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Enhancement of Harris Hawks optimization applied in path planning for an indoor navigation mobile application

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Abstract

The research focuses on the enhancement of Harris Hawks Optimization (HHO) algorithm in achieving an efficient path planning, specifically in indoor environments. It solves problems encountered in HHO; firstly, the exploration operator of HHO is modified to incorporate the survival of the fittest principle, this ensures a controlled diversity by using an Exponential Ranking selection method. The method aims to guide the algorithm to find a more optimal solution while allowing it to search for alternative paths. Secondly, Linear Path Strategy is used to reduce the number of nodes in the paths, therefore minimizing its length and simplifying trajectories. In addition, Linear Path Strategy aims to create smoother paths and avoid obstacles, improving the overall performance of the algorithm. Lastly, general multi-objective formula is defined to evaluate path length and travel time. Considering these factors established a balanced evaluation metric, which provided a detailed assessment of path quality for scenarios like indoor navigation. Comparative analysis was done, and results highlighted the effectiveness of EHHO in generating better paths, in comparison with Ant Colony Optimization (ACO), Grey Wolf Optimization (GWO), and with the current HHO algorithm. It outperformed the algorithms compared in terms of path length, travel time, and efficiency of the execution, especially in a complex environment. In conclusion, EHHO algorithm showed promising results in providing shorter, faster, and more efficient routes, with potential applications across different domains that requires optimal path planning solutions.

Keywords: Harris Hawk Optimization Algorithm; Indoor Navigation System; Multi-objective Path Planning; Linear Path Strategy; Bi-objective function

1. Introduction

Navigation systems like Google Maps, Waze, and GPS have transformed how people navigate, offering convenience, safety, and efficiency. However, while these systems excel outdoors, indoors they face challenges due to signal blockage and limited accuracy. This has led to the development of Indoor Positioning Systems (IPS) for accurate indoor navigation, offering benefits like real-time updates and enhanced accuracy. Path planning, crucial for navigation, involves finding the best route while avoiding obstacles. Traditional algorithms like A* search and Djikstra are widely used but face limitations, especially in complex scenarios.

Researchers have explored the Harris Hawk Optimization (HHO) algorithm for indoor navigation and path planning, finding potential in optimizing paths, especially in grid maps [7]. However, deficiencies in diversity control during the exploration phase have been noted, leading to premature convergence and sub-optimal solutions [1]. While HHO shows promise, particularly in specific scenarios, its effectiveness diminishes in complex environments, indicating the need for improvement [12][10]. These studies highlight the importance of refining HHO to ensure robustness across diverse navigation scenarios.

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Despite advancements in path planning algorithms, certain deficiencies remain unaddressed. The exploration phase of HHO, where a path is randomly selected from the existing population of feasible paths as basis for updating the current path, lessening the control over population diversity. Moreover, the initial path population created using traditional algorithms have many corners that add unnecessary turns and make rough paths. Additionally, the path length is the only cost variable used when there are other factors when finding the optimal path.

Therefore, the primary objective of this study is to enhance the Harris Hawk Optimization algorithm. Specifically, the exploration operator of HHO is modified to incorporate the survival of the fittest principle, and this controls the diversity more strictly using Exponential Ranking selection method. The study would also use the Linear Path Strategy to reduce the nodes of a path to reduce the length and simplify the trajectory of the path. And lastly, the study would define a general multi-objective function formula to evaluate the length and travel time of the path. By proposing specific solutions and modifications, the study seeks to optimize path planning algorithms for efficient navigation primarily within indoor spaces, ultimately providing shorter and faster routes for users.

1.1. The Path Planning Problem

The A* algorithm is a heuristic search algorithm used for path planning. It is an improvement of the Dijkstra algorithm and is designed to find the shortest path from a start node to a goal node by considering both the cost to reach the current node from the start node G(x) and the estimated cost H(x) to reach the goal node from the current node (Tang and Ma, 2021). This evaluation function is defined as:

$$F(x) = G(x) + H(x) \tag{1}$$

Compared to other traditional path planning algorithms such as Dijkstra, the A* algorithm is more efficient due to the introduction of a heuristic function when exploring the next node, which greatly reduces the search times and improves the search speed. The A* algorithm is widely used for global path planning in a static environment and is subject for further enhancement of its path planning efficiency and smoothness [15].

1.2. Harris Hawks Optimization Algorithm

Harris Hawks Optimization (HHO) algorithm is a technique introduced by Heidari et al. in 2019 [1]. The algorithm is inspired by the hunting behavior of Harris hawks, incorporating surprise pounces and attack strategies. The model of HHO involves three main phases: Exploration, Transition from exploration to exploitation, and Exploitation. The phases as defined in the mathematical model of the HHO algorithm is best represented in Figure 1 where it shows that the algorithm is guided by the prey's energy (E) variable which controls the exploration-exploitation balance. This balance help maintain diverse solutions in the beginning but as iterations pass, the hawks will converge to global optima. The candidate solutions are represented as the hawks in the HHO algorithm. Whereas the best candidate solution in each iteration is considered as the prey or nearly optimal solution.

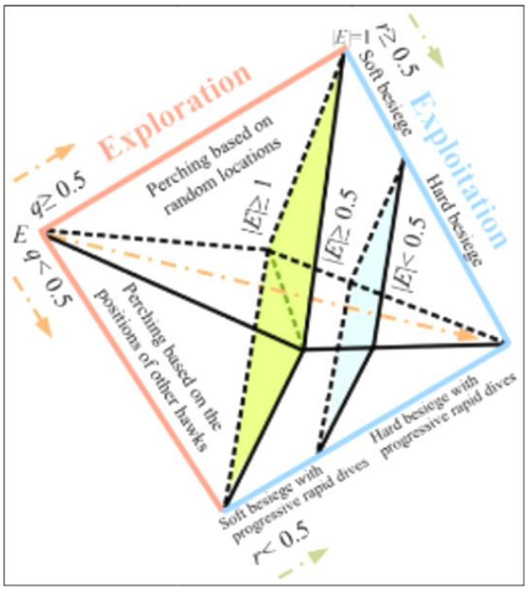

Figure 1 Phases of HHO algorithm

1.2.1. Exploration Phase

In this phase, HHO proposed the exploration mechanism that is similar to how Harris hawks wait and monitor the environment to find the prey. Additionally, as shown in Equation (2), HHO has two perching strategies: (1) based on the positions of family members (other hawks) and (2) based on random locations.

$$X(t+1) = \begin{cases} X_{rand}(t) - r_1 \left|X_{rand}(t) - 2r_2 \cdot X(t)\right|, \ q \geq 0.5 \\ \left(X_{prey}(t) - X_{avg}(t)\right) - r_3(LB + r_4(UB - LB)), \ q < 0.5 \end{cases} \quad (2)$$

Where, X represents a solution from the population, t is the current iteration, X_{rand} is a random solution from the population, X_{prey} is current best solution from the population, X_{avg} represents the average value of the solution population, LB means lower-bound (allowed minimum value of the solutions), UB means upper-bound (allowed maximum value of the solutions), and q and r_{1-4} are random numbers from 0 to 1.

$$X_{avg}(t) = \frac{1}{N}\sum_{i=1}^{N} X_i(t) \quad (3)$$

To calculate the average value of the population, Equation (3) is used; where, N is the population size.

1.2.2. Transition from Exploration to Exploitation

HHO can transfer from exploration to exploitation methods to further adapt based on the prey's escaping energy. The prey's energy (E) decreases significantly during the escaping phase. This model shows the prey's energy reduction as it attempts to avoid being captured, having a direct impact on how HHO progresses through different phases. This is implemented using the equations:

$$E_0 = 2 \cdot r_1 - 1 \quad (4)$$

$$E = 2E_0(1 - \frac{t}{T}) \quad (5)$$

$$J = 2(1 - r_2) \quad (6)$$

Where, E_0 represents the initial energy of the prey, r_{1-2} are random numbers from 0 to 1, E represents the current energy of the prey, T is the maximum number of iterations, and J represents the jump strength of the prey.

1.2.3. Exploitation Phase

In this phase, the Harris hawks execute a surprise pounce, targeting the prey from the previous phase. However, preys attempt to escape from imminent danger, resulting in different escape techniques. Presume that r is the probability of a prey successfully escaping and if r is less than 0.5, which is a low success rate of escape and so the hawk takes advantage by employing the surprise pounce. Regardless of how the prey responds, hawks would employ either a hard or soft besiege to catch the prey, depending on how much energy the prey has left. Hawks gradually approach the prey, and as the escaping prey loses energy over time, the hawks intensify the besiege process for easier capture. Moreover, the HHO algorithm introduced the parameter E to dynamically switch between soft and hard besiege approaches. When the absolute value of E is greater than 0.5, a soft besiege occurs, on the other hand, if the absolute value of E is less than 0.5, it triggers a hard besiege. To address the random escaping tactics of the prey, the chasing strategies employed by the hawks is represented in the HHO algorithm by the following defined mathematical models.

