A Novel HPSO-IGWO Algorithm for Rapidly Searching Optimal Fire Rescue Paths Based on IoT Architecture

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Abstract. It is essential to choose the best fire rescue paths in the fire. By taking the advantage of both the Particle Swarm Optimization (PSO) algorithm and the Grey Wolf Optimizer (GWO) algorithm, a novel Hybrid PSO-Improved GWO (HPSO-IGWO) algorithm for rapidly searching fire rescue paths based on the IoT architecture. Firstly, hybrid particles based on the PSO algorithm and the GWO algorithm are proposed to make the process optimization of these two algorithms. Secondly, the hybrid particles are utilized to search for the optimal fire rescue paths. This not only provides a decision basis for choosing the optimal rescue path in the fire, but also provides theoretical support for the emergency rescue system, and greatly reduces the number of fire casualties. Finally, the experiment is executed for verifying the effectiveness of our proposed HPSO-GWO algorithm.

Keywords: Fire rescue paths · Particle Swarm Optimization (PSO) · Grey Wolf Optimizer (GWO)

1 Introduction

In recent years, with the acceleration of urbanization and the improvement of living standards, there has been a continuous increase in people's demand for entertainment and shopping. Currently， large shopping malls are the best choice due to their various offerings, combining entertainment, shopping, dining, and other functions. This trend has contributed to the annual growth in the number of large shopping malls. In order to attract customers more effectively, most of large shopping malls chose to locate in downtown areas or built near the city landmarks. However, this concentration of commercial structures in densely settled areas presents a significant fire hazard. In the event of a fire, it can lead to a chain reaction with serious accidents. Therefore, it is essential that people pay attention to fire safety in large shopping malls [1].

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This paper focuses on reducing fire casualties from the perspective of escape personnel. It evaluates escape personnel's individual competencies and the trade-offs between their competencies and the risk of explosion. Escape personnel aim to avoid areas with a high probability of explosions and maintain a certain escape distance from potential explosion sites. Responses of escape personnel are influenced by their physical condition: people in better physical condition can escape more quickly, but people in poorer physical condition face an increased risk of moving slowly during escape. This leads to easier death of people in poor physical condition. In this paper, A novel HPSO-IGWO algorithm is proposed, of which takes the advantage of both the Particle Swarm Optimization (PSO) algorithm and the Grey Wolf Optimizer (GWO) algorithm. It can rapidly search fire rescue paths based on the IoT architecture.

2 PSO Implementation Basis: Information Sharing

PSO algorithm is an evolutionary computation technique [2–6] for optimization which is inspired by the social behavior of individuals in groups in nature. The particle swarm algorithm applied to optimization problems is very simple [7]. In each iteration of PSO, every particle evaluates the fitness of its current position (solution) and compare it with the best solution they have arrived at. If the new best solution particle is better, it will replace the individual/group best solution. In the end of each iteration, the new best solution is compared with the previous best solution, if the fitness is better, the record of the best solution of population will be updated. The process will continue until the fitness requirement or the maximum number of iterations is reached. At this point, the final result can be outputted (Fig. 1, Tables 1, 2).

2.1. In the particle swarm optimization algorithm, each person in the fire is represented as a particle. This algorithm aims to find the best escape route for every escaped person. In the process of finding the best of escape routes, two types of behavior are exhibited as follows:

(1) Individual behaviors;
(2) Group behaviors.

Individual behaviors: the escaped person will update his/her position in the process of finding the best route.

Group behaviors: escaped people update their position as they search for the best route based on the direction of the group's escape.

Suppose there is a swarm of N particles at the fire site, each particle has a position vector.

$$X_{id} = \{x_{i1}, x_{i2}, x_{i3}, ..., x_{iN}\}, i = 1, 2, 3, ..., N, d = 1, 2, 3, ..., N \tag{1}$$

Each particle has the best route value called the individual historical optimum.

$$P_{bestid} = \{P_{besti1}, P_{besti2}, P_{besti3}, ..., P_{bestiN}\},\ i = 1, 2, 3, ..., N, d = 1, 2, 3, ..., N \tag{2}$$

