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Single and multiple odor source localization using hybrid nature-inspired algorithm

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Abstract. In this paper, optimization-based approach has been adopted to localize the odor source in an unknown environment. Two scenarios taken into consideration, first single odor source (SOS) with a point source emission at a constant rate and four multiple odor sources (MOS) with point source emissions and different release rates constant in time. In context to SOS, four environments that have distinct dimensional layout have been generated with slight variation in wind velocity and diffusion constant. In case of MOS, there are five environments with same layout but different contributing factors such as wind velocity, placement of odor sources and emission rates which are considered to demonstrate its impact on success rate of algorithms. A recent optimization technique called hybrid teaching learning particle swarm optimization (HTLPSO) has been adopted and implemented in all the arenas, namely SOS and MOS, where mobile robots AKA virtual agents (VAs) are working in collaboration. There are group of VAs deployed in this operation ranging from {3–15}. To investigate the effectiveness of the algorithm, results of HTLPSO are compared with classical particle swarm optimization (PSO) and teaching learning-based optimization (TLBO). It is observed that HTLPSO outperforms TLBO and PSO in arenas with larger dimensions while utilizing few iterations in comparison with other algorithms in case of SOS. HTLPSO also performs best in case of MOS, surviving the effect of wind velocity and change in emission rates. Only when odor sources are placed differently and scattered, TLBO gives the best result. Another highlight of HTLPSO is convergence with high accuracy even with less number of VAs.

Keywords. Optimization; odor source localization; HTLPSO; TLBO; PSO; mobile robots.

1. Introduction

Odor source localization (OSL) has received interest of highest degree in recent times. It is an important exercise for living beings particularly animal kingdom to locate food or their mating partners. It is reported that there occurred 1369 oil leakage accidents in seven US states causing 36 fatalities and 512 injuries [1], while Fukushima nuclear accident (2011) and Eyjafjallajökull volcanic eruption (2010) are among others, having harmful impact on public health and several industries [2]. Researchers started developing robots with skills to locate the sources of hazardous airborne release having humanitarian applications and prevent catastrophic accidents. They can also be used to detect materials such as plant matter and drugs in customs or quarantine application, searching for survivors in earthquake, damaged buildings, landslides or avalanches, detecting fire in its initial stages, locating unexploded mines and bombs, space exploration, etc. [3].

OSL has different level of complexities. These complexities have been simplified to some extent as it was unearthed that OSL process consists of three intertwined stages. It starts with plume finding, plume traversal as an intermediate stage followed by source declaration. There are number of attempts by various researchers to establish earmarked stagewise solutions. For example, Ali Marjovi *et al* [4] and Zohar Pasternak *et al* [5] gave a solution for odor plume finding. Various literatures are available on plume tracing research [6–9] and few on source declaration/identification [10, 11]. Integrating different approaches for each stage may be a novel idea to give a unified solution to this problem and recently applied in [1]. However, the three-stage concept is related to searcher's contact with odor patches of chemical plumes driven by turbulent mixing in spatial and temporal dimensions [12]. Therefore, mobile olfaction with single- and multi-robots has remained the preferred technique for OSL to exploit three stages to the maximum. It is easy to deploy single- and multi-robots for single odor source (SOS) localization [13–17]. Most often multi-robots with intelligent algorithms come to rescue in this scenario and very rare single robot is used. There

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can be more than one odor source releasing chemicals at a constant or different release rates. These are multiple odor sources (MOS) having different locations. Use of multi-robots to localize MOS has been attempted in [18–23]. It is a latest trend to use multi-robots for MOS and accelerated in recent decade. Beside simulations, multi-robots have been providing a leading edge in research in real world experiments [24].

As far as multi-robots are concerned for MOS, collaborative algorithms are in practice such as particle swarm optimization (PSO). It is observed that PSO may be implemented in OSL to locate five odor sources with 10 mobile agents [18]. It provides a comparative simulation experiment based on the performance of PSO, biased random walk (BRW) and gradient based algorithms (GRD). It is found that PSO is best suited to turbulent environments based on average time consumed to locate first three odor sources. However, it lacks in performance when experiments are conducted with variation in emission rate of the sources and in normal stable plume, PSO takes more time than GRD. Another stochastic approach could be ant colony optimization (ACO) with modifications of new definitions of pheromone and heuristics [19]. Two extra search modes viz. local traversal search and global random search may be added to find two odor sources quickly and accurately.