The Soft Besiege attack occurs when $|E| \geq 0.5$ and $r \geq 0.5$, which indicates that the prey has enough energy to attempt an escape. However, the hawks will encircle it then perform a surprise pounce, leading to a gradual exhaustion of the prey and decreased ability to escape. Soft Besiege is implemented using the formula:

$$X(t+1) = \Delta X(t) - E\left|J \cdot X_{prey}(t) - X(t)\right| \quad (7)$$

$$\Delta X(t) = X_{prey}(t) - X(t) \quad (8)$$

Where, ΔX represents the difference of the prey's value and the current hawk's value.

The Hard Besiege attack occurs when $|E| < 0.5$ and $r \geq 0.5$, meaning the prey is exhausted. Furthermore, the hawks minimally encircle the prey before executing the surprise pounce. In this strategy, updates to the current solutions are implemented using the equation:

$$X(t+1) = X_{prey}(t) - E|\Delta X(t)| \tag{9}$$

When $|E| \geq 0.5$ and $r < 0.5$, this indicates that the prey has sufficient energy for a successful escape, a Soft Besiege is implemented prior to the surprise pounce which is employed by HHO with the Levy Flight (LF) concept. The surprise pounce was modelled from the prey's escaping patterns and leapfrog movements, simulating the zigzag deceptive motions observed in real prey behavior. HHO assumes that hawks can select optimal dives toward the prey in competitive scenarios. To execute a Soft Besiege, the hawks decide their next move following the equation:

$$Y_1 = X_{prey}(t) - E|J \cdot X_{prey}(t) - X(t)| \tag{10}$$

In the case when the Soft Besiege attack is unsuccessful, the hawks will implement the surprise pounce by executing irregular, sudden, and swift dives as they approach the prey. It is assumed that these rapid dives align the levy flight patterns as presented in the formula:

$$Z_1 = Y_1 + S \times LF(D) \tag{11}$$

With that, the Soft Besiege with progressive rapid dives can be implemented with the equation:

$$X(t+1) = \begin{cases} Y_1 & if \;\; F(Y_1) < F(X(t)) \\ Z_1 & if \;\; F(Z_1) < F(X(t)) \end{cases} \tag{12}$$

When $|E| < 0.5$ and $r < 0.5$, this shows that the prey lacks energy for escape, a hard besiege is done before the surprise pounce to capture the prey. In hard besiege, the hawks' focus is on reducing the distance between their location and the escaping prey. Hence, the following rule is applied in hard besiege condition:

$$X(t+1) = \begin{cases} Y_2 & if \;\; F(Y_2) < F(X(t)) \\ Z_2 & if \;\; F(Z_2) < F(X(t)) \end{cases} \tag{13}$$

Where, Y_2 and Z_2 are acquired through the application of new rules:

$$Y_2 = X_{prey}(t) - E\left|J \cdot X_{prey}(t) - X_{avg}(t)\right| \tag{14}$$

$$Z_2 = Y_2 + S \times LF(D) \tag{15}$$

In the context of path planning, HHO is applied to find the optimal path in a defined map environment starting with a population of "hawks" representing the feasible paths. The process begins by initializing the population and calculating the fitness of each hawk (path), commonly based on the path's length. The prey represents the fittest path or the one with the least cost. The algorithm iterates until the maximum number of iterations is reached, updating the solutions and decreasing the prey's energy per iteration. Depending on these conditions, the paths are updated using various exploration and exploitation tactics, such as perching, soft besiege, hard besiege, soft besiege with rapid dives, or hard besiege with rapid dives. Finally, the algorithm outputs the fittest path, that is the shortest path.

2. Material and methods

2.1. Initialization of Path Population

During initialization, random solutions are generated to create the population. To form the random feasible paths, a modified A* search algorithm is used. This traditional path finding algorithm, iterates through the available nodes and chooses the next node with a defined heuristic function. Standard A* search heuristic uses the distance between the current node and the goal node. To integrate randomness and generate random paths, the proponents modified the heuristic function from Equation (1) into:

$$H(X) = \sqrt{(x + x_{goal})^2 - (y + y_{goal})^2} \cdot 2r \tag{16}$$

Given that the current node X and goal node have (x, y) coordinates, the Euclidean distance formula is used to get the gap between the two nodes. A random factor that ranges from zero to two (0 – 2) is multiplied to the distance which reduces or increases the heuristic by 1, resulting to a path with random turns that still move towards the destination.

2.2. Exponential Ranking Selection Method

To address the problem of lessened diversity control, the Exponential Ranking selection method is used to get the X_{target} for the first strategy of the exploration phase. Instead of randomly getting a hawk as basis for the update, by incorporating the survival-of-the-fittest concept, HHO would have a higher chance of finding the optimal solution while maintaining diversity during the exploration phase.

Algorithm 1: Exponential Ranking selection method

Inputs: control parameter $s = -0.99$, solution population $X_i (i = 1, 2, \dots, N)$

Outputs: Selected solution X_{target}

```
START
SET total_fitness = 0
SET probabilities = [ ]
FOR (i = 0; i < N; i += 1) DO
        SET fitness = fitness(X_i) · s
        COMPUTE total_fitness += fitness
        SET probabilities[i] = fitness
FOR END
COMPUTE average_fitness = total_fitness/N
FOR (i = 0; i < N; i += 1) DO
        SET probabilities[i] /= average_fitness
FOR END
SELECT X_target solution from X based on probabilities
RETURN X_target
```

The Exponential Ranking selection process is presented as a pseudocode in Algorithm 1. The control parameters indicate the exponential trajectory of the candidates. To use Exponential Ranking, it first traverses through the solution population and multiplies each fitness of the population by the control parameter. The selection probability of the solution is determined by getting the average fitness of the population as base for the probabilities of each solution. This means that solutions with higher fitness will have higher probability. Finally, the solution with the highest probability is selected as the X_{target} for the exploration operator. In line with this, the HHO exploration operator is updated to incorporate the Exponential Ranking selection as follows:

$$X(t+1) = \begin{cases} X_{target}(t) - r_1 \left| X_{target}(t) - 2r_2 \cdot X(t) \right|, & q \geq 0.5 \\ \left(X_{prey}(t) - X_{avg}(t) \right) - r_3 (LB + r_4 (UB - LB)), & q < 0.5 \end{cases} \tag{17}$$

2.3. Linear Path Strategy

To create smoother and shorter paths, the Linear Path Strategy (LPS) is used to reduce the nodes that can lead to unnecessary turns while keeping the shape of the path and adhering to obstacle constraints. The LPS process, initially, takes three consecutive nodes and calculates the distance range between the first and third nodes. When there is no obstacle found within the range, the middle node is removed. Then, the first and third nodes are connected to form the updated path. If otherwise an obstacle is found in the range, the process terminates and will move on to the next three nodes until the last node which will output the linearized path. The core process of LPS demonstrated in Figure 2.

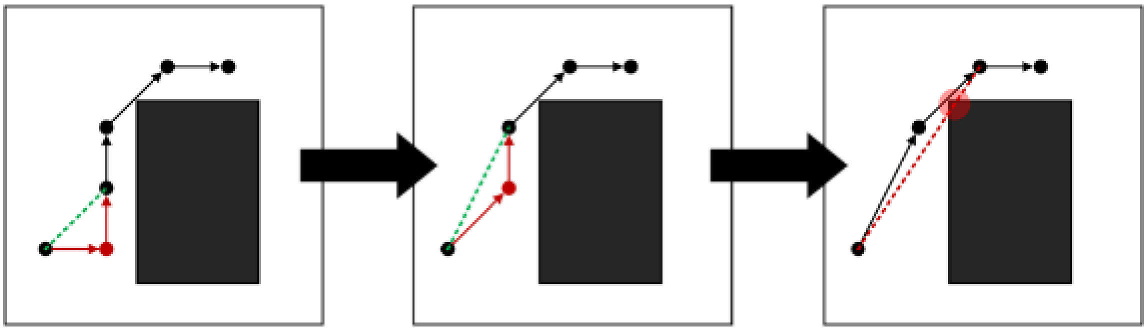

Figure 2 Linear Path Strategy process

The LPS method is further elaborated as a pseudo-code presented in Algorithm 2, showing that the expected output is the linearized path P. It involves an iterative process of removing middle nodes while ensuring the path will not collide with the obstacle in the map.

