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Olarik Surinta
Kevin Kam Fung Yuen (Eds.)

Multi-disciplinary Trends in Artificial Intelligence

15th International Conference, MIWAI 2022
Virtual Event, November 17–19, 2022
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Preface

The Multi-disciplinary International Conference on Artificial Intelligence (MIWAI), formerly called the Multi-disciplinary International Workshop on Artificial Intelligence, is a well-established scientific venue in Artificial Intelligence (AI). The MIWAI series started in 2007 in Thailand as the Mahasarakham International Workshop on Artificial Intelligence and has been held yearly since then. It has emerged as an international workshop with participants from around the world. In 2011, MIWAI was held outside of Thailand for the first time, in Hyderabad, India, so it became the "Multi-disciplinary International Workshop on Artificial Intelligence." Then the event took place in various Asian countries: Ho Chi Minh City; Vietnam (2012); Krabi, Thailand (2013); Bangalore, India (2014); Fuzhou, China (2015); Chiang Mai, Thailand (2016); Bandar Seri Begawan, Brunei (2017); Hanoi, Vietnam (2018); and Kuala Lumpur, Malaysia (2019). In 2018, MIWAI was renamed to the "Multi-disciplinary International Conference on Artificial Intelligence." The event planned for 2020 was postponed, and it was held virtually in 2021 due to the COVID-19 pandemic.

The MIWAI series serves as a forum for AI researchers and practitioners to discuss and deliberate cutting-edge AI research. It also aims to elevate the standards of AI research by providing researchers and students with feedback from an internationally renowned Program Committee.

AI is a broad research area. Theory, methods, and tools in AI sub-areas encompass cognitive science, computational philosophy, computational intelligence, game theory, multi-agent systems, machine learning, natural language processing, representation and reasoning, data mining, speech, computer vision, and deep learning. The above methods have broad applications in big data, bioinformatics, biometrics, decision support systems, knowledge management, privacy, recommender systems, security, software engineering, spam filtering, surveillance, telecommunications, web services, and IoT. Submissions received by MIWAI 2022 were wide-ranging and covered both theory and applications.

This year, the 15th MIWAI was held as a virtual conference during November 17–18, 2022. MIWAI 2022 received 42 full papers from authors in eight countries: France, China, South Korea, India, Malaysia, Philippines, Vietnam, and Thailand. Following the success of previous MIWAI conferences, MIWAI 2022 continued the tradition of a rigorous review process.

In the end, 19 papers were accepted with an acceptance rate of 45.24%. A total of 14 papers were accepted as regular papers and five papers were accepted as short papers. Each submission was carefully reviewed by at least two members of a Program Committee consisting of 78 AI experts from 25 countries, and some papers received up to four reviews when necessary. The reviewing process was double blind. Many of the papers that were excluded from the proceedings showed promise, but the quality of the proceedings had to be maintained. We would like to thank all authors for their submissions. Without their contribution, this conference would not have been possible.

In addition to the papers published in the proceedings, the technical program included a keynote talk and we thank the keynote speaker for accepting our invitation. We are also thankful to the Research Development Institute (RDI), Muban Chombueng Rajabhat University (MCRU), for co-organizing this virtual conference.

We acknowledge the use of the EasyChair conference management system for the paper submission, review, and compilation process. Last but not least, our sincere thanks go to the excellent team at Springer for their support and cooperation in publishing the proceedings as a volume of Lecture Notes in Computer Science.

September 2021

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Contents

Optimizing the Social Force Model Using New Hybrid WOABAT-IFDO in Crowd Evacuation in Panic Situation

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Abstract. This paper addresses the need for improvement in the Social Force Model (SFM) crowd evacuation model in the context of egress studies and current emergency research. As the current classical evacuation model, the Social Force Model lacks decision-making ability for finding the best directions towards an exit. Crowd searching for route choices in crowd evacuation simulations for panic situations remains inaccurate and unrealistic. There is a need for SFM to be incorporated with an intelligent approach in a simulation environment by adding in behaviour of following the position indicator to guide agents towards the exit to ensure minimal evacuation time. Congestion in pedestrian crowds is a critical issue for evacuation management, due to a lack of or lower presence of obstacles. Thus, this research proposes optimization using the one of the latest nature inspired algorithm namely WOABAT-IFDO (Whale-Bat and Improved Fitness-Dependent Optimization) in the SFM interaction component. Optimization takes place by randomly allocating the best position of guide indicator as an aid to the for better evacuation time and exploring the dynamics of obstacle-non obstacle scenarios that can disperse clogging behavior with different set of agent's number for better evacuation time and comparing it with single SFM simulation. Finally, validation is conducted based on the proposed crowd evacuation simulation time, which is further based on standard evacuation guidelines and statistical analysis methods.