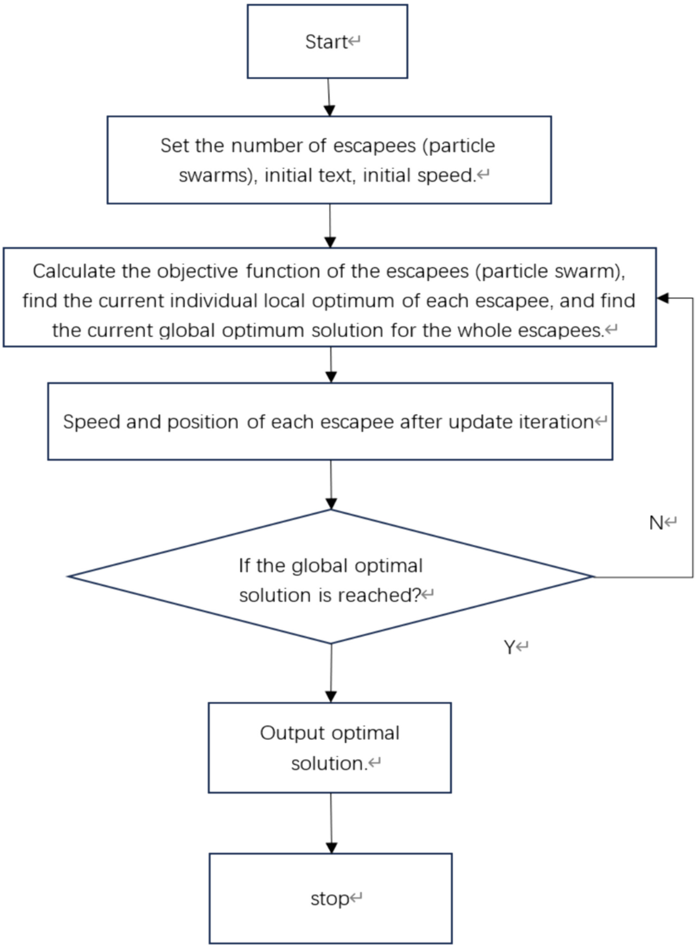


Fig. 1. Flowchart of the PSO algorithm

Table 1. Physical significance of the PSO algorithm

Escapees	PSO
human	particulate
fire area	solution space
circumstances of an injury	degree of adaptation
arrival location	individual solutions in space
The safest way to escape	global optimum solution

Table 2. Parameters that may be used in PSO-based scheduling algorithms for searching fire rescue path.

Parameter name	Connotation
D	solve the space dimension vector
N	particle swarm size
I	iteration number
i	current count
ω	inertia weight
c_1	Individual Learning Factor
c_2	Group Learning Factor
r1,r2	random number [0,1]
x_i	Position of the particle at the ith iteration
v_i	Velocity of the particle at the ith iteration
P_{best}	Optimal position of individual particles
G_{best}	optimal position of the population of particles
f_{best}	Optimal fitness of particle swarms

The best route location for the entire population of particles is denoted as the global optimum:

$$G_{bestid} = \{G_{besti1}, G_{besti2}, G_{besti3}, ..., G_{bestiN}\}, \quad i = 1, 2, 3, ..., N, d = 1, 2, 3, ..., N \tag{3}$$

The speed of each escaped person is inconsistent, and the flight speed of the ith escaped person is noted as:

$$V_{id} = \{V_{i1}, V_{i2}, V_{i3}, ..., V_{iN}\}, i = 1, 2, 3, ..., N, d = 1, 2, 3, ..., N \tag{4}$$

Speed of the ith escaped person after nth iteration:

$$V_{id}(t+1) = +m_1 n_1 (P_{bestid}(t) - x_{id}(t)) + m_2 n_2 (G_{bestid} - x_{id}(t)), \quad \text{i = 1,2,...,N,c = 1,2,...,N} \tag{5}$$

Location Updates:

$$X_{id}(t+1) = X_{id}(t) + V_{id}(t), i = 1, 2, 3, ..., N, d = 1, 2, 3, ..., N \tag{6}$$

3 The Flight Speed of the Escaped People (Particles) Mentioned Earlier Comprises Three Components

(1) **Inertial Component**: It consists of the previous velocity and own displacement of the escaped people (particles). It indicates the degree of dependence of the escaped people (particles) on their motion condition at the fire site.
(2) **Cognitive Component**: It consists of a learning factor, a random number and the positional difference between the current position and the best position previously reached by the escaped person. It indicates how much the escaped person thinks about and how much he trusts the result of his exploration.
(3) **Social Component**: It consists of a learning factor, a random number and the positional difference between the current position and the best position ever reached by the escaped group. It evaluates the degree of confidence in the results of group exploration according to their reflections on the results when the individuals try to escape.