Algorithm 2: Linear Path Strategy
Inputs: Feasible path $P_i\,(i\ = 1,2,\ldots,k)$, where k is the number of nodes
Outputs: Linearized path P
START
SET $i =\ 1$
WHILE $(i < k - 2)$ **DO**
GET coordinates of nodes P_i and P_{i+2}
IF there's no obstacle between nodes P_i and P_{i+2}
REMOVE node P_{i+1}
UPDATE $k =\ k - 1$
ELSE
UPDATE $i\ =\ i + 1$
END WHILE
RETURN linearized path P

2.4. Bi-objective Cost Function

To address the need for finding faster paths, not just shorter paths, a bi-objective function is defined. The first objective is to reduce path length and the Euclidean distance is used to compute the distance which is defined with the formula:

$$f(X)_1 =\ \sum_{i=1}^{k-1} \sqrt{(x_{i+1} - x_i\,)^2 + (y_{i+1} - y\,)^2} \tag{18}$$

Where, path X consists of nodes with (x, y) coordinates and k represents the total number of nodes.

To calculate the travel time of the path, given that the path consists of nodes with (x, y) coordinates and speed rate S. The sum of the length divided by the speed results to the time it takes to travel from the start to the goal.

$$f(X)_2 = \sum_{i=1}^{k-1} \frac{\sqrt{(x_{i+1}-x_i\,)^2+(y_{i+1}-y\,)^2}}{s_i} \tag{19}$$

With these evaluation formulas defined, the general multi-objective function is as follows:

$$\min F(X) = \frac{\sum_{i=1}^{n} \eta_i \cdot f(X)_i}{\sum_{i=1}^{n} \eta_i} \tag{20}$$

The cost function is used to determine the fitness of the path and the objective is to minimize the path length $\boldsymbol{f(X)_1}$ and travel time $\boldsymbol{f(X)_2}$. The individual objective's significance can be adjusted using the weight coefficients η which by default are equal to 1, to indicate the equal significance of the path length and travel time. Once the summation of the weighted costs is computed, it is divided by the sum of all the weights applied per cost objective, resulting to the final fitness score of the path.

2.5. Proposed HHO Framework

The proposed enhancement discussed are summarized in Figure 3, representing the flowchart which highlights the parts of the current HHO algorithm that are modified.

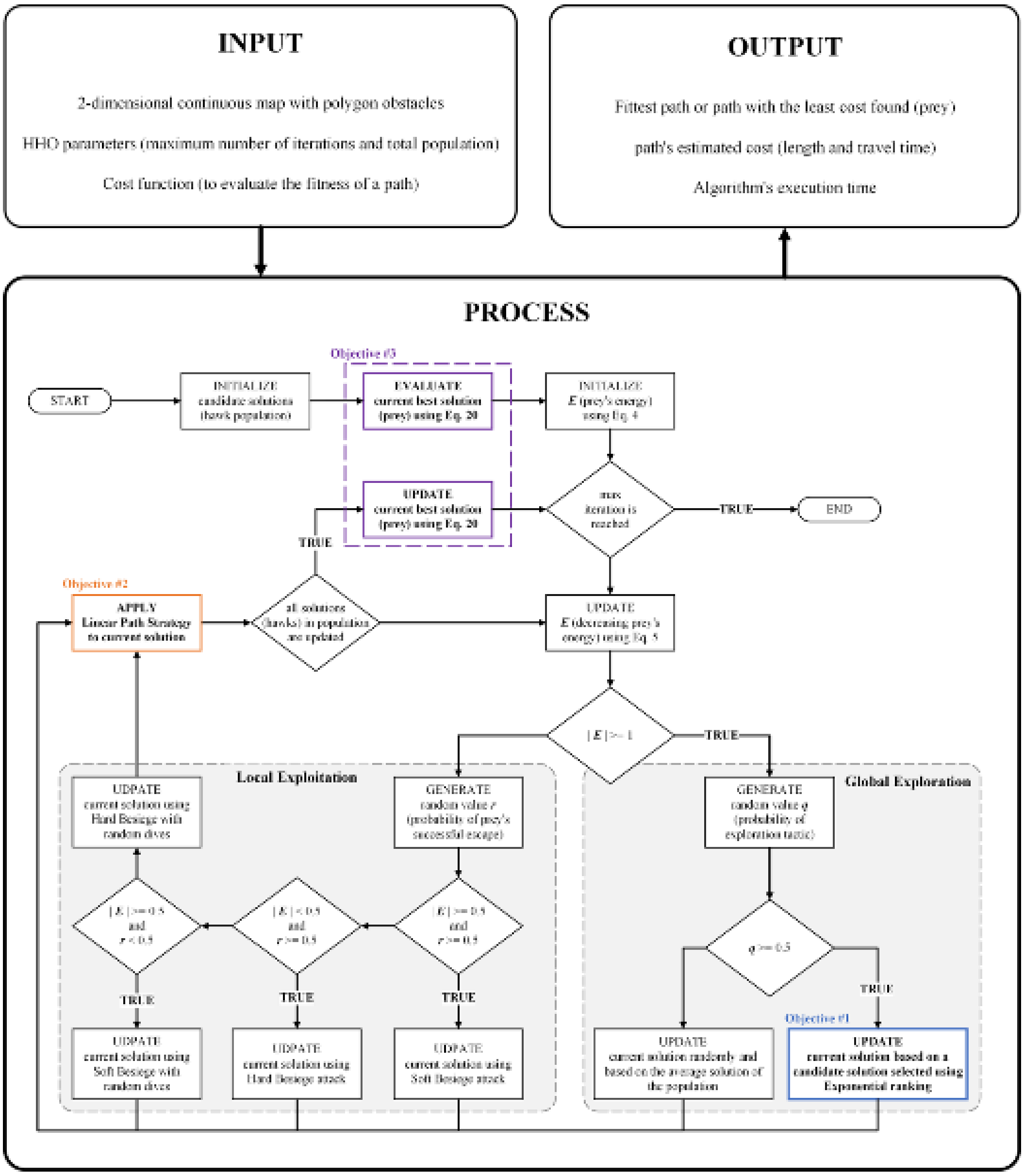

Figure 3 Proposed HHO Framework

3. Results and discussion

3.1. Simulation map and parameters setting

A two-dimensional continuous map is used for the simulation. There are two environments created to test the proposed enhancements to the HHO algorithm. Shown in Figure 4 is a simple and complex 20´20 maps with the obstacles represented by the black-colored areas. Along with the defined obstacle constraints, the expected paths must begin from the start node (blue) to reach the destination node (red).

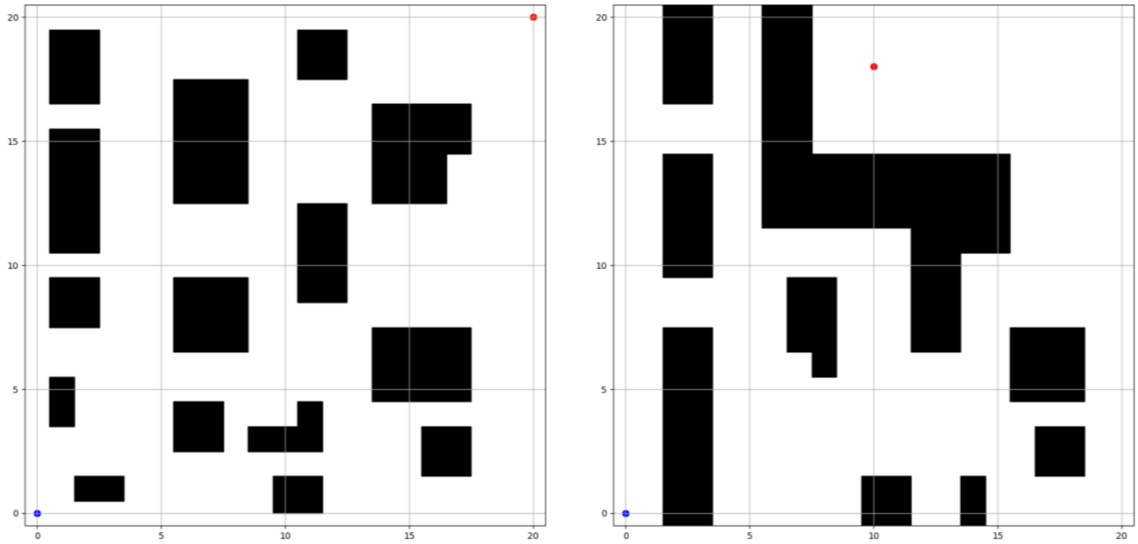

Figure 4 Simple (left) and complex (right) 20´20 maps

The simulation conducted for this study applied the proposed algorithm, EHHO, under similar map environments and control parameters in comparison with other evolutionary algorithms such as: Ant Colony Optimization (ACO), Grey Wolf Optimization (GWO), and the current. Path planning simulations were run using a MacBook Pro laptop with an Apple M1 CPU and 8GB of RAM. The parameters for each algorithm simulated are defined in Table 1 which have the same number of iterations and population size to facilitate an efficient comparison of the algorithms. Python version 3.9.6 was used as the simulation tool for the experiments.