Keywords: Hybrid WOABAT-IFDO and SFM · Nature-inspired optimization · Crowd evacuation simulation · Crowd model validation

1 Introduction

The unexpected occurrence of an emergency in an occupied building may lead to a crowd evacuation in a panic situation. Data regarding time evacuation are difficult to obtain, especially when involving real humans. Thus, there is a need for simulation and modeling as an approach to simulate and analyze crowd evacuation models for fast and efficient evacuations [1]. Computer-based simulations have become vital to analyze and

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measure the process of evacuation and to evaluate its efficiency [2]. There are numerous techniques that can aid in simulating and optimizing current crowd behavior models. The latest development issues in crowd models, such as the Social Force Model, are still a niche area of research, while optimization based on nature is also widely being used as an aid to produce better simulation outcomes. Inaccuracy in agent searching behaviour can affect agent decision-making while finding an exit. Furthermore, there is a need for SFM improvement with an intelligent approach to allow the agents to follow the signage (sign indicator) to ensure minimal evacuation time [3].

Another important issue regarding the efficiency of evacuation time involves the use of obstacles [1] to help agents evacuate faster, as opposed to the theory of anti-arching phenomenon in the exit way. The focus on nature-inspired algorithms has led to numerous insights into several applications. The need for hybrid is essential for enhancing the evacuation process in current simulation model. The major contributions of this paper are as follows: (i) to optimize the position indicator using hybrid WOABAT-IFDO algorithm as an aid to guide agents towards the exit for minimum evacuation time; (ii) to simulate the evacuation process via the new optimized path planning movement (WOABAT-IFDO and SFM); and (iii) to validate evacuation time based on literature and standard real world evacuation times.

Validation attempts evacuation time analysis based on the following null hypotheses:- a) H01: Total of evacuation time from the proposed hybrid (WOABAT_IFDO + SFM) simulation model is less than SFM; b) H02: Total of evacuation time from the proposed hybrid (WOABAT_IFDO + SFM) simulation model is not the same as standard/certified total of evacuation time; and c) H03: The presence of an obstacle (one or more than one obstacles) in this proposed model of evacuation simulation would not significantly affect in minimizing the total of evacuation time. This paper is organized as follows. Section 2 explains related works pertaining to SFM and nature inspired algorithms (swarm intelligence), including the latest optimization algorithms, namely the original Fitness Dependent Optimization (FDO) and Independent Fitness Dependent Optimization (IFDO) algorithm. Section 3 describes the proposed hybrid WOABAT-IFDO for SFM, while Sect. 4 describes the simulation experiments setting and obstacle condition with output visualization to indicate the effectiveness of the proposed optimization in SFM. Finally, the conclusion and future work is explain in Sect. 5.

2 Related Works

Research into crowd simulation, and especially crowd evacuation, remains a hotspot. Research trends have shown significant growth. The interaction between agents during evacuation situation is crucial in contributing better agent movement by optimizing the layout of facilities of buildings [4]. The most renowned crowd model is the Social Force Model. It is said to be the simplest crowd model which can describe crowd movement under microscopic model. The model was introduced by [5] and the equation is as shown in Eq. (1) where m_i denotes as pedestrian mass, t denotes time, denotes time, $\vec{v}_i$ is the speed, τ_i shows the pedestrian acceleration time, v_i^0 is desired velocity and $\overrightarrow{e_i}$ is the desired destination or direction.

$$m_i \underbrace{\frac{d\vec{v}(t)}{dt}}_{Accelaration} = \underbrace{\frac{m_i}{\tau_i}(v_i^0 \overrightarrow{e_i}(t) - \vec{v}_i(t))}_{Driving\ Force} + \underbrace{\sum_{j(\neq i)} \vec{F}_{ij}^{ww}(t)}_{Interactions} + \underbrace{\vec{F}_i^b(t)}_{Borders,\ Fire} + \underbrace{\sum_k \vec{F}_{ik}^{att}(t)}_{Attractions} + \underbrace{\overrightarrow{\xi}_i(t)}_{Fluctuations} \tag{1}$$

