Bulletin of Electrical Engineering and Informatics
Vol. 11, No. 3, June 2022, pp. 1289~1296
ISSN: 2302-9285, DOI: 10.11591/eei.v11i3.3677

New robot path planning optimization using hybrid GWO-PSO algorithm

Ayad Abdulrahem Alabdalbari[1], Issa Ahmed Abed[2]
[1]Department of Computing Engineering, Shahid Chamran University of Ahwaz, Khuzestan, Iran
[2]Basrah Engineering Technical College, Southern Technical University, Basrah, Iraq

Article Info

Article history:

Received Feb 7, 2022
Revised Apr 4, 2022
Accepted Apr 15, 2022

Keywords:

GWO
Optimization
Path planning
PSO
Robot

ABSTRACT

Actually, path planning is one of the most crucial aspects of mobile robots study. The primary goal of this research is to develop a solution to the path planning issues that occur when a “mobile robot” operates in a static environment. The problem is handled by finding a collision-free path that meets the given criteria for the shortest distance with quite the smoothness of the path. Two nature-inspired metaheuristic algorithms are used in the computation. By leading a hybrid “gray wolf optimization” with the “particle swarm optimization” (HGWO-PSO) computation that restricts the distance and follows path perfection guidelines, the primary shape is improved. In addition, simulation findings reveal that the proposed HGWO-PSO method is deeply serious in terms of path optimality when compared to path planning approaches such as group search optimizer GSO, PSO, artificial bee colony ABC, and GWO.

This is an open access article under the CC BY-SA license.

Corresponding Author:

Issa Ahmed Abed
Basrah Engineering Technical College, Southern Technical University
Basrah, Iraq
Email: issaahmedabed@stu.edu.iq

1. INTRODUCTION

Mobile robots are now widely utilized in a diversity of applications, including the military's applications, the space exploration, emergency scenarios such as fire risks, medical applications, and so on. Without any human intervention, the robot accomplished the above-mentioned arduous duties efficiently and successfully. To deal with such a circumstance, the phrase “path planning” was coined. Whether the robot is familiar with the surroundings or not, path planning requires the robot to move along a certain route. During navigation, a mobile robots encounters a variety of obstacles and roadblocks, and it must safely pass those hurdles without colliding with them, as well as identify the best way from the source to the destination point [1]. Generally speaking, difficulties with robot “path planning” are classified as off_line or globally “path planning”, online or locally “path planning” [2]. The environment is well-known to the robot and constant barriers are present during off_line planning. Wherefore, the algorithm has to produce the entire path using coordinate in this form of path scheduling before the robot starts its movement utilizing several techniques. In contrast, local path planning is entirely conducted in an unknown environment, i.e., the development of online paths as the obstacles between the origin and terminus point. The route in both techniques is determined by the environmental information technology provided by sensors. The navigation of mobile robots has primarily four steps [3]; i) perception: sensors provide the robot with information about its environment; ii) localization: extracting keywords from a title is important in cross-referencing and computer searching, and indexing and abstracting services rely on the correctness of the title. A document with an incorrect title may never reach the intended audience. With each repetition, the robot recalls its own position and orientation in the surroundings; iii) cognition and way planning: The robot determines the path to the destination location; iv) mobility control: the robot traces its course by controlling its motion. The research study focuses, on presenting a hybrid approaches that incorporates two algorithms: “gray wolf optimization” (GWO) with “particle swarm optimization” (PSO). Gray wolves like to live in groups, hence the GWO is driven by the gray wolf hunting behavior and leadership hierarchy in nature [4], [5]. They are classified into several leaders, including “alpha, beta, omega, and delta”. Alphas are at the top of the hierarchy and are seen to be the group's most powerful members, therefore they are in charge of making choices regarding hunt, sleep, and wake up time, among other things. In the leadership hierarchy, Beta is the next step up.

The PSO was proposed by “Kennedy and Eberhart” in 1995 as an evolutionary computing technique. “PSO” is based on social phenomena like flock birding and schooling fish, and it works during having a population of candidating solutions (particles) [6], [7]. These particles are causing the search space to move. The particles' movements are determined by their better knowing space position and the swarm's best-known locations. As more suitable sites are discovered, they will be used to guide the swarm's migration. The method is repeated several times in order to achieve the desired result (hopefully). After finishing the search process, one may evaluate the worth of a subset of features by assessing each feature's unique predictive capacity as well as the degree of duplication between them. We use both the strong optimizers described in our hybrid strategy to take advantage of PSO's social behavior as well as GWO's hunting behavior. The population is divided into two categories in the proposed hybrid strategy. The GWO processes are followed by the first group, while the PSO procedures are followed by the second group.