Table 1 Simulation parameters of the algorithms

Algorithm	Parameter	Value
ACO	Total iterations	100
	Total ant population	20
	Pheromone factor	2
	Pheromone evaporation rate	0.1
	alpha (α)	2
	beta (β)	4
GWO	Total iterations	100
	Total search agents	20
HHO	Total iterations	100
	Total hawk population	20
EHHO	Total iterations	100
	Total hawk population	20

3.2. Evaluation Metrics

To determine the effectiveness of the enhanced HHO, all the algorithms will run for 50 simulations, while keeping track of the shortest path produced by each algorithm and the results of each algorithm will be compared along with the execution time to observe the amount of time it takes for each algorithm to produce a path. To not affect the results of the other algorithms, the researchers have kept the cost objective function, that is, minimizing the path length. Since the other algorithms primarily use the path length to measure the optimality of the path, that is the only metric we will use when comparing the algorithms.

To evaluate the effectiveness of the defined multi-objective function, the enhanced HHO will run for 50 simulations starting with using the single-objective function that only measures the path length. Then, another 50 simulations when using the bi-objective function to evaluate the fitness score based on the least path length and travel time. Additionally, a collision risk objective will be added to test the reliability of the general multi-objective function and another 50 simulations will run to compare the three scenarios of differing number of cost objectives. The weight coefficient (η) of each objective was set to 1, indicating equal significance of minimizing the path length, travel time, and collision risk.

3.3. Simulation results and performance comparative analysis

For the experiment, 50 simulations were run per map environment, from which the best path of each algorithm is outputted. The multiple simulations show the stability and consistency of the algorithm to produce optimal paths in a relatively acceptable time.

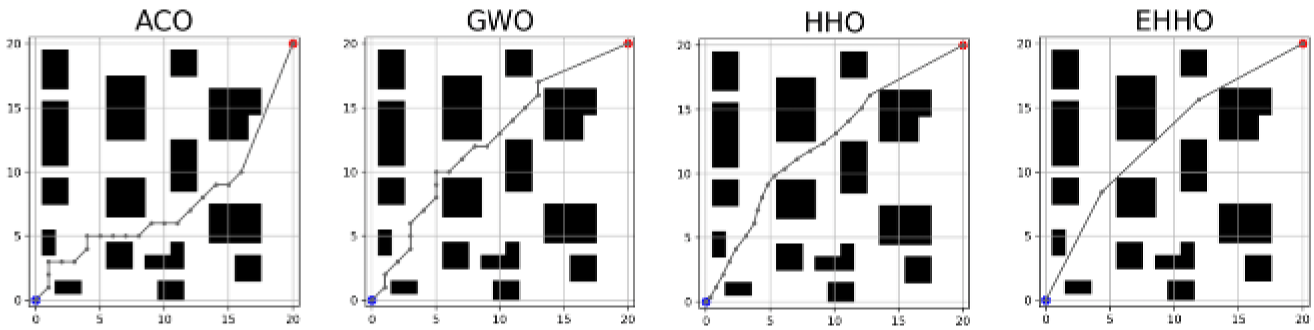

Figure 5 Optimal paths generated by the algorithms in map 1.

Out of the 50 simulations in Map 1, the best paths generated by each algorithm were gathered and compared showing that EHHO produced the shortest path, in the least amount of time. While HHO came a close with second shortest path, followed by GWO, then ACO.

Table 2 Optimal path results for map 1.

Algorithm	Path length	Execution time (seconds)
ACO	32.8468	1.49
GWO	31.5768	1.13
HHO	29.2860	1.22
EHHO	29.1100	0.83

In the simple map, the best run of all algorithms output the optimal paths in Figure 5 which have the results summarized in Table 2 showing the path length and execution time. The convergence curves (Figure 6) of the algorithms represent the evolutionary nature of the method, showing the decreasing cost of the optimal path found per iteration is the main concept of these metaheuristic optimization algorithms.

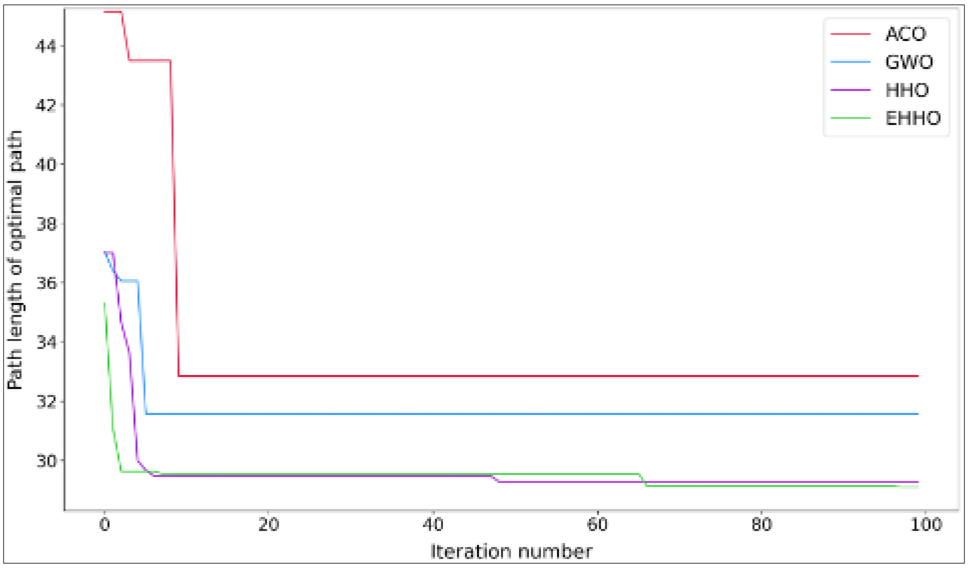

Figure 6 Convergence curve of the algorithms in map 1.

For the second map, the goal node's placement is in a complex area which can be challenging for the algorithms. After running 50 simulations in Map 2, the optimal paths generated by each algorithm are presented in Figure 7 and the details of the resulting paths are listed in Table 3.

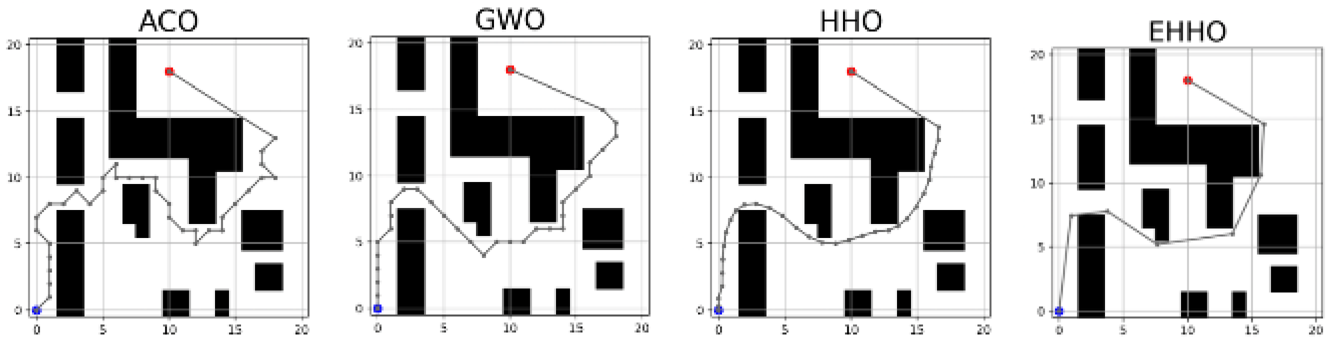

Figure 7 Optimal paths generated by the algorithms in map 2.

Table 3 Optimal path results for map 2.

Algorithm	Path length	Execution time (seconds)
ACO	49.7515	2.21
GWO	44.6186	1.97
HHO	37.3351	2.56
EHHO	37.1865	2.03

The convergence curve of the algorithms after simulation in Map 2 (see Figure 8), show the vast difference of HHO and EHHO from the other algorithm in terms of efficiency.

