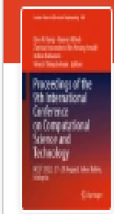

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Abstract

This paper proposes a new hybrid of nature inspired optimization algorithm (IFDO-WOABAT) based on the latest optimization algorithm namely Improved Fitness Dependent Optimization (IFDO) with Whale-Bat Optimization algorithm (WOABAT). The hybrid is essential to overcome the inaccuracy in searching optimal path when dealing with many agents in conjunction with exploration and exploitation element in WOABAT signify the process of searching behaviour and optimizing the speed value of agent. The performance of the new hybrid optimization algorithm is verified using standard classical test function and further evaluated with other four renowned optimization algorithms and the results showed that it is better in most cases compared with the existing algorithms. Ultimately, the algorithm's performance also has been tested in crowd simulation evacuation that involves a different number of agents and

The Hybrid of WOABAT-IFDO Optimization Algorithm and Its Application in Crowd Evacuation Simulation

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Abstract. This paper proposes a new hybrid of nature inspired optimization algorithm (IFDO-WOABAT) based on the latest optimization algorithm namely Improved Fitness Dependent Optimization (IFDO) with Whale-Bat Optimization algorithm (WOABAT). The hybrid is essential to overcome the inaccuracy in searching optimal path when dealing with many agents in conjunction with exploration and exploitation element in WOABAT signify the process of searching behaviour and optimizing the speed value of agent. The performance of the new hybrid optimization algorithm is verified using standard classical test function and further evaluated with other four renowned optimization algorithms and the results showed that it is better in most cases compared with the existing algorithms. Ultimately, the algorithm's performance also has been tested in crowd simulation evacuation that involves a different number of agents and with/without obstacle scenario. The conducted experiment reveals promising results and signify effectiveness in minimizing the evacuation time.

Keywords: Hybrid Whale-Bat with Improved Fitness Dependent Optimization, Nature Inspired Optimization, Crowd Evacuation Simulation.

1 Introduction

In recent trend of crowd evacuation simulation system, there is a need to optimized using different optimization algorithms (hybrid). This is to help finding the best location of the exit door of evacuation area. Some may say that shortest distance towards exit is crucial, but optimization can help decide to find the best or near optimal solution (exit) [1]. The coordination between subgroups within the crowd, and uncertainty in crowd movement due to obstacle's position led to the studies of several soft computing (SC) based for developing intelligent approaches to govern and simulate crowd motion [2]. In the context of optimization issues, a traditional evacuation system indicates only a fixed direction and may mislead people to a dangerous or wrong place. However, only a few studies are dedicated towards this system [3]. The optimization is crucial for retrieving a minimal evacuation time [4]. Optimization algorithms under nature-inspired metaheuristic algorithms has been in research domain and some of the most efficient has been widely proposed in past literature. As coined by [5], they explained the term ‘No Free Lunch Theorems for Optimization’ to indicate that there will always in a need for latest developed algorithms provided that the proposed algorithm is better than previously and much more efficient in terms of performance wise. Traditional algorithms might have problems to cater for real-world problems (high non-linear problem) because of the impossibilities to have every single solution for the problems in terms of time, cost, and space (search space). Thus far, it is recommended that metaheuristic is said to be more suitable to cater for such predicaments [6]. The organization of this paper is as follows: Section 2 will describe about the related works. Section 3 introduces on the proposed method. Section 4 discusses on experiment and simulation analysis and results. Finally in Section 5 is describing the conclusion and future work.

2 Related Works

The current emergency research shows emergency simulation is important for mitigation to avoid risk of human life, but not taken into account the interaction of human i.e. human to obstacles, social interaction with each other that mostly takes place during emergency (optimizing planning behaviour) to shorten the period for this post emergency evacuation time. There is still an issue on how to define the right rules in terms of interactions of the individual speeds that clearly will show the behaviour of agent (particle) of the swarm (crowd) [7].