For the remainder of this work, the content is arranged as followed. Related works is found in section 2. Section 3 describes our suggested HGWO-PSO, as well as the HGWO-PSO algorithm pseudocode and methodology. Section 4: experimentation studying, simulation results, and discussion. Section 5 presented the conclusion of the work.

2. RELATED WORK

Various procedures, like multitude/nature-roused calculations, neural organizations, and fluffy rationale, have been utilized to tackle single/multi-target course arranging issues for "mobile robots". There are some past investigations in the main class that have controlled instances of common multitude practices. The works in [8], [9] utilized the customary enhancement of ant colony (ACO) to tackle issues with course anticipating sophisticated circumstances. An enhanced rendition of ACO (IACO) has been suggested in [10] to acquire quicker union speed and to try not to trap into the neighborhood at least. Contrasted with other calculations, the IACO created an ideal way, notwithstanding, it takes longer effort to combine. Different works have additionally embraced heuristic techniques and utilized these to address various parts of way arranging strategies, for example, bat algorithm (BA) [11], PSO [12] PSO's first model involved studying and graphically simulating the choreography of a flock of birds. Cuckoo search (CS) calculations [13], “bacterial foraging” streamlining [14] this algorithm describes how bacteria behave over broad geographic areas when conducting parallel behavior on different types of nutrients is just like how bacteria over a landscape searches for different nutrients, the artificial immunity algorithm (AIA) [15] From the immune system. An adaptable immunity algorithm is suggested, so the robot obtains a path to the object without being contaminated, as well the whale optimization algorithm (WOA), executed in a fixed climate to fulfill necessities for the most brief and softest way [16]. Genetic algorithms (GA) also its adjusted forms are as often as possible carried out to track down the briefest way for “mobile robot” path plans in various conditions [17], while path plan utilizing neurally organizations was created in [18]. The works in [19], [21] joined two-level route algorithm, where the more elevated level was mostly worried about path plan and direction for the mobile robot, whereas the movement controlling coordinating the “mobile robot” in its arrangement area was remembered for the least leveling. “Mobile robot” power utilization is a significant problem straightforwardly identified with smooth direction arranging. Least energy cornering direction arranging calculation with self-turn and energy compelled target scales were created in [22]. Meta-heuristic algorithm hybridization has also been used to enhance algorithms for “robot” path plan. The aim of “hybridizing” double “meta-heuristic” techniques is to gather every innovation's benefits to design an enhanced one. “Genetic algorithms” and particle swarm optimization involve some “hybridized algorithms” utilized in “robot” path plan as GA-PSO [23].

3. THE PROPOSED HGWO-PSO APPROACH

3.1. The gray wolf optimization

In [4], [24] proposed the GWO algorithm in 2014 to replicate the hierarchies of leadership and hunting system of gray wolves during nature. Gray wolves' hunting strategy and social hierarchy are dependent on the gray wolves algorithm being optimized. So, we can say that there are four groups according to the gray wolves hierarchy. Three wolves, wolf-alpha, wolf-beta, wolf-delta, and wolf-omega. The leader of the dominant wolf is called alpha and follows the alpha wolf other wolves are in the group. The strongest wolf is alpha in terms of group leadership. Beta wolf is the second on the wolf group's social ladder. Beta helps the leader wolf (Alpha) in many events. Delta's wolf should be presented to "alpha" wolves and "beta" wolves, but they are separated into "omega" wolves. Scouts, guards, seniors, fishermen, and carers make up this group. Wolf omega gray wolf numbers are at an all-time low. The following formula can be used to calculate GWO's encircling behavior:

$$\vec{D} = \left|\vec{C} \cdot \overrightarrow{X_P}(t) - \vec{X}(t)\right|$$

$$\vec{X}(t+1) = \overrightarrow{X_P}(t) - \vec{A} \cdot \vec{D} \tag{1}$$

Whereas, t alludes to the present cycle, $\vec{A}$ and $\vec{C}$ are vectors of coefficient, $\overrightarrow{X_P}$ is the relational word, and $\vec{X}$ is the situation of the dim wolf's. These are the vectors determined utilizing the accompanying condition:

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a},\ \vec{C} = 2\overline{.r}_2 \tag{2}$$