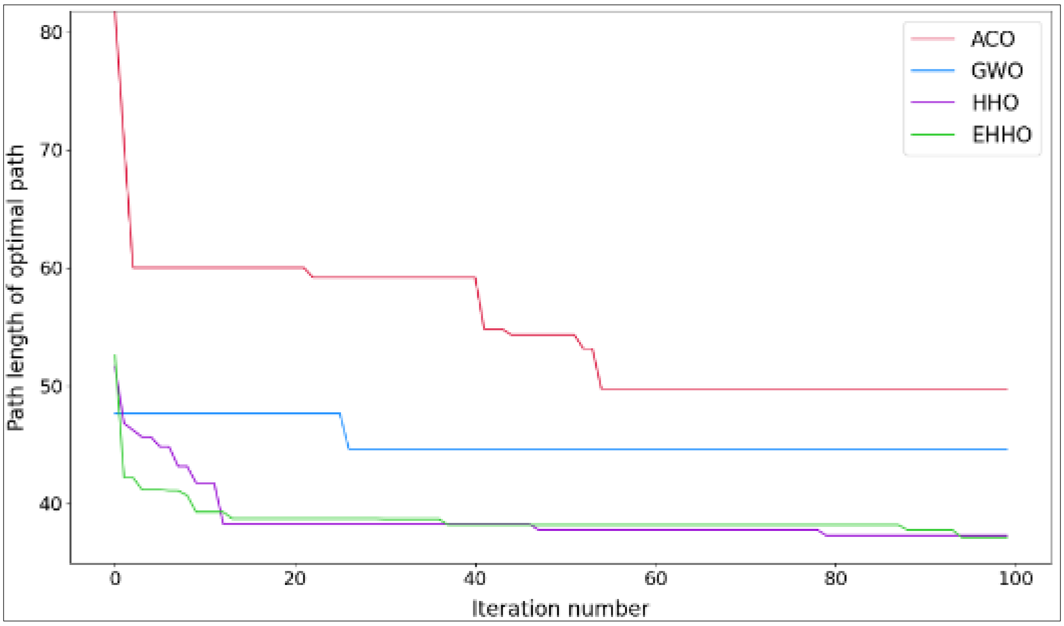

Figure 8 Convergence curve of the algorithms in map 2.

In both environments, EHHO produced the best path in 50 simulations. HHO and EHHO generated the better paths in close range, but EHHO has a shorter implementation time as an advantage in more complex scenarios.

Due to the inherent random nature of evolutionary algorithms such as HHO, the results will not always be the same. The simulation tests of the four algorithms are carried out 50 times separately in maps 1 and 2, respectively, to demonstrate the stability and robustness of the proposed algorithm. The results of the 50 simulations will show the fluctuation of the fitness score and execution time of the algorithms.

Figure 9 shows the path length of the optimal paths found per simulation in Map 1 and, clearly, the EHHO algorithm consistently produced the shortest paths. So even with multiple runs, EHHO show consistent yield of the best path. The overlap of the execution time graph in Figure 10 of GWO, HHO, and EHHO represent the similarity of rates in which these algorithms produce a feasible path, where HHO took the least amount of time.

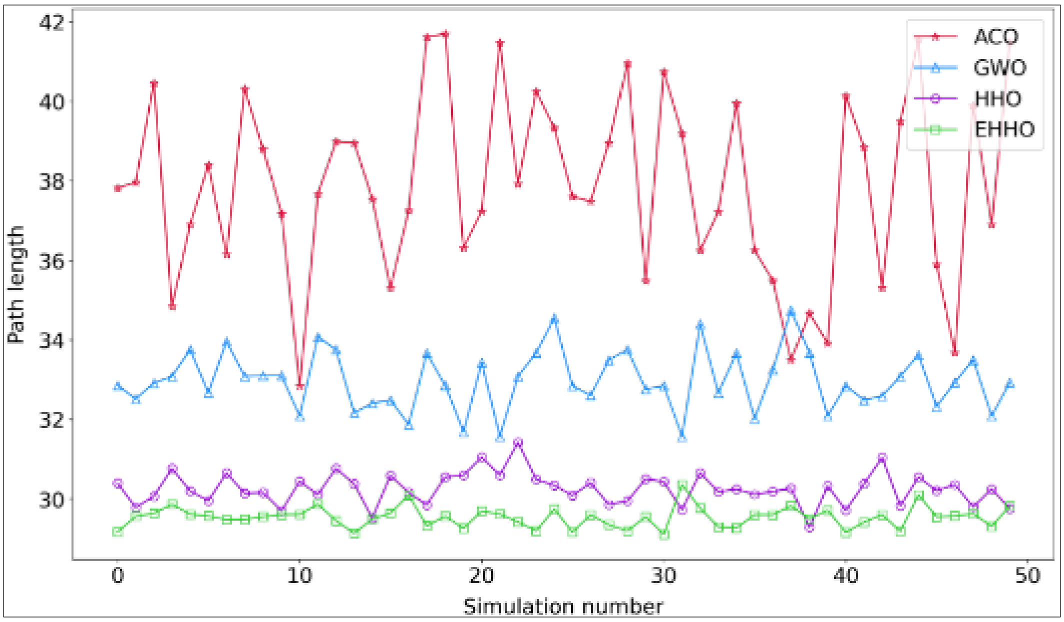

Figure 9 Path length of the algorithms' generated path for 50 simulations in map 1.

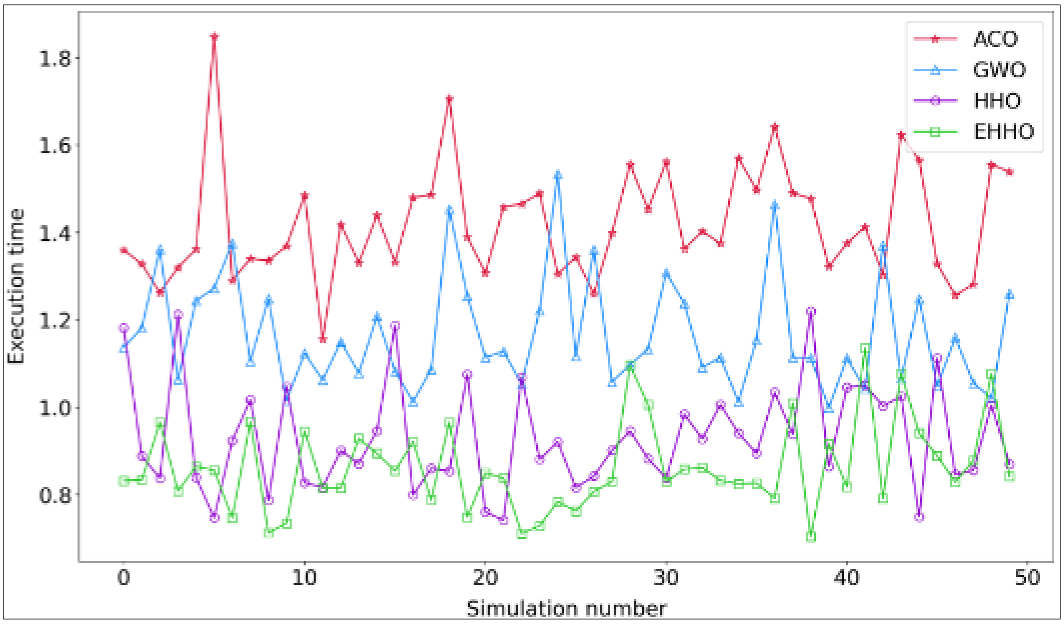

Figure 10 Execution time of the algorithms for multiple simulations in map 1.

In Map 2, the fitness scores of the optimal paths generated in 50 simulations (Figure 11) show that EHHO produced the best paths. In Figure 12, the execution time of HHO and ACO have high variance due to the large gap of the highest and lowest execution time. Whereas GWO and EHHO are relatively stable, EHHO being less so and achieving the lowest execution time compared with the other algorithms.

The results for 50 simulations in Map 2 show that EHHO is more stable in comparison with the current HHO, as when the map gets more complicated, the execution times of HHO are higher than EHHO in most cases.

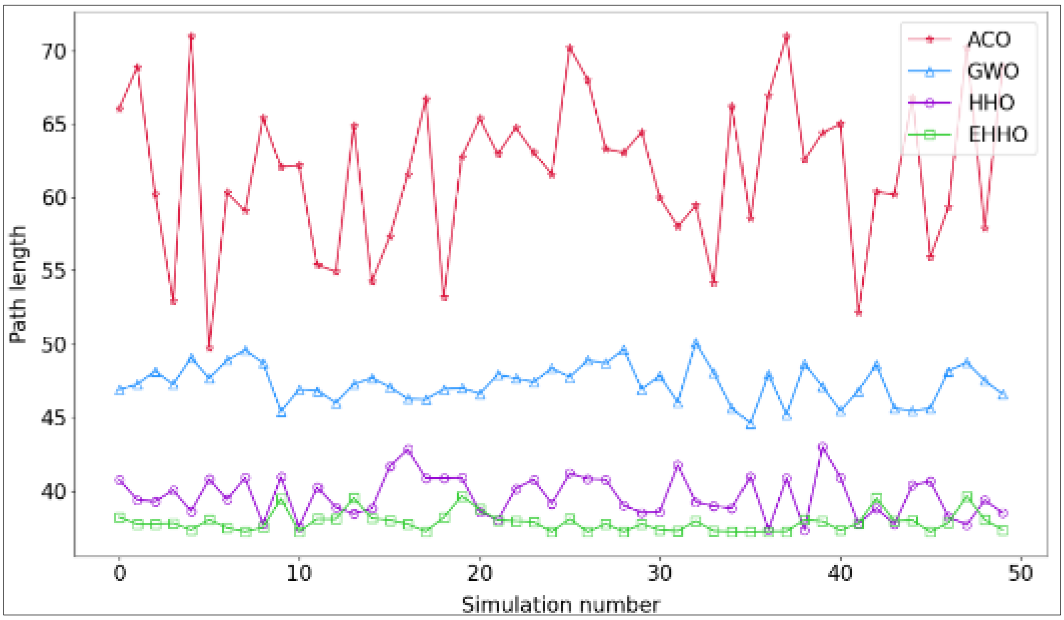

Figure 11 Path length of the algorithms' generated path for 50 simulations in map 2.