Another most notable optimization algorithm under nature inspired is the Ant Colony Optimization. This algorithm has been used to solve the evacuation routing problem, which is based on the organization of the evacuee’s space–time paths within a hierarchical directed network. The results showed that it can reducing evacuation time within the scope of the experiment, total travel distance and congestion. There will be a need to further improve in future research that focus on improving the space–time paths of evacuees [8]. In another work done by [1], the implementation of Cellular Automata integrates with Fuzzy Logic, Kth Nearest Neighbour’s (KNN) has been used to simulate evacuation scenario. They have not incorporated an element to resemble panic situation. Another example of nature inspired algorithm is the Modified Artificial Bee Colony (MOABC) done by [9]. The results from their work have shown that the time for seeking shelter from open area to close area was reduced. The drawback of this work is they still need to model conceptualization in regards of the area characteristics, topography, and agent’s behaviour other than to include other factors namely as traffic and risks along evacuation paths. The latest optimization algorithm such as Improved Fitness Dependent Optimization (IFDO) still cannot deal with searching accuracy when the search agent is more than five. Therefore, it is a need to use large number of search agents to enhance the accuracy of the algorithm with more space and time by further hybrid with other popular nature-inspired algorithms, such as Whale-Bat (WOABAT) algorithm[10].

3 Proposed hybrid of IFDO-WOABAT algorithm

3.1 Evaluation and Experiment Setting on Function Optimization

As usual, the evaluation is normally done for an algorithm to get better comparison. There are two ways for evaluation; (i) by average and standard deviation result and (ii) by comparison of hybrid WOABAT-IFDO with other selected nature inspired metaheuristic algorithms. Based on the first point, the algorithm's performance or evaluation is tested as function optimization problem that use the Classical Benchmark testing. The proposed hybrid WOABAT- IFDO based on a group of 19 classical benchmark test functions. Next, for the second evaluation it is crucial to make a comparison between the proposed WOABAT-IFDO with other selected nature inspired algorithm namely as IFDO, FDO and PSO [10] and WOABAT. As it is important that an algorithm to avoid being trapped in local optimal solution and to get to global optimum solution. Figure 1 the flowchart of WOABAT-IFDO respectively. The testing has been done using MATLAB2020(b) in Windows 10 operating system. The processor is AMD Ryzen 5 4600H with 16 GB RAM. The size of dimension for testing is set to 10, whilst the algorithm is tested 30 times for 500 iterations, 30 scout bee.

Table 1 shows the results of mean and standard deviation for each tested algorithm. It shows that the hybrid algorithm WOABAT-IFDO obtained quite a promising performance compare with other algorithms on almost every benchmark function [10] and shows the same result with addition of WOABAT experiment included. The results showed that the proposed hybrid algorithm obtained most of the minimum results over 19 test functions. The mean value depicts the convergence speed and accuracy of the optimization function of an algorithm. Meanwhile, the standard deviation reflects the dispersion and stability of an algorithm. Thus, the proposed hybrid algorithm WOABAT-IFDO has better optimization accuracy, convergence speed and stability.

A quantitative measurement metrics were adapted for the test function details namely unimodal, multimodal, and composite standards as a feature to measure specific algorithm outcome. As for unimodal benchmark, this is used for testing the exploitation stage and for convergence of an algorithm (targeting on single optimum). On the other hand, multimodal is used for testing the exploration stage and avoidance in local optima condition. Multimodal benchmark functions mean it has multi-ideal or optimal solution for example global and local optimal solutions. As mentioned before, an algorithm should be able to prevent local optimum solutions. Instead, it should get to converge towards global optimum solution. As for the composite benchmark, it comprises of diverse and different region of search landscape and tend to have a very big local optimum. The mean value from the result of test function shows the speed on convergence rate and the accuracy of the proposed algorithm. Based on Table 1 and Table 2, the unimodal standard functions which range from TF1 to TF7, the result of hybrid WOABAT+IFDO in TF7 is comparable with IFDO and FDO. However, TF1 and TF4 showed poor performance in com- parison with the selected algorithms. For multimodal standard which range from TF8 to TF13, the test function result of TF8, TF9 and TF11 showed that the hybrid WOABAT+IFDO outperformed the other competitor algorithm. Moreover, for the composite standard functions range from T14 to T19, the result of

TF15, TF17, TF18 and TF19 for hybrid WOABAT+IFDO showed better performance than other selected algorithms. Generally, the proposed hybrid of WOABAT and IFDO has the capability to exploit the search space with improved exploration stage and overall can move in the direction of optimality and avoid local optima.

