition, $\vec{a}$ expressed in equation (5). In optimization problems, $\vec{a}$ value is a number decreasing from 2 to 0 as the number of iterations increases. But in a real application, the iteration number makes no sense. Therefore, the fitness

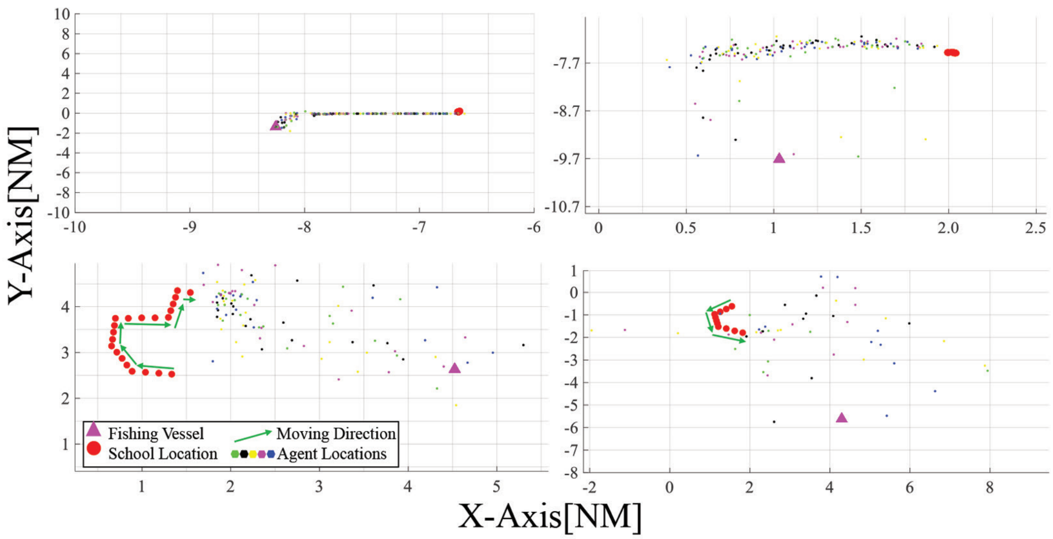

Figure 6. *Some of the performed simulations belong to 2nd scenario*

value should be related to a real parameter. In the applied scenario, fitness value is associated with the distance value of all AUVs to the target (school) and distances with each other in a cyclical process. Distances between AUVs are estimated through communication, whereas SONAR estimates distances to the school. In this study the $\vec{a}$ value was obtained, as shown in equation (13). As seen from the equation, the $\vec{a}$ value decreases as it gets closer to target.

$$\vec{a} = |\text{fitness}/\psi| \quad (13)$$

The fitness value mentioned in the above equation is the distance of the i^{th} individual from the target. ψ is a coefficient, which was determined as 3750. Modeling experience and search space dimensions are important factors when determining this coefficient. The performances obtained in the experiments while determining the ψ coefficient are shown in the graphic below (Figure 7).

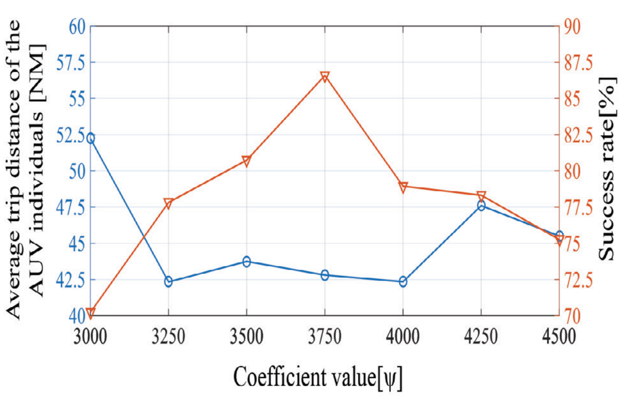

Figure 7. *Success rates and average trip distances under different ψ values*

In this study, a success rate of 86.58% and an average distance of 42.81 NM AUV per individual were found at ψ = 3750, as performed to determine the optimal value. This obtained value was used in the simulation studies. Figure 8 depicts the distance-number of success histograms for 5 AUV individuals resulting from 5000 runs for the determined ψ value. The density at 100 NM bin in the obtained histograms is due to the 100 NM maximum search constraint determined in the studies.