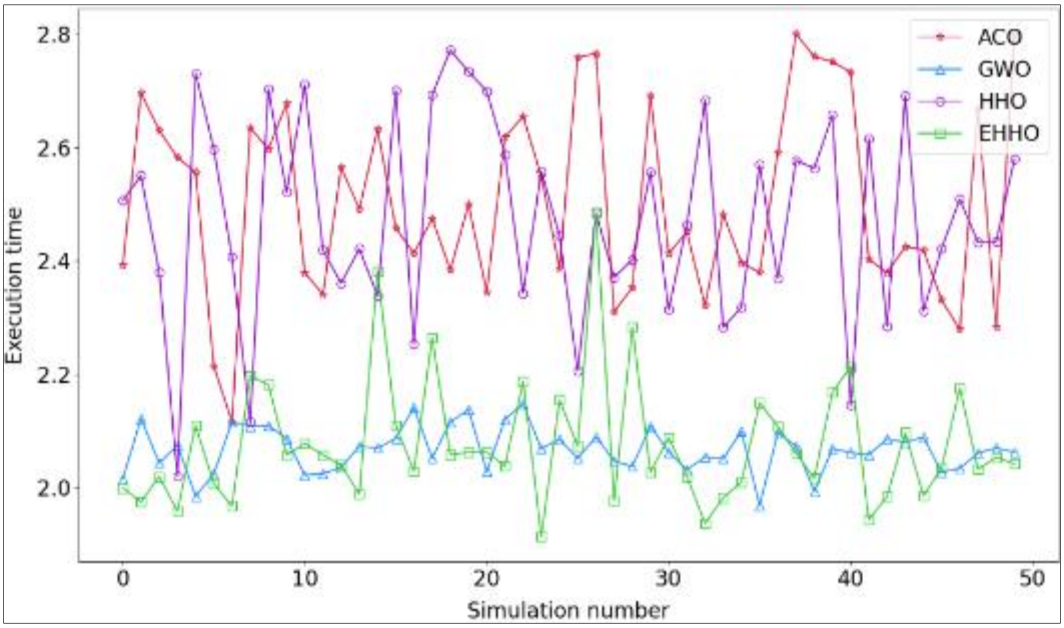

Figure 12 Execution time of the algorithms for multiple simulations in map 2.

To evaluate the effectiveness of defined general multi-objective function, another set of simulation was run to compare the performance of EHHO with one objective (minimize path length), two objectives (minimize path length and travel time), and three objectives (minimize path length, travel time and collision risk). Using both maps, EHHO with differing number of cost objectives ran for 50 simulations and by the end output the path with the best fitness score.

The resulting paths in Map 1 with different number of objectives is shown in Figure 13 with the path details in Table 4. The path produced that only used 1 objective (path length) is found to be longer than the middle path that uses two objectives. Lastly, the path that uses three objectives (path length, travel time, and collision risk), compared with the two paths, clearly does not touch the obstacles at all, achieving the minimal risk for collision.

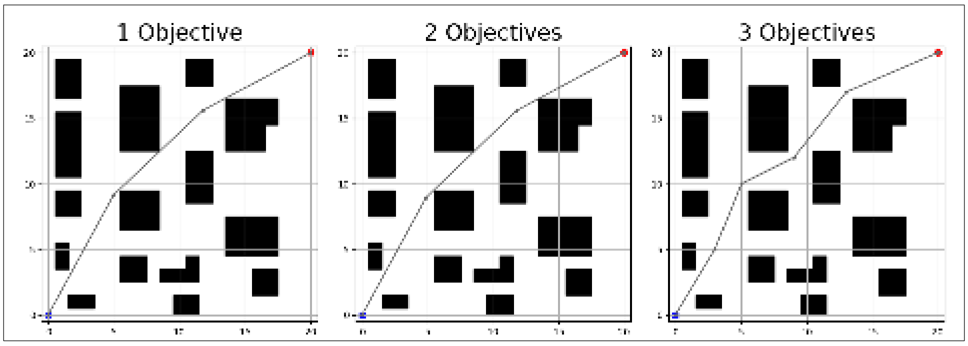

Figure 13 Optimal paths generated by EHHO with different number of objectives in map 1.

Table 4 Optimal path results for map 1.

Number of objectives	Objectives			Fitness score	Execution time (seconds)
	Path length	Travel time	Collision risk		
1	29.1060	--	--	29.1060	0.91
2	29. 0932	38.9849	--	34.0391	0.92
3	29.7072	39.8076	1.9437	23.8195	0.93

In Figure 14, the optimal paths found in Map 2 where EHHO is used with different number of objectives are presented showing minimal difference at first glance but as summarized in Table 5, EHHO using two objectives achieved the shortest path length in the least amount of time.

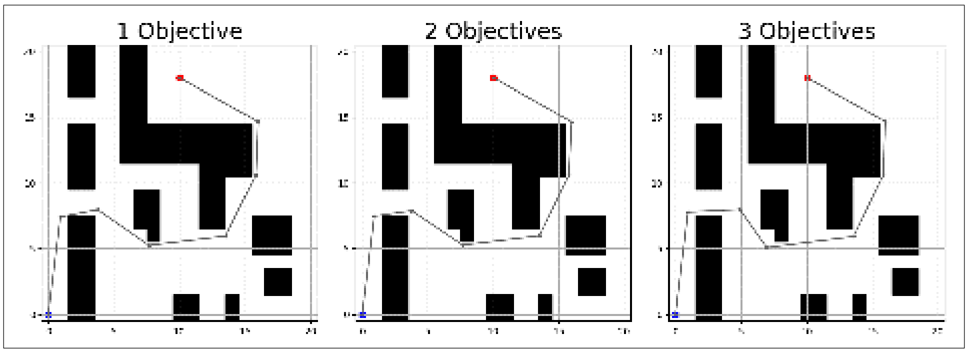

Figure 14 Optimal paths generated by EHHO with different number of objectives in map 2.

Table 5 Optimal path results for map 2.

Number of objectives	Path length	Travel time	Collision risk	Fitness score	Execution time (seconds)
1	37.1257	--	--	37.1257	2.44
2	37. 0648	49.6668	--	43.3658	2.30
3	38.1400	51.1077	4.2418	31.1631	2.43

Aside from the fitness of the optimal path produced, the execution time tells the algorithm's performance with the varying number of objectives. In Figure 15 and Figure 16, it shows the amount of time it took for EHHO to produce an optimal path for 50 simulations in both maps. As seen in the graph, the longest execution time was from using 3 objectives but in most cases, there is no significant difference between the stability of EHHO when multiple objectives are used. The algorithm performance could also be dependent on the complexity of the objective.

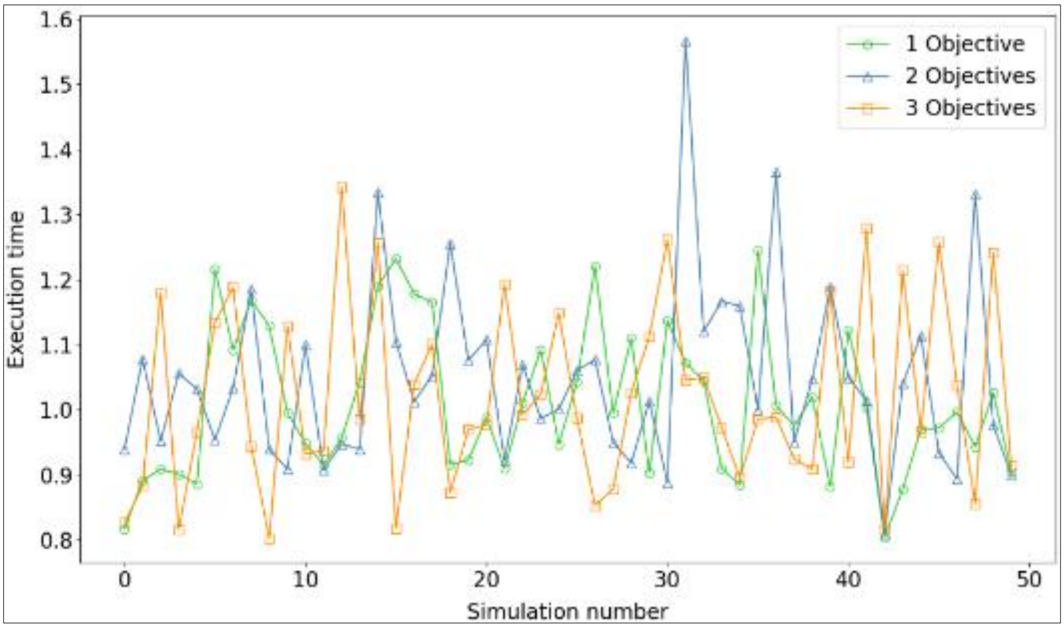

Figure 15 Execution time of EHHO with different number of objectives in map 1.