The GWO algorithm was introduced to manage the phenomena related to dependency and self-learning in response to a fire and explosion incidence. It defines different hierarchies of identities present that exist at a fire and explosion incident. These identities include firefighter, able-bodied young people (male), able-bodied young people (female) and young or elderly persons (who are physically capable of independent mobility). These identities are "hunter-grey wolves", indicating that they play a specific role in responding to fire and explosion incidents, similar to the different levels and roles in a grey wolf pack (Table 3).

Table 3. Hierarchy of the GWO algorithm

identities	hierarchy
firefighter	α
able-bodied young people (male)	β
able-bodied young people (female)	δ
Young or elderly persons (who are physically capable of independent mobility)	ω

Grey wolf packs are divided into 4 hierarchies α, β, δ, ω (physical condition from the largest to the smallest) modelling leadership. Consider α as the individual fitness best solution, followed by β, the best solution as δ, the waiting solution as ω, and ω hunting following α, β, δ bootstrapping.

3.1 "Surrounding the prey"

In the course of the "hunt", the behaviors of the "grey wolf" in rounding up the "prey" is defined as follows:

Formula for distance between individual and casualty:

$$D = |C * X_p(t) - X(t)| \tag{7}$$

"Grey wolf" position update formula:

$$X(t+1) = X_p(t) - A \cdot D \tag{8}$$

coefficient vector:

$$A = 2a \cdot r1 - a \tag{9}$$

$$C = 2 \cdot r2 \tag{10}$$

where: t is the number of iterations, α is the convergence factor, r1 and r2 are random vectors. After the movement of the "grey wolf" group to α, the "grey wolf" identified the location of the injured, under the leadership of α, β, δ. In order to guide the "wolf pack" to rescue the injured surrounded people.

3.2 "Hunting"

In the model of an individual "grey wolf",tracking the location of its prey is described as follows:

(The "wolf pack" will search for "prey" by first identifying α, β, δ. As α, β, δ each approach the target point, their routes of movements are not the same. They have different speeds and directions. So the average position of the three is defined as follows.)

$$D_\alpha = |C_1 \cdot X_\alpha - X| \tag{11}$$

$$D_\beta = |C_2 \cdot X_\beta - X| \tag{12}$$

$$D_\delta = |C_3 \cdot X_\delta - X| \tag{13}$$

where: $D_\alpha, D_\beta, D_\delta$ represent the distance between α, β, δ and other injured individuals, respectively; X_α, X_β, X_δ represent the current position of α, β, δ respectively; C_1, C_2, C_3 is a random vector and X is the current position of the grey wolf.

$$X_1 = X_\alpha - A_1 \cdot D_\alpha \tag{14}$$

$$X_2 = X_\beta - A_2 \cdot D_\beta \tag{15}$$

$$X_3 = X_\delta - A_3 \cdot D_\delta \tag{16}$$

$$X_{t+1} = \frac{X_1 + X_2 + X_3}{3} \tag{17}$$

3.3 Improved GWO Algorithm Description

In the GWO algorithm, the improper initial selection of escaped people result in the objective function leading to slower convergence rates and failing to converge to the best solution. Ultimately, it increases the potential for casualties.

It can increase the diversity of the wolf pack in this new algorithm. And the nonlinear control parameter is used to balance the global search and local search ability of the algorithm and improve the convergence speed of the algorithm. At the same time, the idea of PSO is introduced, it utilize the best value of the individual and the best value of the wolf pack to update the position information of each grey wolf. This method preserves the best position information of the individual and avoids the algorithm falling into a local optimum [8]. The PSO algorithm is reintroduced into the process. In this framework, the PSO algorithm is utilized to sort the generated escape routes and assign routes length and routes nodes to variables α, β and δ, respectively. And the the GWO algorithm follows routes α, β and δ to escape or rescue.

It illustrates that the GWO algorithm updates the position of the “grey wolf” by considering the positions of wolves α, β and. However, it does not consider the problem of information exchange between the "grey wolves", which increases the possibility falling into a local optimum. To solve this problem, a dynamic weighting rule is introduced to maintain the leadership role of “gray wolf α.