Table 1. Comparison of performance on selected optimization algorithms (FDO and IFDO).

Test Function	IFDO_WOABAT		FDO		IFDO	
	Ave	Std	Ave	Std	Ave	Std
*TF1	4.88E-06	1.73E-06	7.47E-21	7.26E-19	5.38E-24	2.74E-23
TF2	0.0058	0.001	9.39E-06	6.91E-06	0.534345844	1.62026
TF3	1.08E-05	4.65E-06	8.55E-07	4.40E-06	2.88E-07	6.90E-07
*TF4	0.0518	0.041	6.69E-04	0.0024887	2.60E-04	9.11E-04
TF5	4.263	1.1094	23.501	59.7883701	1.94E+01	3.31E+01
TF6	5.61E-06	2.06E-06	1.42E-18	4.75E-18	4.22E+06	8.15E-09
TF7	0.5253	0.2892	0.544401	0.3151575	5.68E-01	3.14E-01
TF8	**-2.14E+306**	1.03E+307	-228520	206684.91	-2.92E+06	2.24E+05
TF9	**0.0011**	3.88E-04	14.56544	5.202232	1.35E+01	6.66E+00
TF10	0.003	4.37E-04	4.00E-15	6.38E-16	5.18E-15	1.67E-15
TF11	**1.17E-05**	5.86E-06	0.568776	0.1042672	0.525690405	8.90E-02
TF12	2.24E-04	8.96E-04	19.83835	26.374228	1.81E+01	2.57E+01
TF13	0.0121	0.0151	10.2783	7.42028	4.10E+09	1.50E-05
TF14	1.1634	0.5266	3.79E-07	6.32E-07	2.68E-07	4.68E-07
TF15	**2.41E-16**	4.48E-16	0.001502	0.0012431	4.03E-16	9.25E-16
TF16	-1.0316	4.82E-07	0.006375	0.0105688	9.14E-16	3.61E-16
TF17	**0.3979**	1.87E-07	23.82013	0.2149425	2.38E+01	1.24E-01
TF18	**3.000**	1.95E-05	222.9682	9.96E-06	2.24E+02	2.68E-05
TF19	**-3.8112**	0.1961	22.7801	0.0103584	3.15E+01	1.32E-03

Table 2. Comparison of performance on selected optimization algorithms (FDO and IFDO).

Test Function	IFDO_WOABAT		WOABAT		PSO	
	Ave	Std	Ave	Std	Ave	Std
*TF1	4.88E-06	1.73E-06	1.92E-08	2.30E-08	4.20E-18	1.31E-17
TF2	0.0058	0.001	0.0062	9.79E-04	0.003154	0.009811
TF3	1.08E-05	4.65E-06	0.0155	0.085	0.001891	0.003311
*TF4	0.0518	0.041	4.41E-04	6.69E-05	0.001748	0.002515
TF5	4.263	1.1094	1.2156	2.77	63.45331	80.12726
TF6	5.61E-06	2.06E-06	1.45E-08	2.22E-08	4.36E-17	1.38E-16
TF7	0.5253	0.2892	0.0029	0.0095	0.005973	0.003583
TF8	**-2.14E+306**	1.03E+37	-39.3375	1.45E-14	-7.10E+11	1.20E+12
TF9	**0.0011**	3.88E-04	5.6381	8.1308	10.44724	7.879807
TF10	0.003	4.37E-04	12.6424	5.42E-15	0.280137	0.601817
TF11	**1.17E-05**	5.86E-06	0.2816	0.227	0.083463	0.035067
TF12	2.24E-04	8.96E-04	9.75E-10	1.24E-09	8.57E-11	2.71E-10
TF13	0.0121	0.0151	3.37E-09	4.40E-09	0.002197	0.004633
TF14	1.1634	0.5266	2.7558	3.8086	150	135.4006
TF15	**2.41E-16**	4.48E-16	0.0011	0.0037	188.1951	157.2834
TF16	-1.0316	4.82E-07	6.42E+03	1.85E-12	263.0948	187.1352
TF17	**0.3979**	1.87E-07	5.8444	3.18E-15	466.5429	180.9493
TF18	**3.000**	1.95E-05	8.4	10.9846	136.1759	160.0187
TF19	**-3.8112**	0.1961	-3.8628	8.09E-14	741.6341	206.7296