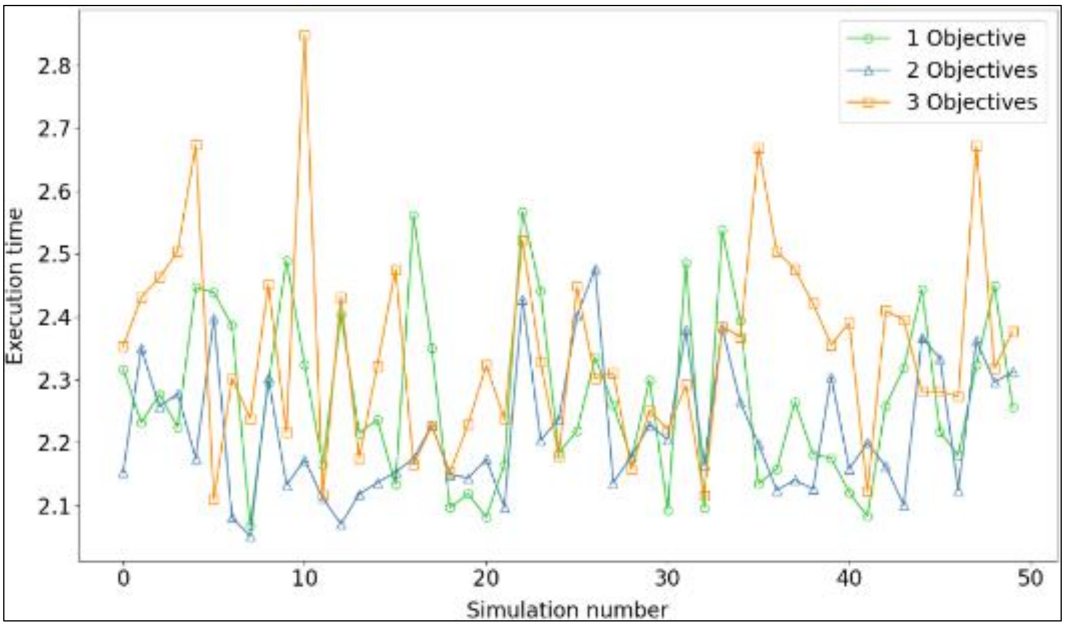

Figure 16 Execution time of EHHO with different number of objectives in map 2.

3.4. Inexplorer: Indoor Navigation Mobile Application

The proponents developed a mobile application called "Inexplorer" for indoor navigation purposes. This application utilizes the enhanced HHO algorithm to suggest paths to users based on their specified starting and destination locations. Inexplorer offers various features, including the ability to view indoor maps, track precise indoor locations, receive optimal path recommendations, and select from 3 route options; the first being optimized path length and travel time equally, the second prioritizes minimizing the path length over the travel time, and the third option does vice versa.

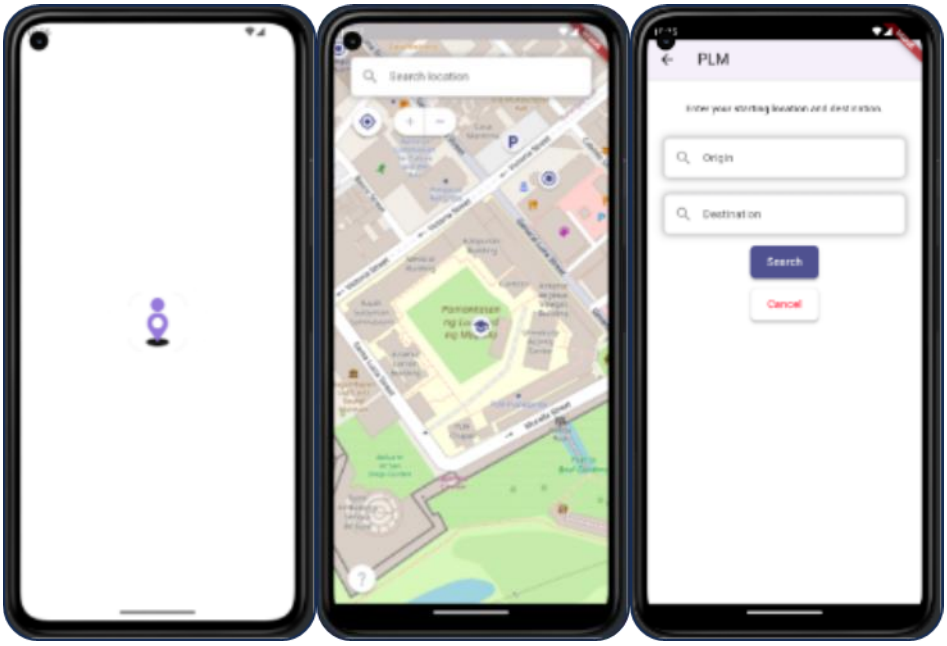

Figure 17 Application launcher with logo (left), Map page (middle), and Directions page (right).

The primary functions of the application were designed into the following user interfaces: Map page and Directions page. The Map page contains the map, where the user can view their current location when outdoors and search for the places in the current map. Upon opening Inexplorer, the Map page shows the global map, similar to existing navigation applications like Google Maps and Waze, the user can search locations recognized by the OpenStreetMap (OSM) database which offers information on the precise locations visible on the surface of the earth detected by GPS satellites.

Inexplorer utilizes the global map information from OSM to determine if a location exists before it can support indoor navigation in any location. The proponents have prepared the indoor map information of Pamantasan ng Lungsod ng Maynila (PLM) to test the Inexplorer application. As seen in Figure 18, selecting a globally identifiable location will trigger an API request to the Inexplorer server to check if a location has indoor navigation support. If so, the "Explore inside" button will appear which will lead the user to the base indoor map of their desired location, in this case the grounds of PLM.

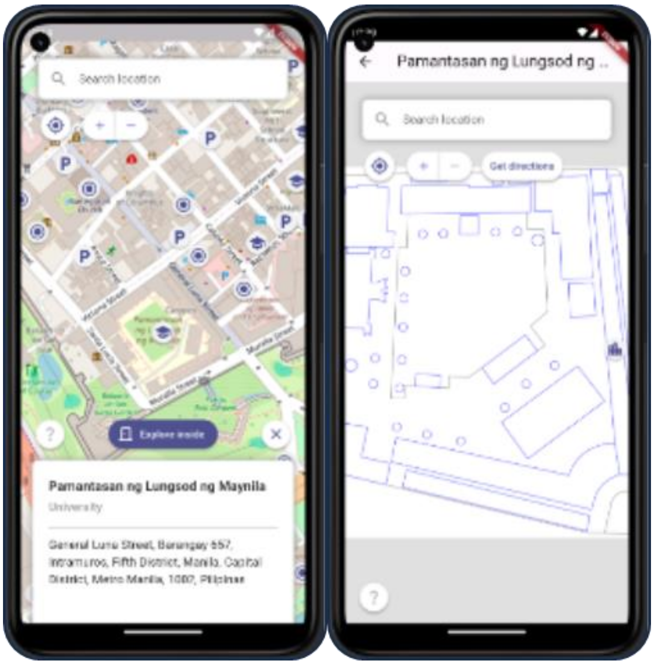

Figure 18 Selected location supported by Inexplorer (left) and base indoor map of PLM (right).