As PSO gained tremendous popularity and widely implemented until it is found that robots have a tendency to move towards the same local optimum (no odor source presence) [25], eventually leading to slow convergence rate and finally fail to locate the source due to reduced mobility. Also robots fail to pick concentration values of its counterparts showing lack of collaboration and raising another limitation of this approach [26].

The drawbacks in PSO have been eradicated to some extent by various strategies proposed such as adjusting the learning factors and the inertia weight [27]. The inertia weight may be increased to increase the chances of algorithm stabilization. Other approaches could be randomizing the inertia weight (w) in the range of {0.5, 1}w [28], or linearly decreasing w [29] and keep updating the two learning factors based on the wind [30].

Furthermore, an algorithm based on modified particle swarm optimization (MPSO) which includes chemotactic and anemotaxis properties suited to advection diffusion model may be used [20]. It also includes niche characteristics to solve multi-peak and multi-source problem. The globally best score may be reinitialized whenever the robots are trapped in a local optimum that helps the PSO to Detect and Respond (DR) [31]. Modification is also possible with "request and reset strategy" to enhance guaranteed convergence particle swarm optimizer (GCPSO) and Dissipative PSO (DPSO) [32]. Also, odor source localization strategy can be improved through a cooperative distributed approach in unknown structured environments with multiple mobile robots [21]. The method is a decentralized frontier based algorithm enhanced by a cost/utility evaluation function that considers the odor concentration and airflow at each frontier. The method performs well in both simulation and real-world environments with different number of robots and different scenarios.

In localizing MOS, a multi-robot cooperation method based on niche PSO may be used [22]. A niche can be formed with neighboring robots when the first odor packet is found that is well inside the plume area. It can lead of organization of multiple niches in pursuit of multiple odor sources. Size of the niche may be adjusted dynamically on the basis of aggregation degree of robots. To avoid searching the same area repeatedly a niche merging behavior may also be deployed on the basis of similarity of niches. A diverse PSO based multi-robot cooperative approach for multiple odor source localization could be used. It introduced group related subtasks such as plume following through the introduction of methods for group formation, maintenance of group aggregation, group closeness measurement, group dismantling, and next movement calculation of the robot. It is able to localize odor sources in parallel [23].

Besides these approaches, modified variants of nature-inspired algorithms and their hybrid forms may be used for MOS localization. Modified PSO for MOS has been successful up to some extent but suffers in computation speed as well as requires large number of mobile agents. Besides modifications in parameters of PSO, there are other efforts to combine different algorithms with PSO to achieve hybridization. As compared to improvement in PSO through parameter modification, its hybridization has been less valued and explored and only finite number of evidences are available. More details can be found in [33] and [34]. In these algorithms, an estimated separate and combined odor source probabilities have been used instead of real odor concentration as the local and global fitness functions, respectively. Other well established optimization techniques such as bacterial foraging optimization (BFO) can find a suitable hybridization partner like particle swarm optimization (PSO) [16]. This hybridization can be strengthened with elimination dispersal which is used to avoid stagnation in local optima whereas chemotaxis can also be combined with PSO. Chemotaxis helps in tracing the plume area. Gravitational search algorithm and PSO may be hybridized for odor source localization while using the concept of search counter [35]. Another approach could be concatenating grey wolf optimizer with PSO [36]. However, all these algorithms require algorithmic, and control parameters that affect the algorithm computational efficiency. In contrast to these algorithms in which parameter tuning is required, a parameter less algorithm known as teaching learning based optimization (TLBO) algorithm could be used [37]. Nevertheless, its hybridization version may also be used. It is reported that hybrid teaching learning particle swarm optimization outperforms the well-established benchmark algorithms for synthesis of mechanisms to generate path [38]. Therefore, this paper presents its implementation for OSL and this is our area of interest.