However, one of the most important issues is realism [5], as SFM lacks considering the decision-making processes that can further enhance efficiency during evacuation. The nature of SFM itself is moving by force, or being attracted by other agent's forces; thus, overall, the movement seems to follow the forces of others towards the goal. This emerging behaviour of following the forces can be seen in panic situation. Other issues, such as clogging exit ways, may need more scenarios described via obstacle interaction [6]. The SFM also has issues such as a constant gap of one agent leaving from a group while waiting to be evacuated (seeking another option) [7]. Hence, a path might be unknown to an agent. The use of signage during the evacuation may seem appropriate, but there is a need for further experimentation on how to best allocate the guide indicator (signage) concerning the facility layout to properly guide the agents to the exit point. The main criteria of the position of signage would be on a wall or on the ground. For this research, the main position would be the ground position, as it has less risks fir security and allows more interaction among agents during evacuation process [8]. Another recent work by [9] described there is a need to simulate crowd evacuation that includes signage scenario in panic situation. One of the latest optimization algorithms introduced by [10] is suitable to be used for evacuation purposes. The optimization algorithm is best hybridized with the latest optimization algorithms, namely Whale Optimization [11] and Bat algorithm (WOA-BAT algorithm) [12], as coined by [13] with a recent optimization algorithm.

T good thing about WOABAT hybridization algorithm is it produces better results with minimal iterations incurred. Therefore, the process of searching towards the defined solution will be faster. Nonetheless, the WOABAT algorithm is suggested to aid in crowd evacuation simulation for certain improvement strategies. Another most recent optimization algorithm, namely the Improvement of Fitness Dependent Optimization (IFDO) [14], which is based on Fitness Dependent Algorithm [15], is said to be more efficient in selecting parameters, agent's alignment, and cohesion. It is also good in updating the artificial scout bees (agent), thus making the algorithm to perform better in terms of exploration to find an optimal solution. Another reason for improvement is the definition of weight function (*wf*) in each iteration of each agent once the solution has been found, making the algorithm able to avoid the unnecessary exploitation process. Nevertheless, the IFDO also can converge to global optimality faster due to its ability to cover reasonable search space. The new movement in IFDO [14] is additional an element of alignment and cohesion, which is expressed as follows:

$$X\_(i, t+1) = X\_(i, t) + Pace + (\text{alignment} \ * \ 1/\text{cohesion}) \tag{2}$$

However, there is a limitation that needs to be dealt with IFDO, as the performance is depends on several search agents. In the work of [14], they demonstrated that the crowd only involved quite a small number of agents (>5 agents). The algorithm has a limitation in dealing with accuracy in searching process, such as locating the exit way when the number of simulation agents is increased to more than 5 agents.

3 The Hybrid of WOABAT-IFDO and SFM Optimization Design Framework

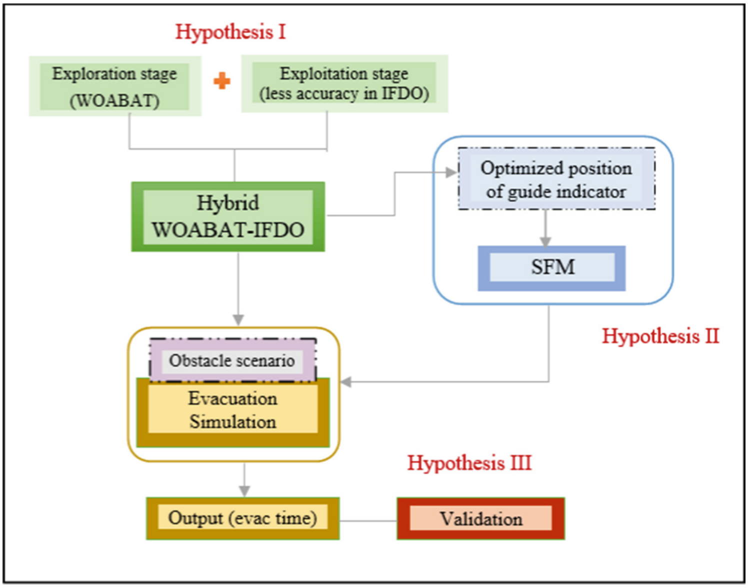

Fig. 1. The design framework for hybrid WOBAT-IFDO optimization in SFM

This section discusses the WOABAT-IFDO hybrid optimization is integrated into SFM (Interaction) module. Figure 1 shows the design framework for the proposed hybrid WOABAT-IFDO optimization in SFM. Originally, the hybrid WOABAT-IFDO has been proposed in our previous work and the details of the benchmark analysis result for the optimization algorithm for comparison of performance of IFDO, FDO, WOA-BAT and PSO to new IFDO_WOABAT in 10 dimensions [16]. From the analysis, it shows WOABAT-IFDO gives the minimum results(fastest) in terms of reaching towards solution. This integration for optimization in SFM interaction component will remark as the novelty of the proposed design framework to lead to a better selection of exit by the particles (agent) in the crowd. The details of parameters in interaction component derived from Eq. (1) is shown in Eq. (3) where the sum of component interactions can be categorized as psychological, physical interactions and interaction between people.