Whereas and is straightforwardly reduced from 2 to 0 all through the range of accentuations $\overrightarrow{r_1}$ and $\overrightarrow{r_2}$ is the discretionary number within the scope [0, 1]. The integral package shows up at the preying and attacking through invigorating the positioning subject to besting spaces of the "alpha, beta, delta" use the going with conditions:

$$\vec{D}\alpha = \left|\vec{C}_1.\vec{X}\alpha(t) - \vec{X}(t)\right|$$

$$\vec{D}\beta = \left|\vec{C}_2.\vec{X}\beta(t) - \vec{X}(t)\right|$$

$$\vec{D}\delta = \left|\vec{C}_3.\vec{X}\delta(t) - \vec{X}(t)\right| \tag{3}$$

$$\vec{X}_1 = \vec{X}\alpha(t) - \vec{A}_1.(\vec{D}\alpha)$$

$$\vec{X}_3 = \vec{X}_\delta(t) - \vec{A}_3(\vec{D}\delta) \tag{4}$$

$$\vec{X}(t+1) = \frac{\overrightarrow{X_1} + \overrightarrow{X_2} + \overrightarrow{X_3}}{3} \tag{5}$$

3.2. Particle swarm optimization

Kennedy with Eberhart applied the PSO algorithm for the first time in [6], [25], and its fundamental decision was largely influenced by animal social behavior simulations. Bird flocking and fish schooling is examples of this. Before feeding, either disperse or congregate while looking for the birds. Select an area where they will be able to obtain food. Despite this, birds migrate from one location to another in search of food. A bird that has a strong sense of smell is always present, that is, a bird with a strong sense of smell is always present. The bird is aware of the food source's location. Each particle's velocity is updated in each iteration as a function of both the particle's social and internal behavior. PSO's virtue of being able to update without affecting prior work makes it one of a kind when it comes to evolutionary algorithms. In (6) governs the velocity and location of each particle (7).

$$v_i^{k+1} = v_i^k + c_1 r_1 (p_i^k - x_i^k) + c_2 r_2 (g_{best} - x_i^k) \tag{6}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{7}$$

3.3. The hybrid GWO-PSO

According to research by Singh and Singh [26], the hybrid GWO-PSO algorithm was suggested. The basic concept behind HGWO-PSO is to improve the algorithm's ability to leverage PSO while also exploring GWO to achieve both optimizer strengths. Instead of using traditional mathematical equations, the first three agents' positions in the quest space are revised in HPSOGWO, and the grey wolf's exploitation and exploration are governed by the inertia constant. GWO is a calculation dependent on the populace. GWO starts with an underlying irregular populace and they are changed during the emphasis. GWO keeps a harmony among abuse and exported. Exported is a strategy to investigate quest possibilities for space focuses in the field of searching.

Abuse is the procedure of utilizing the promise pointing to track down the best encouraging pointing in searching place. Each individual is considered as the solution to the problems at hand. At that point, for all arrangements, the wellness work is determined. Hence, alpha, beta, with gamma can be distinguished. The accompanying conditions are utilized to refresh the situation of all wolf. This was modeled mathematically as:

$$\vec{D}\alpha = \left|\overrightarrow{C_1}.\overrightarrow{X_\alpha}(t) - W * \vec{X}(t)\right|$$

$$\vec{D}\beta = \left| \overrightarrow{C_2}.\overrightarrow{X_\beta}\,(t) - W * \vec{X}\,(t) \right|$$

$$\vec{D}\delta = \left| \overrightarrow{C_3}.\overrightarrow{X_\delta}(t) - W * \vec{X}\,(t) \right| \tag{8}$$

The velocity and positions have been changed to combining PSO and GWO variants:

$$v_i^{k+1} = w * (v_i^k + c_1 r_1 (x_1 - x_i^k) + c_2 r_2 (x_2 - x_i^k) + c_3 r_3\,(x_3 - x_i^k)) \tag{9}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{10}$$

The pseudo-code as well flow chart of the HGWO-PSO algorithm has been shown in Figure 1 and Figure 2.

```
Initializations
Initialized  A, a, C and w
                                 // w = 0.5 + rand ()/2
Random Initialized  an agents of  n  wolves' positioning ∈ [1,0].
Baseding  fitness functioning  attained  the α , β , δ  solutions.
Evaluates the fitness of agents  used Eq. (8)
while (t < max_iter)
for every one  population
Updates  the velocity used Eq. (9)
Updates  the position used Eq. (10)
end
Updates  A, a, C and w
Evaluates all particles uses objective functioning
Updates  the position of  three better agents α, β, δ
t= t + 1
end while
return // X_α
```