To the best of our knowledge, in case of MOS, factor such as source declaration according to emission rate has not been considered till date. Source with highest emission must be found initially followed by the other sources declaration should be in order of decreasing emission rates. Even when search is in parallel to locate all odor sources the same sequence has to be maintained. Layout is a big concern in algorithms that must cope up with different environment size to establish it feasibility. Environmental factors such as diffusion constant, wind velocity must be taken into consideration as well. It has also been found in recent research papers that effect of placements of odor sources on success rate of algorithms has not been considered or in other words reshuffling is ignored.

This paper has been outlined as: Section 2 gives the type of simulation environment; Section 3 gives the details and complete implementation of algorithms. In Section 4, details about experimental procedures are discussed and its evaluation tools have been furnished in Section 5. Section 6 presents results and its analysis with relevant data. Lastly, Section 7 deals with the conclusions and future scope.

2. Environments considered

In this section various environments are discussed in detail considered for OSL.

2.1 *Single odor source (SOS)*

To investigate algorithms, a simulated environment is generated based on advection diffusion model [39, 40]. It can be also termed as static plume model [41] which comprises averaged time Gaussian plume model. In this model, uniform wind velocity is considered along positive x co-ordinate. The diffusion coefficient of gas in the medium is assumed to be constant and isotropic. The mathematical expression for concentration 'c' of chemical gas at any point x $= (x, y)$ in the domain of interest is given by:

$$\mathrm{c}(\mathrm{x}, \infty, x', y') = \frac{q_o \, exp\left(-\frac{v(d-x+x')}{2k}\right)}{2\pi kd} \tag{1}$$

where 'q_o' is chemical release rate, 'v' is the wind velocity in positive direction of x co-ordinate, d is Euclidean distance between the point source and the point of interest, 'k' is the diffusion coefficient and (x', y') are the coordinates of point source. Different simulation environments whose dimensions vary from 20 m $\times$ 20 m to as large as 1000 m $\times$ 1000 m has been generated to study its impact on success rate of algorithms. Each environment has slight change in either one or more parameters such as 'q_o' chemical release rate, 'v' the wind velocity and 'k' the diffusion coefficient. Table 1 summarizes parameter values which are used for generating four different environments. Figure 1(a)–(d) corresponds to the environment type I, II, III and IV respectively.

Virtual agents (VA) start its search operation from random points at the beginning of simulation. This layout has been bounded at its perimeter so that VA remains inside the arena throughout its search operation.

2.2 *Multiple odor sources (MOS)*

A general form of two-dimensional Gaussian plume model equation for single odor source is given by Eq. (2) below,

$$C(x, y, z) = \frac{q_o}{2\pi u \sigma_y \sigma_z} \exp \left[\frac{(y-y_o)^2}{2\sigma_y^2}\right] \left\{ \exp\left[-\frac{(z-z_o)^2}{2\sigma_z^2}\right] + \exp\left[-\frac{(z+z_o)^2}{2\sigma_z^2}\right] \right\} \tag{2}$$

Here 'C' is the concentration at desired point (x, y, z) in the given domain. 'q_o' is chemical release rate, 'u' the wind velocity in positive direction of x-coordinate. (x_o, y_o, z_o) is location of source. σ_y and σ_z are the standard deviation in lateral and vertical directions respectively. Herein $(z = z_o)$ has been considered.