$$\vec{F}_{ij}^{ww}(t) = \underbrace{\vec{F}_{ij}^{psy}(t)}_{\substack{Psychological \\ Repulsion}} + \underbrace{\vec{F}_{ij}^{ph}(t)}_{\substack{Physical \\ Interactions}} + \underbrace{\vec{F}_{ij}^{att}(t)}_{\substack{Interaction \\ between \\ People}} \tag{3}$$

From Eq. (3), the parameter will be selected and combined with the proposed hybrid optimization technique to get the estimated results for simulation evacuation time. The parameters may contain various numbers of obstacles or placements to attain the outcome in different perspectives. Work from other researchers have also modified the component consist of interaction, as in Eq. (3), for they need to be extended to include parameters for group avoidance in the component. This is due to the limitations of psychological repulsion, such as avoiding and following behavior in the current component, to reproduce the agents in a group while moving in same direction towards the same goal. The extended SFM in this component adds on turning and attractive force among group members; thus, pedestrians in the same group can gather and form a spatial structure that is conducive to walking and improve communication among agents [17].

Algorithm 1 shows the proposed WOABAT-IFDO in SFM algorithm. The integration from the new hybrid into the SFM interaction component will ensure the designation of a random guide indicator as an aid for the agent selecting the near optimal or shortest path towards the exit. This can reduce the effects of the agent from moving away from the group during evacuation process. The input data thus includes *n* number on agents, exits and obstacles. Performance is measured by the results of the simulation evacuation time and decision-making process (accuracy), that also will be repeated and compared with one simulation to another to get minimal time.

Algorithm 1. The proposed WOABAT-IFDO in SFM algorithm.

Input: *n* total number of agents, *n* number of obstacles, *n* number of exits
Output: *n* total agent evacuated by time t

Step 1: Initialize the number agent *n*, iteration (MaxGen), and the related parameters.
Step 2: Evaluate the fitness weight based on agent and position update
Step 3: Update the individuals' positions based on WOABAT-IFDO computation
Step 4: Use WOABAT-IFDO to optimize the placement of best indicator position as a guide in SFM interaction component and guide towards exit
Step 5: Return to Step 2 for iteration has been achieved, otherwise, exit the iterations and output the result.

The simulation was developed using MATLAB R2020b under Windows 10 operating system. The parameter in SFM for the simulation is walking speed(adult) = 1.47m/s, radius size (agent) = 0.2, $C\_obs = 1$, $\tau = 0.5s$, while the setting simulation evacuation scene includes hall area = 49.7m x 57.2m, exit(Xe) = 1, exit width = 9m, obstacle (Xn) = 1–15, and particles (a) = range from 50–500 agents. Whilst for the hybrid optimization (WOABAT-IFDO) parameter is scout-bee-number = 10,weight_factor = 1,max_gen = 3000, $fmin = 0$, f$max = 2$, lb = min(Area) is populated area, $b\_WOA =$

0.001, and number of indicators = 2. The walking speed is based on general adult speed and the radius size are referenced from the published work in literature [18–20], whilst the simulation experiment is using 500 agents is based on the work of [21]. Figure 2 shows the simulation output and the map area used in the simulation is based on the Borneo Convention Centre Kuching (BCCK) main hall area [22].

3.1 Evacuation Time Validation

The validation for the evacuation time is as follows: First null hypothesis, H_{01}: Total of evacuation time from the proposed hybrid (WOABAT_IFDO + SFM) simulation model is less than SFM and is tested using one tailed T-test & Man-Whitney test. Second null hypothesis, H_{02}: Total of evacuation time from the proposed hybrid (WOABAT_IFDO + SFM) simulation model is not the same as standard/certified total of evacuation time, and is tested using using Mann-Whitney Test. Finally, the third null hypothesis H_{03}: The presence of an obstacle (one or more than one obstacles) in this proposed model of evacuation simulation would not significantly affect minimizing the total of evacuation time and is tested using ANOVA Test with Post Hoc. This validation standards are based on available literature and previous research work (Fire Rescue Service Department) [23–26]. The elements to be compared is such as algorithm effectiveness (running time) via evacuation time and the accuracy of predicting the position of optimal exit path and avoiding obstacles.