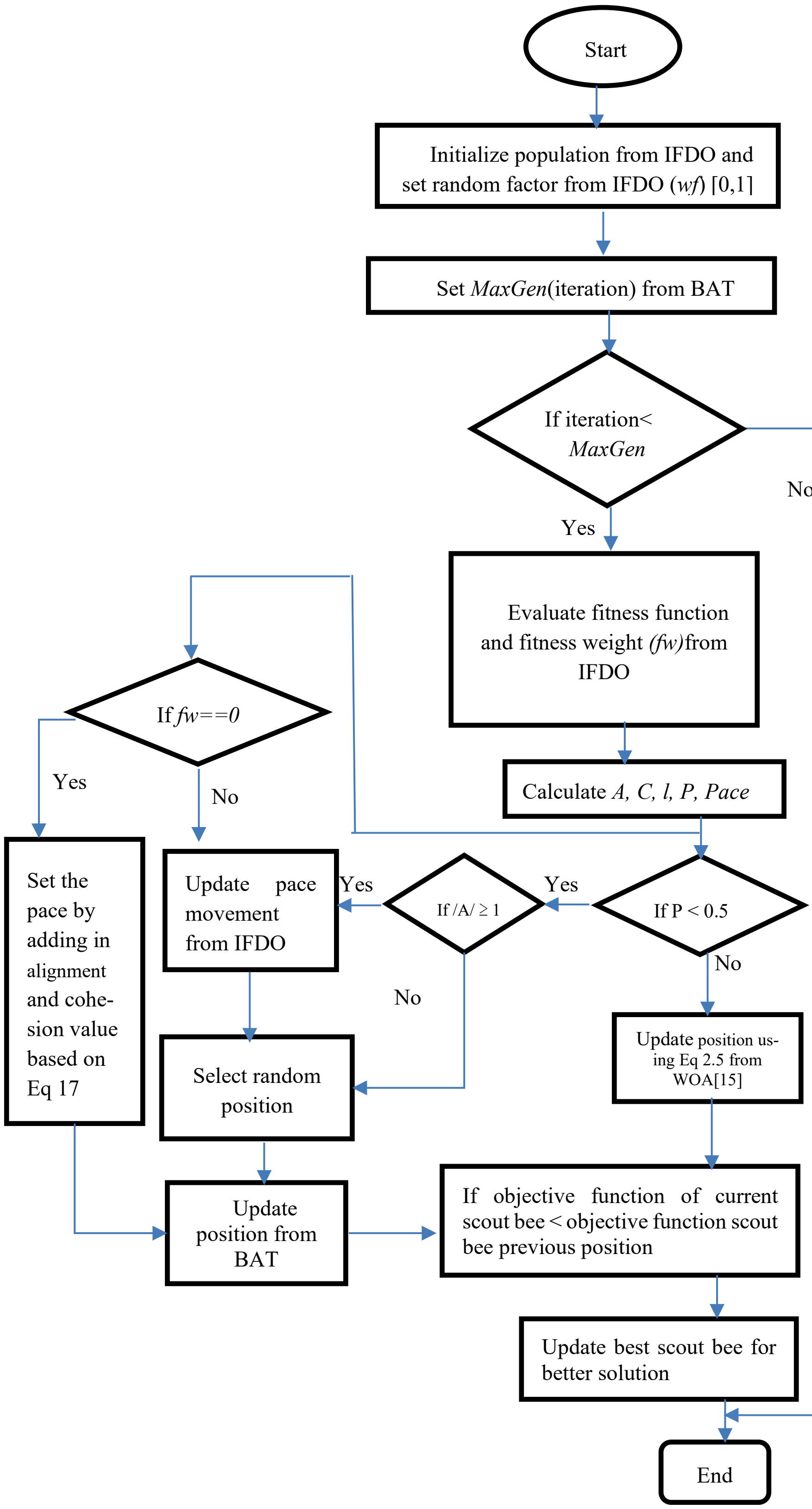

Fig. 1. The proposed hybrid WOABAT-IFDO flowchart

3.2 Crowd evacuation simulation experiment

The hybrid WOABAT-IFDO algorithm can be applied in many ways either to optimize other crowd model or as the optimizer for a path planning of agent for evacuation simulation. For this paper, it will encompass on the later purpose. The environment of simulation is developed using MATLAB R2020b under Windows 10 operating system. The simulation will have few scenarios which include obstacle and non-obstacles condition. The parameter for the simulations is de- tailed as in Table 3 and Table 4 which is based on the map area focusing on the near main entrance that normally done for exhibition event location that can be accessed via Borneo Convention Centre Kuching website [11] . The walking speed is based on general adult speed and the radius size are based on the data that has been published in literature [12] and [13].

Table 3. The environment of evacuation setting under BCCK selected hall layout.

Input	Value/Number
Walking speed (adult) Ra- dius size(agent)	1.47m/s (14.77)* 0.2 (2)*
Area	49.7m x 57.2m (main populated area)
Exit(X_e)	1
Exit Width	9m (90)
Obstacle(X_n)	1-15
Particles (a)	Range from 50-1000

Table 4. Model parameters for evacuation.

Parameter	Maxgen	Fmin	Fmax	b_woa	lb=min(Area) populated area	p_sigma	C_obs	stepsize
Value	3000	0	2	0.001		0.2	0.1	14.77

From the optimization performance experiment from Table 1 and 2, the fitness that has been assigned for this evacuation shows better evacuation of agents during evacuation procedure. The agent's position and direction are impacted with different scenario of obstacles involve and position of exit. The impact from obstacle is derived from bat algorithm [14] as expressed in Eq (1) below:

$$cost(p,q) = exp\left(-\left(\frac{(p_x - q_x)^2}{(\sigma_{px}+\sigma_{qx})^2}\right) + \left(\frac{(p_y - q_y)^2}{(\sigma_{py}+\sigma_{qy})^2}\right)\right) \tag{1}$$

The px, qx shows the position of agent (individual p), whilst the qx, qy shows the position of certain dynamic and static obstacle that represent the setting in the environment. The sigma denoted the agent size and area of obstacle's coverage. The overall cost function that corresponds as fitness (Fobj) is formulated based on Eq (2) [14] below:

$$F_{obj}(p) = C_{obs} X \max_{o \in O} (cost(p,O)) + \frac{1}{cost(p,g)} \tag{2}$$

The O shows the static and dynamic obstacles (if any exist), whilst g denotes exit position. Cobs means the value of obstacle's weight coefficient; the higher the value of Cobs, the bigger the influence of the obstacle has towards agents going to the exit way. From IFDO evaluation, the following expression Eq (3) [10] for search landscape is expressed as follows:

$$nl = \frac{lB}{2*PI} \tag{3}$$

The n is to denote which scout (agent) involves in deciding the alignment and cohesion based on and Eq. (18) and Eq. (19) [10]. The IFDO moved the (scout) agents' population randomly during initialization stage. For scout that maintain its position during its global best in predetermined time, it will move randomly until the movement get the better position. The range of search landscape is being reduced (shrink) based on WOA algorithm based on Eq (4) and Eq (5) [15] as to allow for any scout (agent) new position can be decided better in more focus range between current position and targeted new position. The time for evacuation is analyzed and compared with different number of agents and obstacles using algorithms namely WOABAT, BAT, WOA, FDO, IFDO and PSO and the output of simulation as shown in Figure 2.