Dynamic weighting rules:

$$C_1 = \frac{random(0, 1)}{2} \tag{18}$$

$$C_2 = \frac{1 - random(0, 1)}{2} \tag{19}$$

$$C_3 = 0.5 \tag{20}$$

$$W_{(t+1)} = C_3 W_1 + C_2 W_2 + C_1 W_3 \tag{21}$$

The dynamic weighting rule is designed to maintain the relative proportions of “grey wolves”. And random inertia weights are introduced for β and δ.This rule facilitates the communication between the two sub-populations, it enables the exchange of information in the population and accelerates the transfer of information between different “wolves”. Because α is experienced and gradually tends to find the best solution. It is regarded as the "grey wolf leader". By using different coefficients, communication between β and δ is enhanced to diversify the population dynamics. As a result, it reduces the sensitivity of the algorithm to local optimal solutions and accelerates the overall convergence to the global optimal solution.

4 A New HPSO-IGWO Algorithm

Many researchers have proposed hybridized variants of several heuristic variants. According to Talbi [9], two variants can be hybridized in low level or high level with relay or coevolutionary techniques as heterogeneous or homogeneous. We hybridize PSO with GWO algorithm using low-level coevolutionary mixed hybrid [10].

$$\overrightarrow{d_\alpha} = \left|\overrightarrow{c_1} \cdot \overrightarrow{x_\alpha} - \omega * \overrightarrow{x}\right| \tag{22}$$

$$\overrightarrow{d_\beta} = \left|\overrightarrow{c_2} \cdot \overrightarrow{x_\beta} - \omega * \overrightarrow{x}\right| \tag{23}$$

$$\overrightarrow{d_\delta} = \left|\overrightarrow{c_3} \cdot \overrightarrow{x_\delta} - \omega * \overrightarrow{x}\right| \tag{24}$$

The updated velocity and equation:

$$v_i^{k+1} = \omega * \left(v_i^k + c_1 r_1\left(x_1 - x_i^k\right) + c_2 r_2 (x_2 - x_i^k) + c_3 r_3\left(x_3 - x_i^k\right)\right) \tag{25}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{26}$$

4.1 Stop Scrambling Strategies and Greedy Mechanisms

The GWO is a new efficient population-based optimizer. The GWO algorithm can reveal an efficient performance compared to other well-established optimizers. However, because of the insufficient diversity of wolves in some cases, a problem of concern is that the GWO still is prone to stagnation at local optima. To solve the problem, an interruption perturbation strategy is introduced, drawing inspiration from Lévy flight. Lévy flights are a particular class of generalized random walk in which the step lengths during the walk are described by a 'heavy-tailed' probability distribution. They can describe all stochastic processes that are scale invariant [11–13]. In this paper, an improved modified GWO algorithm is proposed for solving both global and real-world optimization problems [11].

$$\sigma_u = \left[\frac{\Gamma(1+\beta)\sin(\frac{\pi\beta}{2})}{\Gamma(\frac{1+\beta}{2})\beta \times 2^{\frac{\beta-1}{2}}}\right] \tag{27}$$

$$\sigma_u = 1 \tag{28}$$

$$S = \frac{u}{|v|^{\frac{1}{\beta}}} \tag{29}$$

In the formula: s is a random step size, u and v are normally distributed parameters, Γ is a gamma function, and β is a random value chosen in the interval [0,2] at each iteration. In the strategy of Lévy's flight algorithm, it can generate many small and sudden long-distance jumps, which can help the "grey wolf" in the process of exploring the "prey" balance, and reach the global optimum as soon as possible.

4.2 Spoiler Strategy

$$W_i^{t+1} = W^* + randn \times Levy(W_i) + randn \times \left| W^* - W_i^t \right| \tag{30}$$

$$Levy(W_i) = ts(W^* - W_i^t) \tag{31}$$

In this formula, *randn* is the normal distribution of the random two; $t \in [-1, 1]$ is the scale factor; W^* is the global optimum, which may change with the number of iterations.

4.3 Analysis

Lévy flight has the ability to generate a large number of small jumps and the occasional sudden long jumps. These movements facilitate random position updates to prevent the 'grey wolf' from falling into local optimal solutions. However, Lévy flight cannot guarantee an improvement in fitness compared to the original solution [13].

Motivated by the above, the Lévy flight algorithm is seamlessly integrated with the First-Come-First-Served (FCFS) priority scheduling algorithm. FCFS is an effective way to minimize casualties by consistently prioritizing the process currently at the top of the rescue queue for execution.