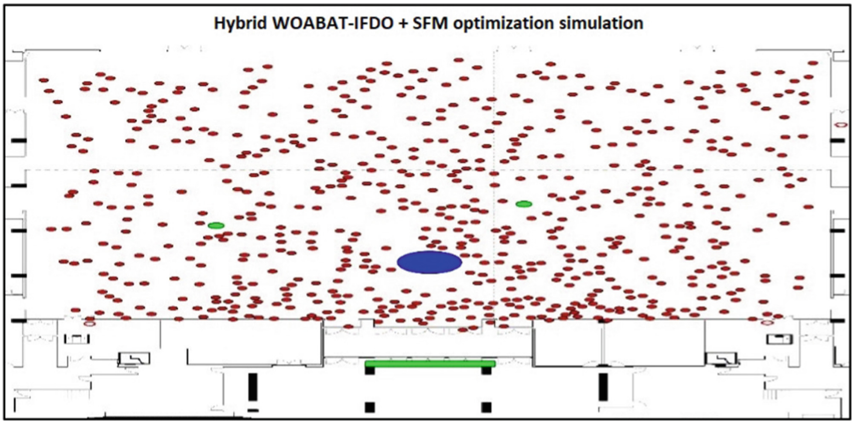

Fig. 2. Example of the evacuation scenario based on 200–500 agents with 15 obstacles. The simulation is repeatedly run with other different scenario such as no obstacle condition and with 2,6 and 15 obstacle(s) with red particle denotes the agents, blue denotes the obstacles, the circle green is automated guide indicator position and horizontal green area denotes the exit (Color figure online).

4 Result of Evacuation Time Hybrid WOABAT-IFDO in SFM vs Single SFM

Table 1 shows that the time taken for SFM that optimized using WOABAT_IFDO algorithm is lower than that of only single SFM simulation time in almost all situations. Optimization randomly uses the possible position of guidance indicator as signage during evacuation simulations. Figure 3 shows the results of hybrid WOABAT-IFDO in SFM compared to single SFM. The dotted line from the resulting graph is the baseline which is the single SFM running to be compared with SFM using WOABAT_IFDO optimization algorithm.

Table 1. The mean evacuation time for SFM +IFDO_WOABAT vs single SFM

Agent No	SFM+IFDO_WOABAT			SFM only	SFM+IFDO_WOABAT			SFM only
	No obstacle (s)	Position of G.I(1)	Position of G.I(2)	No obstacle (s)	1 obstacle (s)	Position of G.I(1)	Position of G.I(2)	1 obstacle (s)
50	149	42,47	45,60	170	151	38,51	35,60	160
100	173	32,59	41,60	181	154	18,44	34,61	167
200	200	40,55	45,64	233	190	34,55	35,61	195
300	250	34,72	44,61	268	203	50,43	33,59	243
400	267	22,46	43,59	271	245	22,52	37,58	251
500	281	15,43	42,58	285	257	15,43	34,58	262

Agent No	SFM+IFDO_WOABAT			SFM only	SFM+IFDO_WOABAT			SFM only
	2 obstacles (s)	Position of G.I(1)	Position of G.I(2)	2 obstacles (s)	6 obstacles (s)	Position of G.I(1)	Position of G.I(2)	6 obstacles (s)
50	132	18,60	40,62	148	189	20,60	36,65	190
100	156	19,60	40,65	174	215	18,63	35,65	230
200	178	18,59	42,59	203	225	23,58	36,56	261
300	210	20,60	43,60	245	242	22,60	33,63	270
400	235	19,62	39,60	261	256	20,57	38,58	283
500	242	18,58	40,61	272	260	21,58	37,60	298

Agent No	SFM+IFDO_WOABAT			SFM only
	15 obstacles (s)	Position of G.I(1)	Position of G.I(2)	15 obstacles (s)
50	175	23,61	38,58	180
100	201	18,58	38,57	221
200	229	22,60	35,60	260
300	243	23,60	40,59	263
400	251	22, 60	37,61	280
500	273	24,61	39,62	293