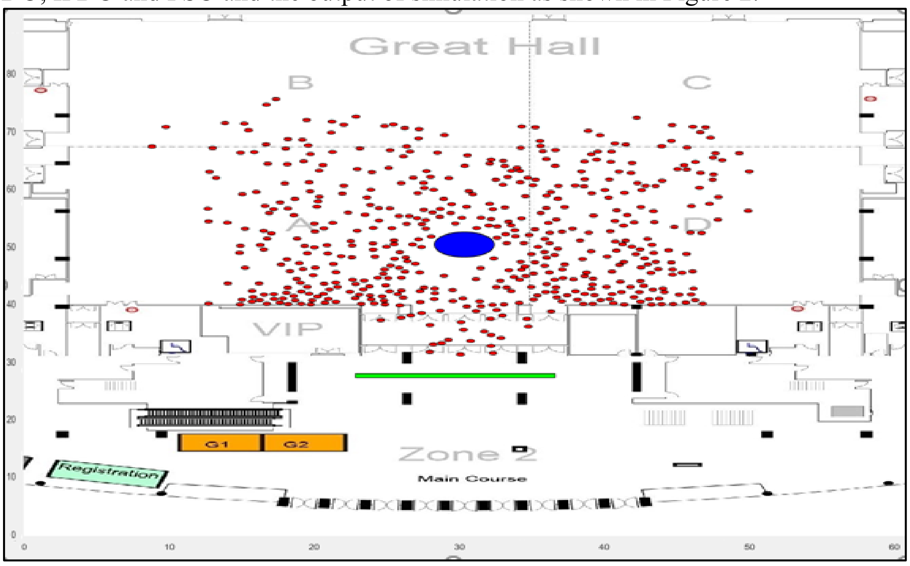

Fig. 2. Example of the evacuation scenario based on 200-1000 agents with 1 obstacle. The simulation is repeatedly run with other different scenario such as no obstacle condition and with 2,6 and 15 obstacle(s) with red particle denotes the agents and green area denotes the exit.

4 Results and Discussions

Table 5. The results of mean evacuation time for 200-1000 agents and selected algorithms. WOABAT-IFDO is demonstrating majority minimal evacuation time compared with others (in bold).

Parti-cles	Algo/Scene	No Obstacle	1 Obstacle	2 Obstacles	6 Obstacles	15 Obstacles
200	**Woabat_IFDO**	**54.75**	**54.89**	**55.38**	**60.13**	**57.00**
	WoaBat only	72.36	62.00	59.20	70.60	67.80
	IFDO only	62.00	56.33	61.89	73.18	57.27
	FDO only	85.73	86.27	88.27	90.36	84.18
	BAT only	55.78	55.88	57.57	61.88	57.50
400	**Woabat_IFDO**	**67.45**	**66.09**	**64.64**	**68.00**	**66.67**
	WoaBat only	83.73	81.11	81.27	81.20	81.82
	IFDO only	81.73	80.60	80.18	76.36	80.00
	FDO only	108.27	104.73	106.45	104.14	101.80
	BAT only	70.75	67.88	65.17	69.20	67.83
600	**Woabat_IFDO**	**81.18**	**86.30**	**84.80**	**84.60**	**81.80**
	WoaBat only	109.91	105.73	106.18	104.00	104.25
	IFDO only	114.00	109.73	107.67	105.13	98.22
	FDO only	125.50	125.90	126.36	126.60	115.50
	BAT only	84.00	79.50	82.80	87.60	79.29
800	**Woabat_IFDO**	**97.75**	**96.38**	**95.13**	**97.43**	**96.89**
	WoaBat only	130.20	127.67	126.80	134.20	126.40
	IFDO only	129.50	128.67	126.00	122.17	123.40
	FDO only	144.88	141.40	140.40	150.80	133.80
	BAT only	99.89	98.00	97.86	112.13	98.89
1000	**Woabat_IFDO**	**124.40**	**116.60**	**113.00**	**118.00**	**108.00**
	WoaBat only	155.20	153.60	144.40	154.00	152.40
	IFDO only	162.20	157.80	156.00	153.00	138.40
	FDO only	166.20	162.20	165.40	171.20	151.20
	BAT only	125.60	120.00	116.40	125.33	110.25