5 At the Fire Blasting Site, the Previously Defined Identities are not the Sole Occupants; There Are also Specific Categorizations for Casualties

(1) Critical Injuries: These critically injured patients need immediate treatment. Timely intervention can provide a chance of survival.
(2) Stable Injuries: Patients with stable injuries are able to maintain a steady respiratory cycle despite being injured and unable to walk. The treatment of their injuries can wait a little while. It is not immediately life-threatening and does not cause muscle disability.
(3) Minor Injuries: These patients with minor injuries are still able to move on their own. They are assigned a lower priority for treatment and can assist rescuers with initial assistance.
(4) Non-responsive Injuries: Patients in this category have non-beating hearts and have ceased breathing due to severe injuries. These people are confirmed dead or near dead at the scene, and they are given the lowest priority for treatment (Table 4)

Each casualty has a priority, which is represented by the number of priorities.

If the priorities are different, the process with the highest priority is scheduled; if the priorities are the same, it is scheduled in FCFS order, and the casualty with the same priority who has waited the longest in the rescue queue is selected, to avoid the death of currently surviving casualties due to excessive waiting time.

Table 4. Priority of the scheduling algorithm

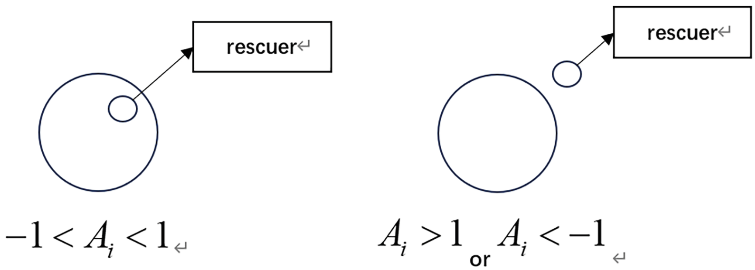
Classification of casualties	priority
Injuries are critical, and these are the types of patients who need immediate treatment for their injuries If treated in time they have a chance of survival	1
Patients with stable injuries, but who are unable to walk, have stable respiratory circulation, and have significant trauma.but can still wait briefly without endangering their lives or causing muscular disability	2
They are minor injuries and can move on their own, these patients are given a third order of treatment and even these patients can be used as a human resource to help the rescuers in first aid	3
Injured patients whose hearts are not beating and who are not breathing due to the severity of their injuries and who have been confirmed dead or dying at the scene are among the lowest priority patients	4

The rescuers are prioritized to rescue casualties with high priority, it reduces the number of deaths. Define the above classification of casualties as "prey" status in the GWO algorithm, and "hunter-grey wolf" (α,β,δ,ω) play an important role in the collective rescue process by completing the following steps under the leadership of α during the rescue process:

① Finding and approaching the injured
② Judging the classification of casualties
③ Whether or not assistance is provided

5.1 Attacking "Prey"

When the rescuers stop moving, in order to stimulate the approaching casualties, the value of a will gradually decrease during the iterations and the value of A will stabilize, this ultimately determines whether or not the next casualty is rescued or selected. (n is the current number of iterations, N is the maximum number of iterations.)