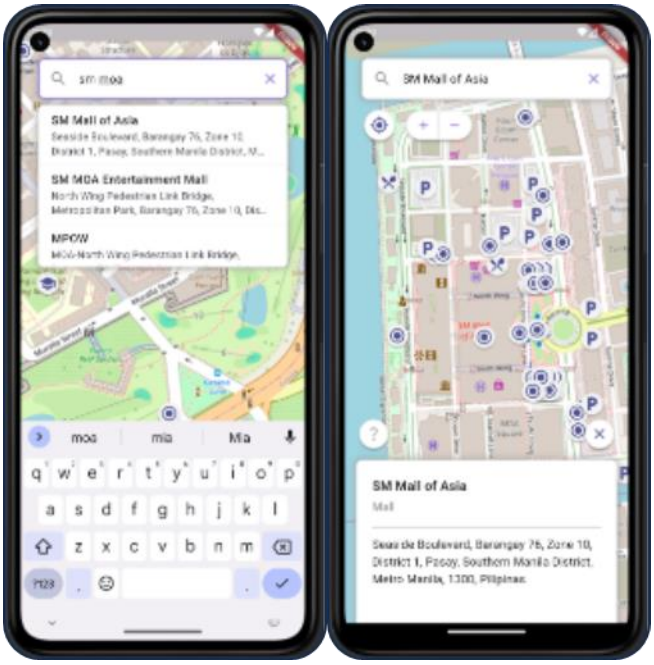

Figure 19 Searching global location (left) and a selected location not supported by Inexplorer (right).

Aside from that, the search bar on the top of the map enables the user to search for locations which will give them suggestions of recognized places they may be referring to. Other map manipulation features are available which includes zooming and finding the current location of the user with the use of GPS technology.

In the Directions page, the users can ask for route recommendations by giving their starting location and desired destination. The users can input their origin and destination locations using the provided text fields which automatically gives suggestions of recognized indoor locations that the user may be referring to. If both the origin and destination locations are properly set, the user can press the "Search" button which will trigger the Inexplorer API to process the request and give the optimal path possible using the EHHO algorithm.

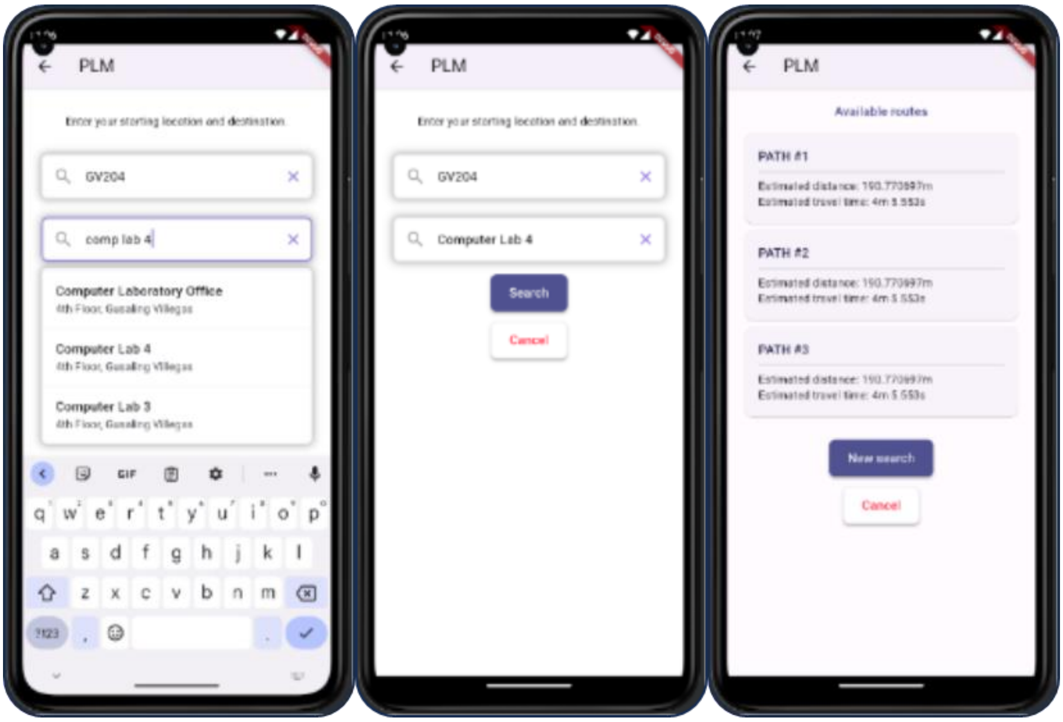

Figure 20 Input start and goal location (left), validated start and goal location (middle), and result routes (right).

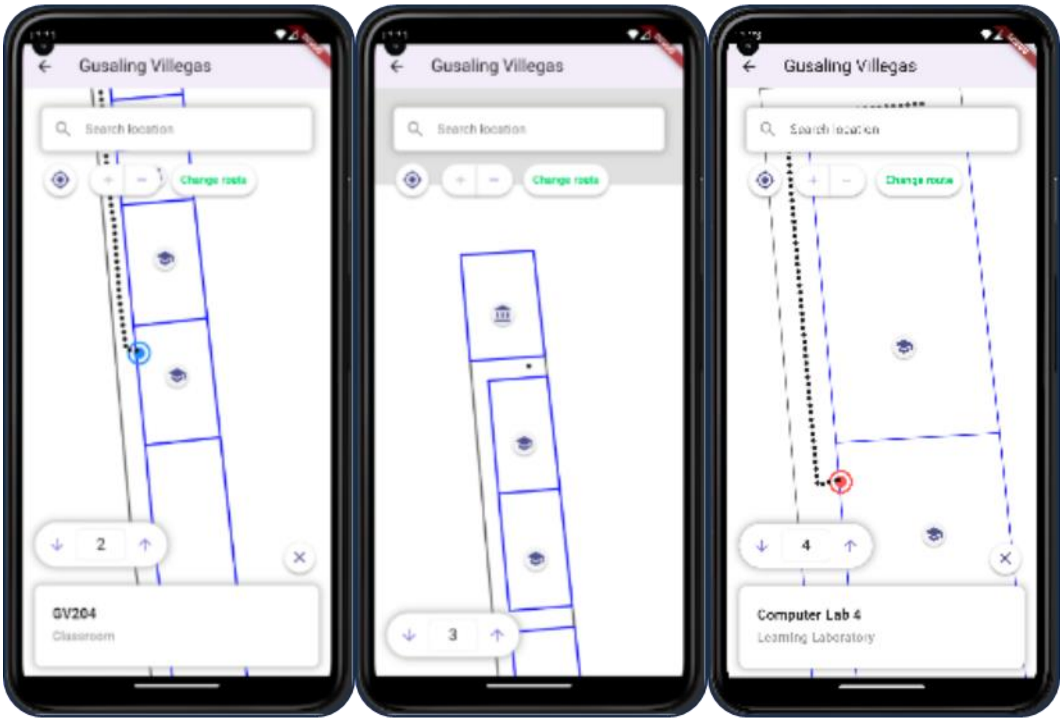

Figure 21 Input start and goal location (left), validated start and goal location (middle), and result routes (right).

Once the recommended paths are loaded, the user can view 3 recommended routes that show each of the path's estimated distance and travel time. Clicking one of the results will lead the user back to the Map page and the path is presented from the starting point to the goal point. The blue dot marker on the map represents the starting location of the path, and following the dotted line, the user can traverse the indoor map until reaching the red dot marker which signifies the end of the route.

The user can go back to the Directions page and view the other routes generated, by clicking the "Change route" button where the "Get directions" button previously was. From there, the user can choose to cancel and go back to the Map page which will remove the route on the map, or the user can choose to search a new route for a different destination.

Overall, the Inexplorer application has achieved its purpose to provide indoor navigation assistance by recommending optimal paths using the enhanced Harris Hawks optimization algorithm within the premises of PLM in an appealing user interface.

4. Conclusion

To conclude, the result of the study highlights the effectiveness of the Enhanced Harris Hawks Optimization algorithm in generating better paths comparing it with Ant Colony Optimization (ACO), Grey Wolf Optimization, and with the current HHO algorithm. Two map environments, simple and complex, were utilized to test the algorithms' performance, with obstacles represented by the black-colored areas. Each algorithm was subjected to 50 simulations per map, aiming to identify the optimal path from a start node to a destination node. In the evaluation metrics, it showed that the bi-objective function employed effectively balances the importance of minimizing path length and travel time, thereby providing a robust algorithm performance. Additionally, the execution time of each algorithm was considered as it will provide valuable insights into the computational effectiveness of each algorithm, with EHHO showing favorable results in this aspect as well. Results indicated that EHHO consistently outperformed other algorithms across simulations, producing shorter path lengths and faster execution times, particularly evident in complex map environments. Furthermore, convergence curves showed how the algorithms evolve over time. EHHO and HHO move towards optimal solutions, while GWO and ACO tend to converge prematurely or produce less desirable paths.

In addition, the researchers developed a mobile indoor navigation application called, "Inexplorer", which leveraged the strengths of EHHO to offer users efficient navigation assistance, allowing for optimal path recommendations based on specified starting and destination locations. Through user-friendly interfaces, "Inexplorer" enables users to seamlessly plan routes within indoor spaces, enhancing their overall navigation experience.

The Harris Hawks Optimization algorithm, being a versatile optimization technique, finds application across various domains, including path planning. The enhancements proposed in the study represent valuable advancements that can serve as a foundation for future research involving HHO.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

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