Figure 1. HGWO-PSO algorithm pseudo-code

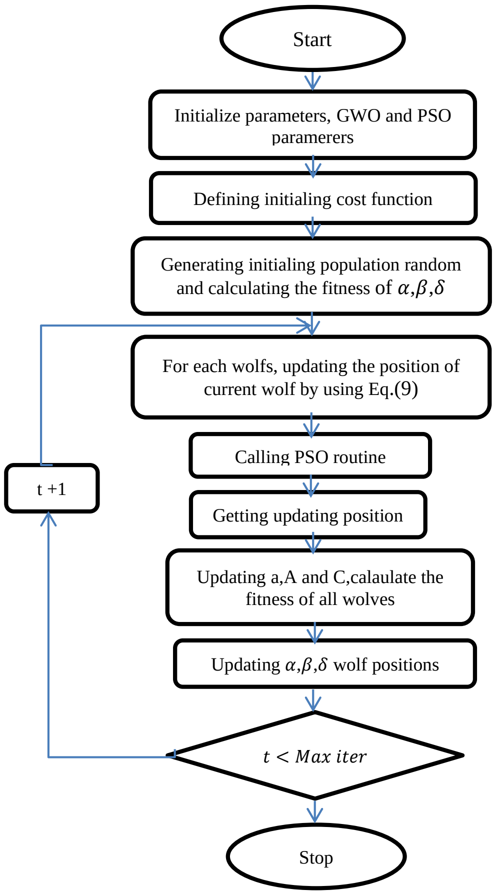

Figure 2. Flow-chart for "HGWO-PSO" technique

4. SIMULATION RESULTS AND DISCUSSION

In this undertaking, the robot way plan technique has been effectively planned also reproduced using the MatLab2020a reenactment program with m records. All the examined too recommended computer-based intelligence methods in past parts have been carried out and analyzed under the predefined robot determinations to see which calculations. The new recommended strategy HGWO-PSO mixture gray wolf optimization and PSO procedure has been carried out also contrasted and other tried methods.

The last simulated intelligence procedure has shown an enormous improvement in the consequences of the "robot" way plan with amazing execution. Every one of the continued outcomes have been recorded also delineated in the beneath figures. In the amusement, the test has perused the reenactments covered for the moving robot route organizing in static conditions, while the conceivable relevant examination joins a closeness near earlier ventures. All preliminaries are refined the going with courses of action in the wake of executing the estimations on various occasions used MATLAB R2020a programming languaging. The MATLAB codes are running on a PC structure with a 2.40 GHz Center i5-6200U central processor, and 8G Smash. A fundamental environment that contains three circle-shaped static obstacles with different reach is attempted first. To show the introduction of the "HGWO-PSO" computation for the way organizing issue, the red square exhibits the starting spot of the versatile robot and the green square shows the goal point. To apply the "HGWO-PSO" computation to handle this issue, a 2-D workspace of the robot's development arranged by the hidden and the goal positions, worth of tangles, and handles. All the vital limits (most noteworthy accentuation, people, worth of runs) presented.

4.1. Robot path planning with obstacles

In this scenarios, four environments during fine static obstacles used to show the path planning algorithm's efficacy in a "mobile robot". The settings for these environments are listed in Table 1. In this paper, and as we can observe from the obtained results that the "HGWO-PSO" technique has shown a perfect robot path plan as compared with other path optimization approaches in literature. The mentioned approach has shown the least distance during simulation test of the system. Actually, the new suggested "HGWO-PSO" approach have provide an optimal robot path distance for all the tested cases during simulation program. This made the suggested technique to be dominant among all other tested approaches. as shown in Table 2.

Table 1. Simulation issues taken for test

Scenarios	Maxit	No. Pop	No. obstacles	No. of handle points	Start point	Target point
1	30	30	3	2	(0,0)	(8,8)
2	50	50	7	3	(0,0)	(10,10)
3	100	50	8	4	(0,0)	(20,20)
4	150	50	9	5	(0,0)	(30,30)