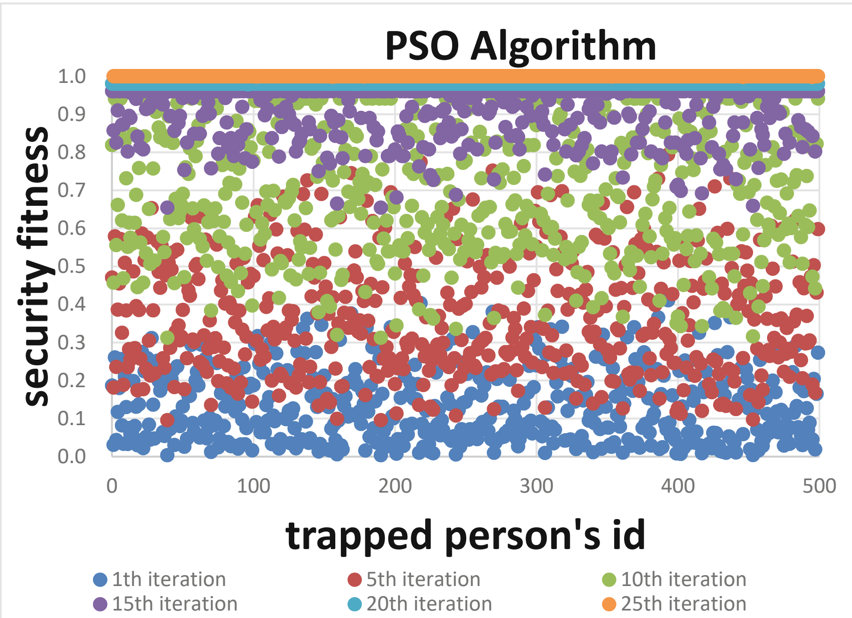
$$a = 2 - 2 \cdot n/N \tag{32}$$

$$A = rand(-a, a) \tag{33}$$

After patrolling the “prey”, it is able to determine which of the above scenarios the casualty falls into (Priority 1 - Priority 4), setting the judgement value to S_i and storing the results of each iteration of the calculation into A_i when the priority is $-1 < A_i < 1$. The “wolves” attack the “prey” according to priority scheduling - this is a local optimum. When the priority is $A_i > 1$ or $A_i < -1$, the “grey wolf” stays away from the “prey” and explores the rest of the area (in order to find the global optimal solution and save as many people as possible). Judging the value of S_i at each iteration. If $1 < S_i < 3$,then conduct rescue; if $S_i > 4$, then give up and move on to the next casualty, in order to minimize the number of casualties and help more to survive. (The priorities of rescue is mentioned above and can be further divided, but we don’t deep in here.)

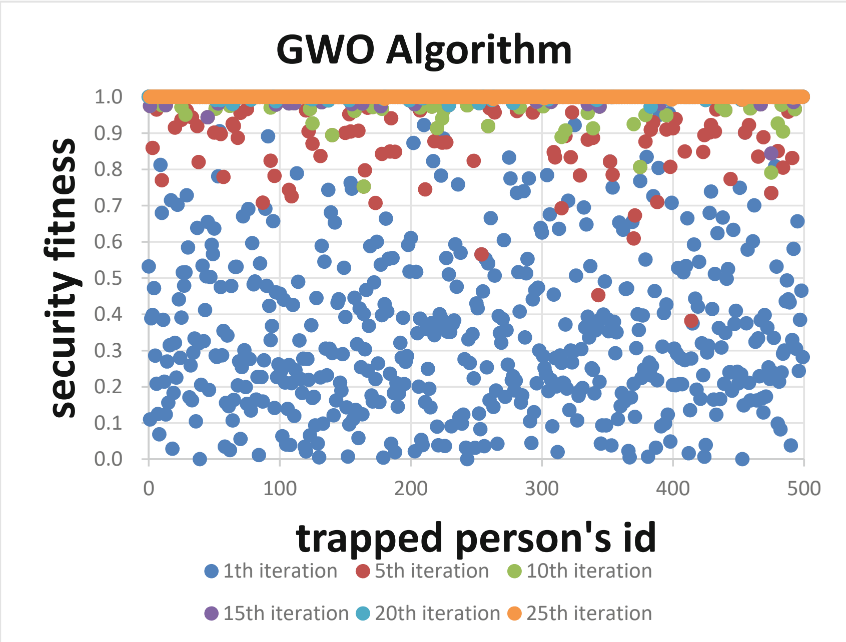
6 The Ablation Experiment (PSO, GWO, HPSO-GWO)

At the beginning of the PSO algorithm experiment, it is assumed that each trapped person in the fire area could be regarded as a particle which could constantly update the position of the individual and the group during the iterative process. After the constant and random movement, the individual and the global optimums are eventually reached, with the final iteration converging to 1. The following images are based on the algorithm in the context of a fire scene (specify security fitness > 0.99 for convergence):



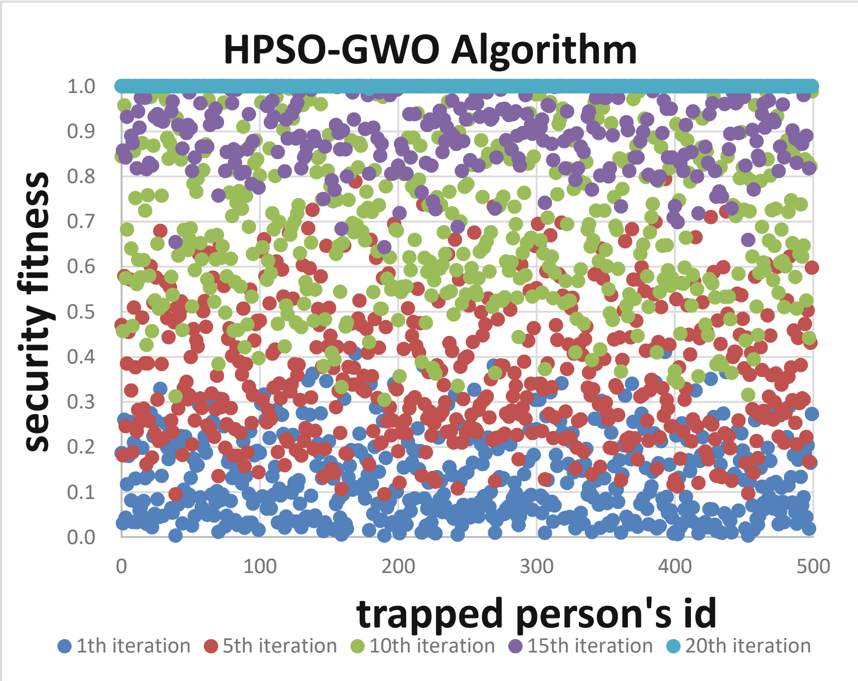
(a) obtained resulted after respective initialization,1th,5th,10th,15th,20th,25th. **(Marker: the algorithm stabilized after the 25th iteration with results converging to 1).**