From the histograms, AUVs find the school of fish in the 25-50 NM band with a considerable rate. The simulation results are obtained by accepting the school speed as 6 m/s. Table 2 shows the performances obtained at different school speeds due to 5000 runs.

Table 2. *Performances in different school fish speeds*

School speed [m/s]	Average AUV distance [NM]	Successful voyages	Unsuccessful voyages	Success rate [%]
2	49.28	3554	1446	71.08
3	43.95	3894	1106	77.88
4	47.68	3897	1103	77.94
5	47.81	3817	1183	76.34
6	42.81	4329	671	86.58
7	44.9	4272	728	85.44
8	49.92	3940	1060	78.8
9	47.52	3917	1083	78.34
10	46.88	4088	912	81.67

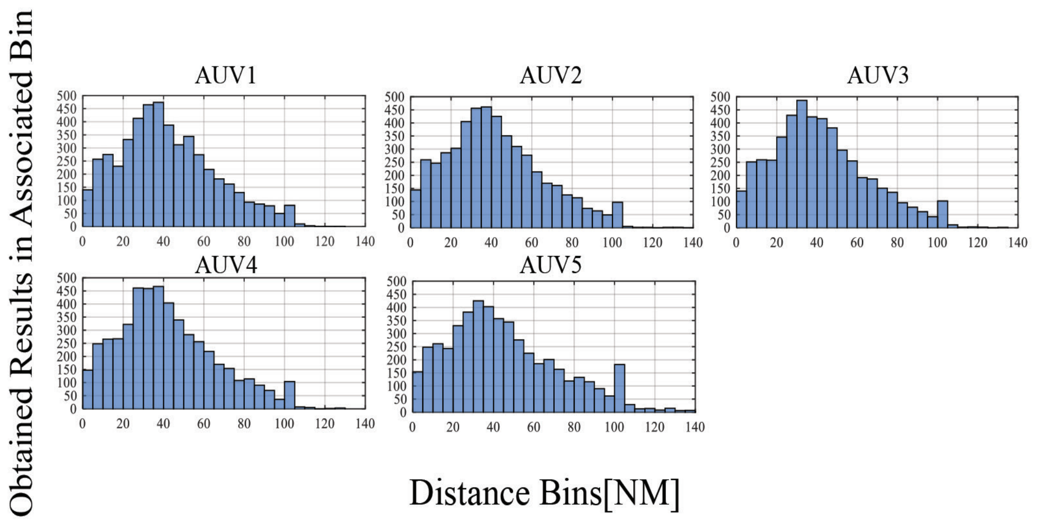

Figure 8. *Distance-number of success histograms of each AUV individual (for 5000 runs)*

AUV: Autonomous underwater vehicle

When the table is examined, the success rate at 2-10 m/s school speeds is between 71.08 and 86.58%. AUVs travel the average distance varied between 42.81 and 49.92 NM. These results show that it can be used for school at speeds of 2-10 m/s. Furthermore, as technology advances, the speed and maneuverability of AUVs will undoubtedly increase, enhancing their success rates.

5. Conclusions and Recommendations

When the simulation studies and results are examined, it is found that a fishing vessel that performs fish exploration activities using the conventional method has a success rate of 29.4% in 5000 voyages and has covered an average of 84.62 NM. This means that the conventional method has a low success rate. Conversely, the fishing vessel traveled 423,100 NM in 5000 voyages. Since this situation increases fuel consumption, product prices will rise. And, long-distance travel will naturally increase carbon emissions and cause environmental pollution.

In the proposed method, 86.58% success was achieved in 5000 voyages in the simulations, and AUV individuals traveled an average of 42.81 NM. In these simulation results, the average covered distance is 9.82 NM since the fishing vessel moves only from the point where its initial position to the school point that the AUVs have found. Therefore, considering 5000 voyages, the total covered distance is about 49,100 NM. As can be seen, the success rate increases 2.94 times, while the distance traveled decreases by 8.61 times. Also, the distances covered by AUVs appear to be within the range they can travel with a full charge. Considering that these distances and AUV speeds will increase with the advancing technology, the proposed approach is a suitable solution. AUVs can meet their energy needs through energy harvesting methods such as PV panels, small wind turbines mounted on the fishing vessel, or fusions, allowing AUVs to be charged on a fishing vessel. Consequently, the results of the simulation studies and the applicability of the proposed method clearly show that this approach can be used in the future. Moreover, the proposed approach can be used in applications such as military infiltration and submarine operations, with minor modifications and the destruction of enemy units.

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