Table 2. The optimal path by a comparison of the outcomes for scenarios

Scenarios	Method	Processing time	Optimum distance	AVG	STD
1	PSO	1.66E+01	11.4303	11.61022	0.20746
	GSO	2.29E+01	11.8235	12.96715	0.4551
	ABC	1.61E+01	11.0745	11.24853	0.37009
	GWO	1.61E+01	10.9735	11.73763	0.12672
	HGWO-PSO	1.63E+01	9.11807	10.98604	0.10161
2	PSO	2.88E+01	14.4358	15.0858	1.0758
	GSO	2.92E+01	14.8405	16.9258	0.9575
	ABC	2.89E+01	13.9321	15.8904	1.4303
	GWO	2.89E+01	14.2328	16.1854	0.6616
	HGWO-PSO	2.88E+01	14.4358	15.0858	1.0758
3	PSO	5.63E+01	28.921	32.5159	0.9211
	GSO	5.69E+01	30.6514	34.7563	0.8767
	ABC	5.97E+01	28.683	33.9038	1.4186
	GWO	5.83E+01	28.8319	31.3833	1.3153
	HGWO-PSO	5.77E+01	26.0501	30.9583	1.0060
4	PSO	9.08E+01	43.2976	44.9073	2.7545
	GSO	8.74E+01	47.2996	58.5364	2.2600
	ABC	9.63E+01	43.0149	56.6925	5.1580
	GWO	8.68E+01	42.3869	47.4416	5.2693
	HGWO-PSO	8.74E+01	37.4156	43.7089	5.5410

4.1.1. The first scenario: static environment path planner

For this scenario, a static obstacle course is used to show the path planning algorithms efficacy in a "mobile robot". There are three different-sized static objects situated in a static environment. The beginning point was $SPPos$=(0,0), the target point was $GPPos$=(8,8), and the radius of the "mobile robot" was rMR=0.5(m) as shown in Figures 3 and 4.

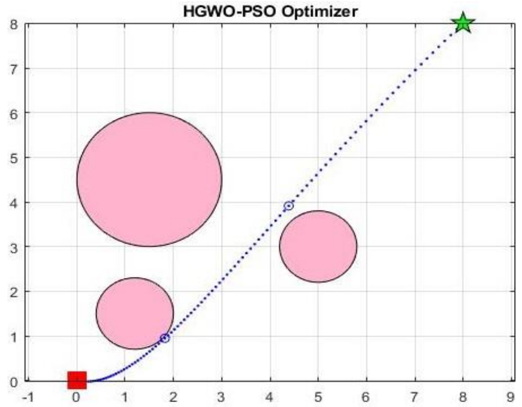

Figure 3. Simulations results for (scenario 1)

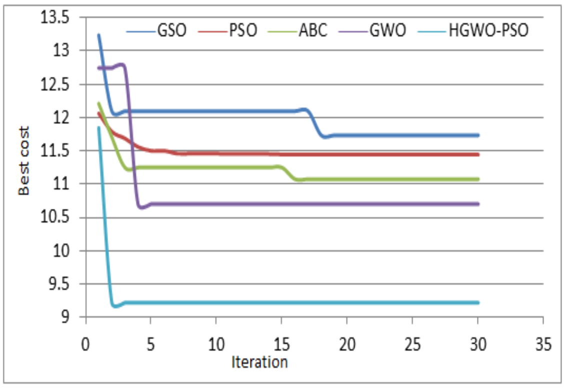

Figure 4. Best cost vs iteration simulation results comparison of (scenario 1)

4.1.2. The second scenario: static environment path planner

For this scenario, a static obstacles are employed to show the path planning algorithms success for a "mobile robot". There are seven different sizes of static obstacles in the environment. The beginning point was $SPPos$=(0,0), the target point was $GPPos$=(10,10), and the radius of the "mobile robot" was rMR=0.5(m) as shown in Figures 5 and 6.

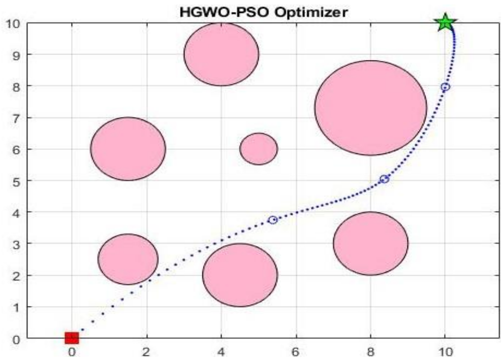

Figure 5. Simulations results for (scenario 2)

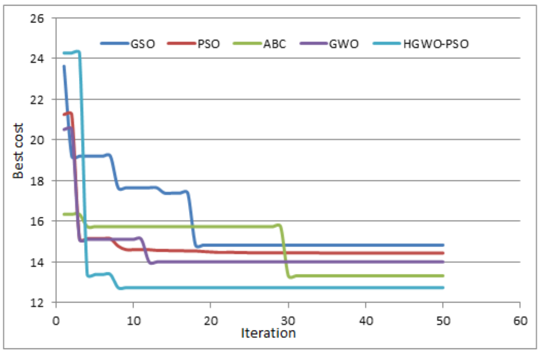

Figure 6. Best cost vs iteration simulation results comparion of (scenario 2)

4.1.3. The third scenario: static environment path planner

For this Scenario, a static obstacle course is used to show the path planning algorithms efficacy in a "mobile robot". The static environment is made up of eight different-sized static obstacles. The beginning point was $SPPos$=(0,0), the target point was $GPPos$=(20,20), and the radius of the "mobile robot" was rMR=0.5(m) as shown in Figures 7 and 8.