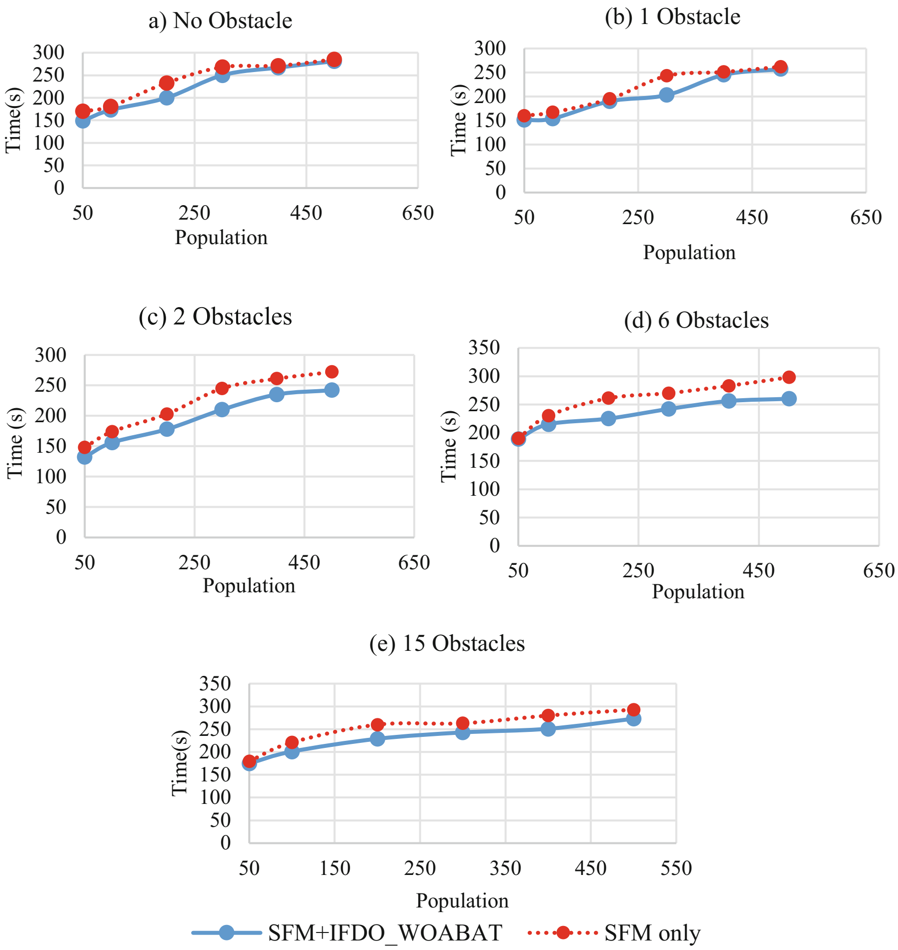

Fig. 3. (a)–(e) shows the graph analysis for the evacuation time for SFM with WOABAT-IFDO optimization compared to single SFM.

4.1 Analysis of the Hypothesis for Evacuation Time Validation

Null Hypothesis 1: H_{01}: Total of evacuation time from the proposed hybrid (WOA-BAT_IFDO + SFM) simulation model is not less than SFM.

Table 2. The t-test performed for first null hypothesis.

Levene's test for equality of variances		t	df	t-Test for equality of means				95%-Confidence interval of the difference	
F	Sig			Significance		Mean diff	Std. error difference	Lower	Upper
				One-sided p	Two-Sided p				
3.023	0.083	−5.29	598	< .001	< .001	−19.21333	3.62955	−26.34154	−12.08512

Based on [21] and [22], the statistical one-tailed T-test and Mann-Whitney U-Test are used to analyze the mean time of evacuation time, and for mean evacuation simulation time using single SFM and mean simulation evacuation time from the proposed hybrid WOABAT-IFDO in SFM. From the analysis, the first null hypothesis is rejected. At alpha level 0.05, the test indicated that the mean time for SFM ($M = 233.7967$, $SD = 45.65988$) was significantly higher than the proposed WOABAT_IFDO ($M = 214.5833$, $SD = 43.2118$). The Man-Whitney test also indicated that there were significant differences between all the mean evacuation times.

Null hypothesis 2: H_{02}: Total of evacuation time from the proposed hybrid (WOABAT_IFDO + SFM) simulation model is not the same as standard/certified total of evacuation time. According to standard evacuation procedure, the total evacuation time ideally is 3 min [19], with a TET of 20 min [20] and less than 6 min for up to 1000 people from public hall [21]. According to the simulation results of WOABAT_IFDO + SFM, the average total evacuation time is 4.35 min (261s). Based on Table 3 and Table 4, the second null hypothesis is rejected. At alpha level 0.05, the test indicated significance, thus reflecting the standard or certified evacuation time.

Table 3. The mean ranks for optimized SFM and single SFM.

Optimization SFM and SFM only	N	Mean rank	Sum of ranks
Hybrid + SFM(s)	300	261.93	78577.50
SFM only (s)	300	339.08	101722.50

Table 4. Hypothesis test summaries

Null hypothesis	Test	Sig. a,b	Decision
The distribution of Second(s) is the same across categories of Optimization SFM and SFM only	Independent Samples Mann- Whitney U Test	< .001	Reject the null hypothesis

a. This significance level is 0.05

Null Hypothesis 3: H_{03}: The presence of an obstacle (one or more than one obstacles) in this proposed model of evacuation simulation would not significantly affect in minimizing the total of evacuation time. The mean differences in various obstacle scenarios are presented in Table 5, whilst Table 6 presents the significant values and mean values based on ANOVA test.