It is then assumed that the fire area constitutes a population relationship similar to that of a wolf pack in nature. In this area, the "first level leader" who is responsible for leading the entire population, is the optimal solution of the algorithm; the "second level leader" who takes responsibility for assisting the "first level leader", is the suboptimal solution; the "third level leader" is under the direction of the "first level leader" as well as the "second level leader"; and the "fourth level leader" follows the above "leaders", leading the "wounded" in the fire area out of the danger zone according to the "hierarchical order", thereby obtaining the global optimal value. The following images are based on the GWO algorithm in the context of a fire scene (specify security fitness > 0.99 for convergence):



(b) obtained resulted after respective initialization,1th,5th,10th,15th,20th,25th. **(Marker: faster iteration results, but more jumps that is unstable).**

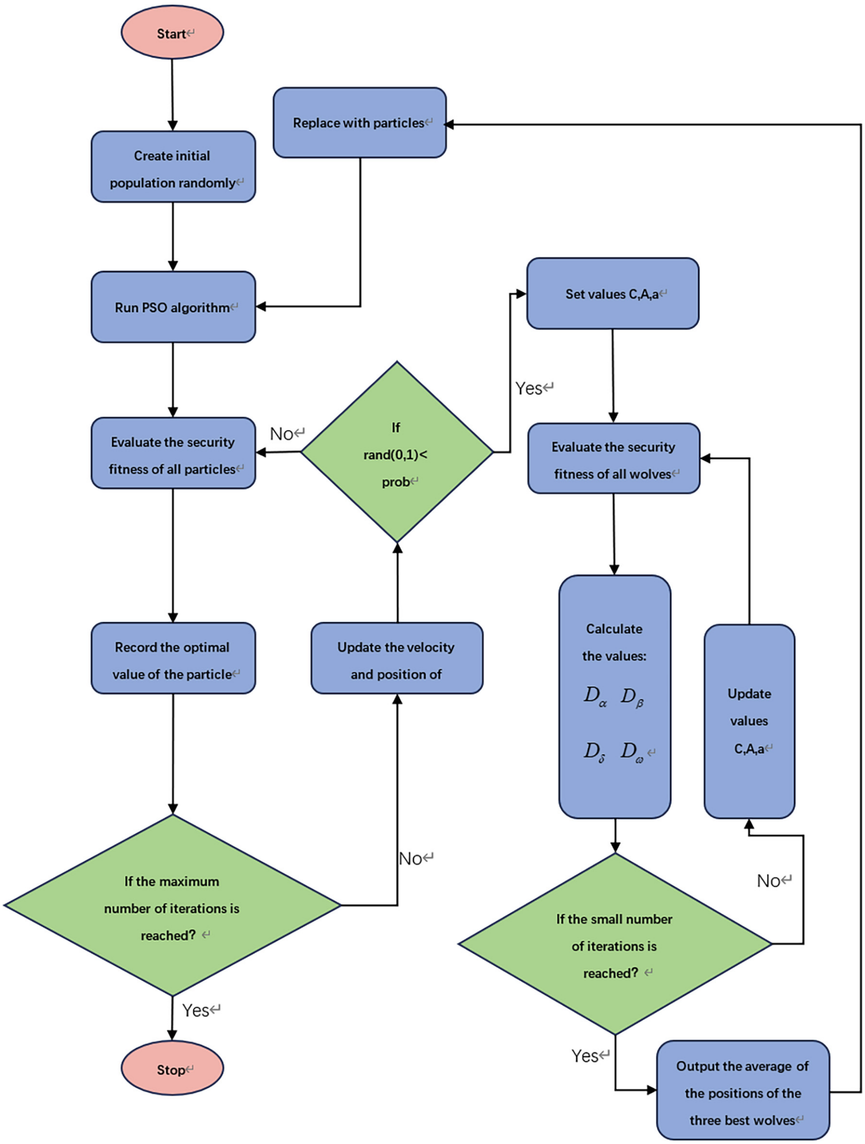
To optimize the two algorithms, a solution is needed to reduce the PSO algorithm to reduce the possibility of falling into local minima. In the proposed hybrid algorithm, the GWO algorithm is used to support the PSO algorithm to solve this problem. Therefore, mixing two algorithms to form the HPSO-GWO algorithm cloud help reduce the possibility of falling into a local optimum, for the reason that the GWO algorithm has the ability to explore the region. The following hybrid HPSO-GWO algorithm is based on the fireground context (specify security fitness > 0.99 for convergence):