Figure 3 (a) shows that the proposed hybrid WOABAT-IFDO algorithm in evacuation simulation with no obstacle in population setting from 200 to 1000 agents. The mean average of time taken shows that the WOABAT-IFDO is 54.75s and 124.4s therefore is faster compared to other algorithms respectively. The time is gradually increase when the number of agents is higher, but overall WOABAT-IFDO marked the fastest evacuation time. Figure 3 (b) shows that the proposed hybrid WOABAT-IFDO algorithm in evacuation simulation with one (1) obstacle in population setting from 200 to 1000 agents. The mean average of time taken shows that the WOABAT- IFDO is faster compared to other algorithms which is 54.89s and 116.6s respectively, whilst gradually increased with the increasing number of total agents.

Figure 3 (c) shows that the proposed hybrid WOABAT-IFDO algorithm in evacuation simulation with two (2) obstacles in population setting from 200 to 1000 agents. The mean average of time taken for 200 population size of WOABAT-IFDO is 55.38s and 113s. gradually increased with the increasing number of total agents. This time of evacuation during 400 population shows slightly faster evacuation time that is 64.64s compared to one (1) obstacle that showed 66.09s condition due to influence of more than one obstacle. Figure 3(d) shows that the proposed hybrid WOABAT-IFDO algorithm in evacuation simulation with six (6) obstacles in population setting from 200 to 1000 agents. The mean average of time taken for 200 population size of WOABAT-IFDO is 60.13s whilst for 1000 population is 118s. The trending shows it is gradually increased with the increasing number of total agents. The theory of many obstacles can elevate evacuation time does not portray in this condition of square shape obstacle even the quantity of obstacle is higher compared to previous condition.