Table 5. The ANOVA test for mean square and significant value

Seconds(s)	Sum of squares	df	Mean square	F	Sig
(a) The ANOVA test for mean square and significant value					
Between groups	153773.357	4	38443.339	21.115	< .001
Within groups	1083272.983	595	1820.627		
Total	1237046.340	599			

For the third hypothesis, based on the ANOVA test, the mean differs significantly, $F(4,595) = 21.115$, $p < 0.001$, $n2 = 0.124$(eta-squared). $n2 = 0.124$ shows that there is a large effect. However, for the post hoc test, the mean differences of no obstacle compared with 1–6 obstacles are significant at the chosen alpha = 0.05. Thus, the third hypothesis is rejected. However, in 15 obstacles scenario, the mean difference is not significant compared with non-obstacle. This may indicate that there is a need to further investigate on ideal obstacle's placement.

Table 6. Mean different in various obstacle scenarios

(I) Scenario with different set of obstacles	(J) Scenario with different set of obstacles	Mean difference (I-J)	Std. error	Sig	95% Confidence interval	
					Lower bound	Upper bound
(b) Mean different in various obstacle scenarios						
No obstacle	1 obstacle	20.72500*	5.50852	.002	5.6528	35.7972
	2 obstacles	22.59167*	5.50852	<.001	7.5195	37.6639
	6 obstacles	−15.90000*	5.50852	.033	−30.9722	−.8278
	15 obstacles	−11.74167	5.50852	.208	−26.8139	3.3305
1 obstacle	No obstacle	−20.72500*	5.50852	.002	−35.7972	−5.6528
	2 obstacles	1.86667	5.50852	.997	−13.2055	16.9389
	6 obstacles	−36.62500*	5.50852	<.001	−51.6972	−21.5528
	15 obstacles	−32.46667*	5.50852	<.001	−47.5389	−17.3945
2 obstacles	No obstacle	−22.59167*	5.50852	<.001	−37.6639	−7.5195
	1 obstacle	−1.86667	5.50852	.997	−16.9389	13.2055
	6 obstacles	−38.49167*	5.50852	<.001	−53.5639	−23.4195
	15 obstacles	−34.33333*	5.50852	<.001	−49.4055	−19.2611
6 obstacles	No obstacle	15.90000*	5.50852	.033	.8278	30.9722
	1 obstacle	36.62500*	5.50852	<.001	21.5528	51.6972
	2 obstacles	38.49167*	5.50852	<.001	23.4195	53.5639
	15 obstacles	4.15833	5.50852	.943	−10.9139	19.2305
15 obstacles	No obstacle	11.74167	5.50852	.208	−3.3305	26.8139
	1 obstacle	32.46667*	5.50852	<.001	17.3945	47.5389
	2 obstacles	34.33333*	5.50852	<.001	19.2611	49.4055

5 Conclusions

In this paper, the new hybrid WOABAT-IFDO algorithm in the SFM model has been proposed to optimize the guide indicator position in a crowd evacuation situation. The results show that the integration of hybrid nature inspired optimization in the crowd model give less time in evacuation simulation compared to single social force model. The validation is therefore crucial to a standard evacuation time. In future, there will be a need to study more about various obstacles and shape conditions that may influence evacuation time.