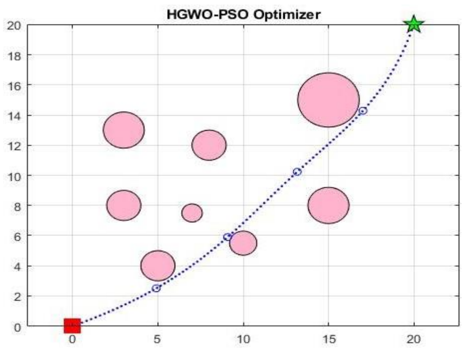

Figure 7. Simulations results for (scenario 3)

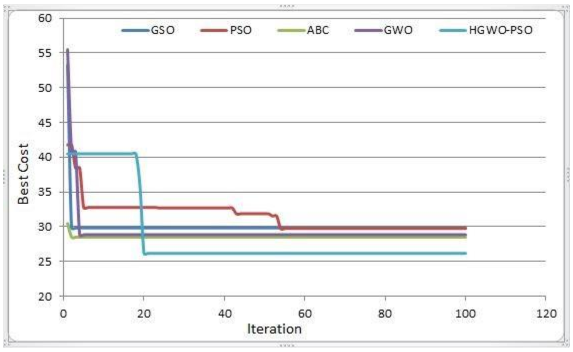

Figure 8. Best cost vs iteration simulation results comparion of (scenario 3)

4.1.4. The fourth scenario: static environment path planner

For this scenario, a static obstacle course is used to show the path planning algorithms efficacy in a "mobile robot". The static environment is made up of eight different-sized static obstacles. The beginning point was $SPPos$=(0,0), the target point was $GPPos$=(30,30), and the radius of "mobile robot" was rMR=0.5(m) as shown in Figures 9 and 10.

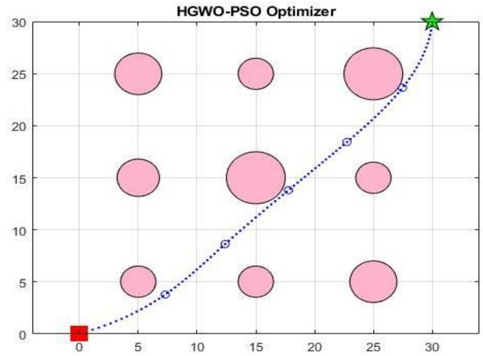

Figure 9. Simulations results for (scenario 4)

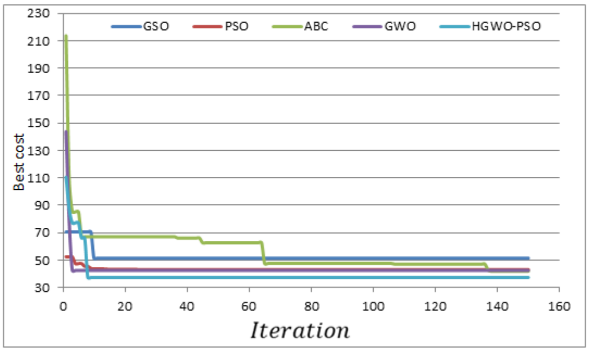

Figure 10. Best cost vs iteration simulation results comparion of (scenario 4)

5. CONCLUSION

In this work, robot path plan streamlining has been explored using distinctive artificial intelligence procedures for 2-dimensional versatile robot movement. From the execution got results, it has been demonstrated and seen that the best robot path plan is what comes about by using the HGWO-PSO strategy among any remaining way improvement draws near. During the structure's entertainment preliminary, the referred to philosophy showed little distance. Everything considered the recommended HGWO-PSO approach has given an ideal robot route distance for all the attempted cases during the multiplication program. This made the recommended technique to be winning among any excess attempted approaches. The clarification of such dominance has been unveiled due to the creamer blend between the two modernized thinking strategies, the GWO and the PSO approaches. The results show that HGWO-PSO was able to produce extremely competitive results compared to well-known heuristics like as PSO, GSO, ABC, GWO. Future work in order to obtain a shorter with more flexible paths and to bypass “obstacles and obstacles placed in front of the robot’s path line, we suggest resorting to smart algorithms that are more efficient and faster and respond to natural determinants on the one hand and on the other hand. On the other hand, do not spend more time and effort in implementing the optimal access process” and the best. Where available in the literature.