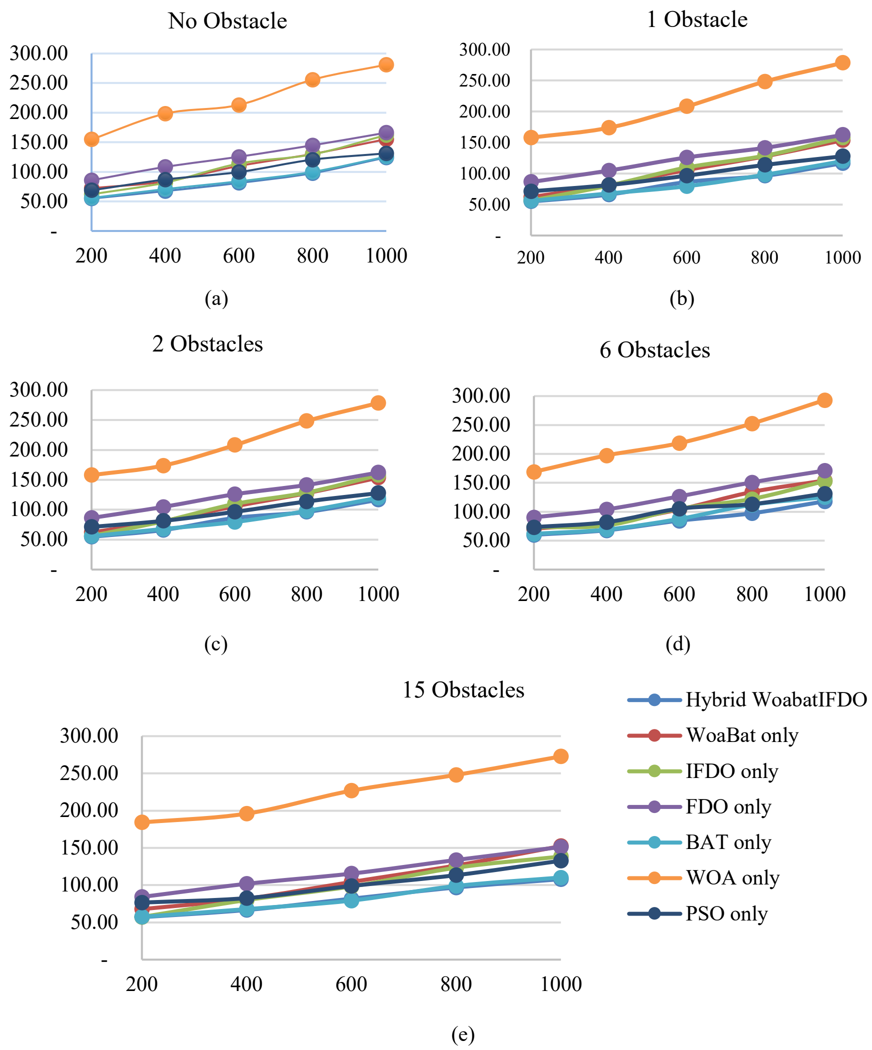

Fig. 3. (a)-(e): The evacuation time vs agent graph for 200-1000 agents various scenarios.

Finally, in Figure 3 (e), it shows that the proposed hybrid WOABAT-IFDO algorithm in evacuation simulation with fifteen (15) obstacles in population setting from 200 to 1000 agents. The mean average of time taken for 200 population size of WOABAT-IFDO is 57s whilst for 1000 population is 108s. The time shows increasing trend and faster than two, one and non-obstacle conditions in 600 to 1000 population, but slightly slower time for 200 and 400 number of total agents with same condition of obstacle. The time taken for evacuation simulation from the proposed hybrid of WOABAT-IFDO is less than other selected algorithms.

From the simulation results, it is observed that the evacuation time taken for hybrid WOABAT-IFDO is less than the rest of the algorithm. This is due to the alignment and cohesion updated as the particles seems more aligned and move coherently towards the exit(back to the nature of IFDO). At the same time, the use of WoaBat for exploration and exploiting the point and updating current position contribute to better searching and faster global convergence, hence reduce the time for evacuation. For single WOABAT, it still has exploration and exploitation capability but searching behaviour haven't been enhance as particle still wandering to find exit way. In this simulation, whilst for single IFDO, it is slightly slower than WOABAT algorithm since the particles only focus on group alignment and coherent value. Whale algorithm from simulation observation there is also a behaviour of last particle wandering as the coherency works better when in swarm or with other particles nearby to help moving towards the exit way. As for Bat algorithm, in average this algorithm can search faster but the movement is unrealistic as if the bat 'jump' into the possible solution which cannot be consider as real behaviour in evacuation procedure. Nevertheless, for PSO, the particles searching behaviour which is equal to the local search behaviour tends to wander (trapped in local minima), thus contributes to slow convergence (slow getting to the exit/goal). The movement seems not realistic as it depicts a discrete movement behaviour[16].

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4 Conclusions and future work

In this paper, the new WOABAT-IFDO algorithm has been proposed to boost the accuracy of searching process by enhancing the IFDO with hybridizing it with other latest nature-inspired algorithms WOA-BAT optimization algorithm. The hybrid is the concept of complementing in both of exploitation and exploration stage from WOABAT as well as embedding the element of alignment and cohesion as new pace value in IFDO. The proposed WOABAT-IFDO is being tested based on Classical Benchmark to test the performance of the algorithm and against other closely related nature-inspired algorithms. Extensively, the WOABAT-IFDO is applied to crowd evacuation simulation and the results showed efficient level in reducing the evacuation time with no- obstacle and obstacle condition. Although the results are quite competitive with BAT and IFDO in few experiments simulation, the hybrid WOABAT-IFDO is still notably well accepted as an efficient algorithm among all based on the percentage differences. The research project to optimize crowd evacuation model by incorporating with other evacuation model such as social force model with further validation on crowd evacuation time in future simulation work.

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