References

1. Li, L., Liu, H., Han, Y.: Optimal design of obstacles in emergency evacuation using an arch formation based fitness function. In: Computer Supported Cooperative Work and Social Computing Communications in Computer and Information Science, pp. 129–145. https://doi.org/10.1007/978-981-13-3044-5_10 (2018)
2. Tan, L., Hu, M.Y., Lin, H.: Agent-based simulation of building evacuation: combining human behavior with predictable spatial accessibility in a fire emergency. Inform. Sci. **295**, 53–66 (2015)
3. Cao, N., Zhao, L., Chen, M., Luo, R.: Fuzzy social force model for pedestrian evacuation under view-limited condition. Math. Probl. Eng. **2020**, 1–16 (2020). https://doi.org/10.1155/2020/2879802
4. Zhou, M., Dong, H., Ioannou, P.A., Zhao, Y., Wang, F.: Guided crowd evacuation: approaches and challenges. IEEE/CAA J. Automatica Sinica **6**(5), 1081–1094 (2019)
5. Helbing, D., Farkas, I., Vicsek, T.: Simulating dynamical features of escape panic. Nature **407**, 487–490 (2000)
6. Liu, H., Chen, H., Hong, R., Liu, H., You, W.: Mapping knowledge structure and research trends of emergency evacuation studies. Saf. Sci. **121**, 348–361 (2020)
7. Liao, C., Zhu, K., Guo, H., Tang, J.: Simulation research on safe flow rate of bidirectional crowds using bayesian-nash equilibrium. Complexity **2019**, 1–15 (2019)
8. Wang, L., Shen, S.: A pedestrian dynamics model based on heuristics considering contact force information and static friction. Transportmetrica B: Transp. Dyn. **7**(1), 1117–1129 (2019). https://doi.org/10.1080/21680566.2019.1568926
9. Minghua, L., Chengyong, X., Yan, X., Li, M., Yu, W.: Dynamic sign guidance optimization for crowd evacuation considering flow equilibrium. J. Adv. Transport. **2022**, 2555350 (2022). https://doi.org/10.1155/2022/2555350
10. Yuan, Z., Jia, H., Zhang, L., Bian, L.: A social force evacuation model considering the effect of emergency signs. Simulation **9**, 723–737 (2017). https://doi.org/10.1177/0037549717741350
11. Fausto, F., Reyna-Orta, A., Cuevas, E., Andrade, Á.G., Perez-Cisneros, M.: From ants to whales: metaheuristics for all tastes. Artif. Intell. Rev. **53**(1), 753–810 (2019). https://doi.org/10.1007/s10462-018-09676-2
12. Mirjalili, S., Lewis, A.: The whale optimization algorithm. Adv. Eng. Softw. **95**, 51–67 (2016)
13. Mohammed, H., Umar, S., Rashid, T.: A systematic and meta-analysis survey of whale optimization algorithm. Comput. Intell. Neurosci. **2019**, 1–25 (2019). https://doi.org/10.1155/2019/8718571
14. Muhammed, D.A., Saeed, S.A.M., Rashid, T.A.: Improved fitness-dependent optimizer algorithm. Access IEEE **8**, 19074–19088 (2020)
15. Abdullah, J.M., Rashid, T.A.: Fitness dependent optimizer: inspired by the bee swarming reproductive process. Neural Evol. Comput. IEEE Access **7**, 43473–43486 (2019). https://doi.org/10.1109/ACCESS2907012
16. Sharbini, H., Sallehuddin, R., Haron, H.: The hybrid of WOABAT-IFDO optimization algorithm and its application in crowd evacuation simulation. In: The 9th International Conference on Computational Science and Technology 2022 (forthcoming)
17. Huang, L., et al.: Social force model-based group behavior simulation in virtual geographic environments. ISPRS Int. J. Geo-Inform. **7**(2), 79 (2018). https://doi.org/10.3390/ijgi7020079.J
18. Li, M., Zhao, Y., He, L., Chen, W., Xu, X.: The parameter calibration and optimization of social force model for the real-Life 2013 Ya'an earthquake evacuation in China. Saf. Sci. **79**, 243–253 (2015). https://doi.org/10.1016/j.ssci.2015.06.018

19. Seah, et al.: Agent-Based Modelling and Simulation. Singapore Management University Report (2018)
20. Wang, S., Liu, H., Gao, K., Zhang, J.: A multi-species artificial bee colony algorithm and its application for crowd simulation. IEEE Access **7**, 2549–2558 (2019). https://doi.org/10.1109/ACCESS.2018.2886629
21. Hussain, N., Cheah, W.: Modelling of crowd evacuation with communication strategy using social force model. J. Optim. Ind. Eng. **15**(1), 233–241 (2022)
22. BCCK Homepage. https://www.bcck.com.my/public/files/BCCKEmergencyProcedures2ndednCompatibilityMode.pdf. Accessed 25 Oct 2022
23. Fire Service Features of Buildings and Fire Protection Systems Occupational Safety and Health Administration U.S. Department of Labor OSHA 3256-07N (2006). https://www.osha.gov/sites/default/files/publications/OSHA3256.pdf
24. Degala: Minimizing the emergency evacuation time of a building component. Master Thesis, The University of Akron (2017)
25. Weerasekara, N.N.: Modeling and simulation of evacuation plan for hancock stadium. Theses and Dissertations. https://ir.library.illinoisstate.edu/etd/389 (2015)
26. Deng, X,: An aircraft evacuation simulation baseline using DES for passenger path planning. Dissertations and Theses. https://commons.erau.edu/edt/207 (2016)