REFERENCES

[1] H. S. Dewang, P. K. Mohanty and S. Kundu, “A robust path planning for mobile robot using smart particle swarm optimization,” *Procedia computer science*, vol. 133, pp. 290-297, 2018, doi: 10.1016/j.procs.2018.07.036.
[2] P. K. Mohanty and D. R. Parhi, “Controlling the Motion of an Autonomous Mobile Robot Using Various Techniques: aReview,” *Journal of Advance Mechanical Engineering*, vol. 1, pp. 24-39, 2013, doi: 10.7726/jame.2013.1003.
[3] R. Siegwart, I. R. Nourbakhsh and D. Scaramuzza, “Introduction to autonomous Robots,” *second edition The MIT press*. Cambridge, Masachusetts, London, England.
[4] S. Mirjalili, S. M. Mirjalili and A. Lewis, “Grey wolf optimizer,” *Advances in Engineering Software*, vol. 69, pp. 46-61, 2014, doi: 10.1016/j.advengsoft.2013.12.007.
[5] H. Hassan, A. I. El-Desouky, A. Ibrahim, E. M. El-Kenawy and R. Arnous, “Enhanced QoS-Based Model for Trust Assessment in Cloud Computing Environment,” *IEEE Access*, vol. 8, pp. 43752-43763, 2020, doi: 10.1109/ACCESS.2020.2978452.
[6] J. Kennedy and R. Eberhart, “Particle swarm optimization,” *Proceedings of ICNN'95 - International Conference on Neural Networks*, 1995, vol.4, pp. 1942-1948, doi: 10.1109/ICNN.1995.488968.
[7] Y. Shi and R. C. Eberhart, “A modified particle swarm optimizer,” *Proceedings of Congress on Evolu-tionary Computation*, 1998, pp. 73-79.
[8] R. Rashid, N. Perumal, I. Elamvazuthi, M. K. Tageldeen, M. K. A. A. Khan and S. Parasuraman, “Mobile robot path planning using Ant Colony Optimization,” *2nd IEEE International Symposium on Robotics and Manufacturing Automation (ROMA)*, 2016, pp. 1-6, doi: 10.1109/ROMA.2016.7847836.
[9] I. K. Ibraheem and F. H. Ajeil, “Path Planning of an autonomous Mobile Robot using Swarm Based Optimization Techniques,” *Al-Khwarizmi Engineering Journal (Alkej)*, vol. 12, no. 4, pp. 12-25, 2016, doi: 10.22153/kej.2016.08.002.
[10] J. Ou and M. Wang, “Path Planning for Omnidirectional Wheeled Mobile Robot by Improved Ant Colony Optimization,” *Chinese Control Conference (CCC)*, 2019, pp. 2668-2673, doi: 10.23919/ChiCC.2019.8866228.
[11] G. Wang, L. Guo, H. Duan, L. Liu, H. Wang, “A bat algorithm with mutation for UCAV path planning,” *The Scientific World Journal*, vol. 2012, no. 418946, pp.1-16, 2012, doi: 10.1100/2012/418946.

[12] H. S. Dewang, P. K. Mohanty and S. Kundu, "A Robust Path Planning for Mobile Robot Using Smart Particle Swarm Optimization," *Procedia Computer Science*, vol. 133, pp. 290-297, 2018, doi: 10.1016/j.procs.2018.07.036.

[13] W. Wang, M. Cao, S. Ma, C. Ren, X. Zhu and H. Lu, "Multi-robot odor source search based on Cuckoo search algorithm in ventilated indoor environment," *12th World Congress on Intelligent Control and Automation (WCICA)*, 2016, pp. 1496-1501, doi: 10.1109/WCICA.2016.7578817.

[14] M. A. Hossain and I. Ferdous, "Autonomous robot path planning in dynamic environment using a new optimization technique inspired by bacterial foraging technique," *Robotics and Autonomous Systems*, vol. 64, pp. 137-141, 2015, doi: 10.1016/j.robot.2014.07.002.