(a) obtained resulted after respective initialization,1th,5th,10th,15th,20th. **(Maker: faster and more stable iteration results).**

Specify security fitness > 0.99 for convergence, although the PSO algorithm shows outstanding performance in any practical problems that could obtain correct results, the PSO algorithm tends to fall into the local optimum rather than giving the integrate one during the iteration. Thus, the velocity of convergence is slow. The GWO algorithm has the capability of exploring, which could extend its move outward continually to find the global optimum. As mentioned above, the PSO algorithm has advantages for fast random guidance, and the GWO algorithm could explore convergence of the HPSO-GWO algorithm with the fastest and most stable speed. On the basis of these, under the circumstance of a fire scene, the faster and more precise path is needed to have more efficient rescue and minimize casualties, which is the most important thing in fire rescue.

6.1 The following is the Flowchart of this Hybrid Algorithm



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References

1. Cheng, T. F.: Research on fire risk evaluation and evacuation of large shopping malls (Master's thesis, Shenyang University of Aeronautics and Astronautics) (2022). https://kns.cnki.net/KCMS/detail/detail.aspx?dbname=CMFDTEMP&filename=1023014644.nh
2. Fernández Martínez, J.L., García Gonzalo, E.: The generalized PSO: a new door to PSO evolution. J. Artif. Evol. Appl. 2008 (2008)
3. Xiong, X., Hu, X., Guo, H.: A hybrid optimized grey seasonal variation index model improved by whale optimization algorithm for forecasting the residential electricity consumption. Energy **234**, 121127 (2021)
4. Xiong, X., Hu, X., Tian, T., Guo, H., Liao, H.: A novel optimized initial condition and seasonal division based grey seasonal variation index model for hydropower generation. Appl. Energy **328**, 120180 (2022)
5. Li, Z.K., Hu, X., Guo, H., Xiong, X.: A novel weighted average weakening buffer operator based fractional order accumulation seasonal grouping grey model for predicting the hydropower generation. Energy **277**, 127568 (2023)
6. Hu, X., Xiong, X., Wu, Y., Shi, M.J., Wei, P., Ma, C.M.: A hybrid clustered SFLA-PSO algorithm for optimizing the timely and real-time rumor refutations in online social networks. Expert Syst. Appl. **212**, 118638 (2023)
7. Kennedy, J., Eberhart, R.: Particle swarm optimization. in Proceedings of the IEEE International Conference on Neural Networks (ICNN'95), vol. 4, pp. 1942–1948, Perth, WA, Australia (1995)
8. Teng, Z.J., Lv, J.L., Guo, L.W.: An improved hybrid grey wolf optimization algorithm. Soft. Comput. **23**, 6617–6631 (2019)
9. Talbi, E.-G.: A taxonomy of hybrid metaheuristics. J. Heuristics **8**(5), 541–564 (2002)
10. Singh, N., Singh, S.B.: Hybrid algorithm of particle swarm optimization and grey wolf optimizer for improving convergence performance. J. Appl. Math. 2017 (2017)
11. Heidari, A.A., Pahlavani, P.: An efficient modified grey wolf optimizer with Lévy flight for optimization tasks. Appl. Soft Comput. **60**, 115–134 (2017)
12. Mandelbrot, B.: The Fractal Geometry of Nature. Freeman, New York (1977)
13. Lévy, P.: Théorie de l'Addition des Variables Aléatoires. Gauthier-Villars, Paris (1954)