[15] P. K. Das, S. K. Pradhan, S. N. Patro and B. K. Balabantaray, "Artificial immune system-based path planning of mobile robot," *Soft Computing Techniques in Vision Science*, pp. 195-207, 2012, doi: 10.1007/978-3-642-25507-6_17.

[16] T. K. Dao, T. S. Pan and J. S. Pan, "A multi-objective optimal mobile robot path planning based on whale optimization algorithm," *IEEE 13th International Conference on Signal Processing (ICSP)*, 2016, pp. 337-342, doi: 10.1109/ICSP.2016.7877851.

[17] C. Lamini, S. Benhlima, and A. Elbekri, "Genetic algorithm-based approach for autonomous mobile robot path planning," *Procedia Computer Science*, vol. 127, pp. 180-189, 2018, doi: 10.1016/j.procs.2018.01.113.

[18] U. A. Syed, F. Kunwar, and M. Iqbal, "Guided Autowave Pulse Coupled Neural Network (GAPCNN) based real time path planning and an obstacle avoidance scheme for mobile robots," *Robotics and Autonomous Systems*, vol. 62, no. 4, pp;. 474-486, 2014, doi: 10.1016/j.robot.2013.12.004.

[19] W. J. Chen, B. G. Jhong, and M. Y. Chen, "Design of Path Planning and Obstacle Avoidance for a Wheeled Mobile Robot," *International Journal of Fuzzy Systems*, vol. 18, pp. 1080-1091, 2016, doi: 10.1007/s40815-016-0224-7.

[20] A. Bakdi, A. Hentout, H. Boutami, A. Maoudj, O. Hachour and B. Bouzouia, "Optimal path planning and execution for mobile robots using genetic algorithm and adaptive fuzzy-logic control," *Robotics and Autonomous Systems*, vol. 89, pp. 95-109, 2017, doi: 10.1016/j.robot.2016.12.008.

[21] M. Emam and A. Fakharian, "Path following of an omni-directional four-wheeled mobile robot," *Artificial Intelligence and Robotics (IRANOPEN)*, 2016, pp. 36-41, doi: 10.1109/RIOS.2016.7529487.

[22] H. Kim, and B. K. Kim, "Minimum-energy cornering trajectory planning with self-rotation for three-wheeled omni-directional mobile robots," *International Journal of Control, Automation and Systems*, vol. 15, pp. 1857-1866. 2017, doi: 10.1007/s12555-016-0111-x.

[23] R. Rashid, N. Perumal, I. Elamvazuthi, M. K. Tageldeen, M. K. A. A. Khan and S. Parasuraman, "Mobile robot path planning using Ant Colony Optimization," *2nd IEEE International Symposium on Robotics and Manufacturing Automation (ROMA)*, 2016, pp. 1-6, doi: 10.1109/ROMA.2016.7847836.

[24] L. Dogan and U. Yuzgec, "Robot Path Planning using Gray Wolf Optimizer," *International Conference on Advanced Technologies, Computer Engineering and Science*, 2018.

[25] I. A. Abed, M. M. Ali and A. A. A. Kadhim, "Using particle swarm optimization to solve test functions problems," *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 6, pp. 3422-3431, 2021, doi: 10.11591/eei.v10i6.3244.

[26] N. Singh and S. B. Singh, "Hybrid algorithm of particle swarm optimization and Grey Wolf optimizer for improving convergence performance," *Journal of Applied Mathematics*, vol. 2017, no. 2030489, pp. 1-16, 2017, doi: 10.1155/2017/2030489.

BIOGRAPHIES OF AUTHORS

Ayad Abdulrahem Alabdalbari received the B.Sc. from Shatt Al-Arab University College of Basrah, Iraq in 2012, and M.Sc. degrees in Computer Engineering from Shahid Chamran University of Ahwaz, Iran in 2021. Currently he has working in the planning and scheduling department for maintenance at Basrah Gas Company, Iraq. He can be contacted at email: ayadabdulrahem25@gmail.com.

Issa Ahmed Abed received his BSc. and MSc. in Control and Computing from the Department of Electrical Engineering, University of Basrah, Iraq in 2002 and 2005, respectively. While his Ph.D. is also in Control and Computing from University Tenaga Nasional, Malaysia in 2014. Currently, he is an Asst. Prof. and the head of control and automation Department at Engineering Technical College Basrah, Southern Technical University, Iraq. His areas of interest include artificial intelligence, solar energy, control systems, robotics, and image processing. He can be contacted at email: issaahmedabed@stu.edu.iq.