The same above Eq. (2) can be used to find concentration at a point of interest for multiple odor sources. In that case it is sum of all concentrations due to individual odor source at that point. A case study has been done on multiple odor sources by [42]. This basic idea was applied to find the cumulative concentration at a point due to different odor sources. In the present case four odor sources are considered. Sources have locations $\overrightarrow{Z_s} = \left(X_{s,}, Y_s, H_s\right)$ where X_s, Y_s and H_s are the x coordinate, y coordinate and height of the source for s = 1, 2, 3 and 4 respectively. Also, four odor sources have emission rates Q_s. The positive x axis is aligned with the wind direction. The contribution from an individual source S_s to the contaminant concentration at any point (x, y, z) is then given by the Gaussian plume solution which is denoted by $C\left(x_s', y_s', z; Q_s, H_s\right)$ where Q_s is contaminant emission rate constant in time. Here the coordinates are shifted as

$$x_s' = x - X_s \tag{3}$$

$$y_s' = y - Y_s \tag{4}$$

Therefore, total concentration at a point from all the point sources is simply given by the sum as follows

$$C_T(x, y, z) = \sum_{s=1}^{4} C\left(x_s', y_s', z, Q_s, H_s\right) \tag{5}$$

For stability class 'C', σ_y and σ_z are calculated with the help of diffusion parameters. Other details of simulated

Table 1. Parameter values for distinct environments.

Area	Parameters						
	v (m/s)	k	q_o (mg/s)	x' (m)	y' (m)	Environment type	Figure
20 m × 20 m	0.04	0.006	0.3	5	12	I	1(a)
100 m × 100 m	0.04	0.003	1	20	50	II	1(b)
500 m × 500 m	0.03	0.003	5	40	250	III	1(c)
1000 m × 1000 m	0.03	0.003	10	40	500	IV	1(d)

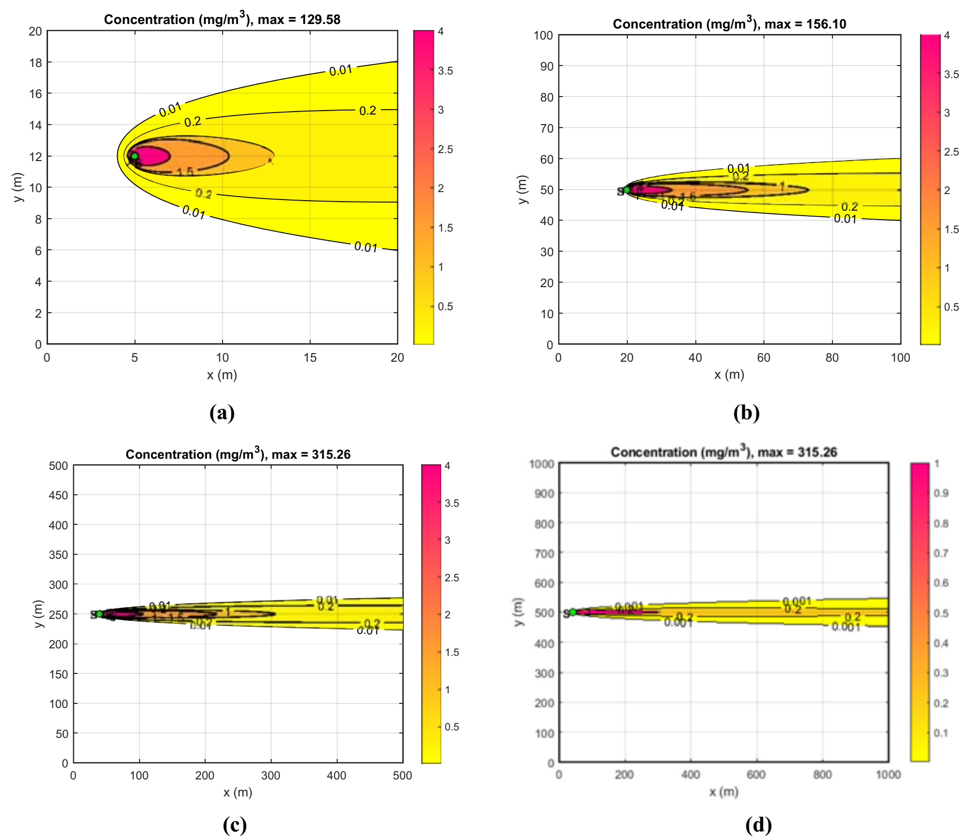


Figure 1. (**a**) Simulation environment type I with source at (5, 12). (**b**) Simulation environment type II with source at (20, 50). (**c**) Simulation environment type III with source at (40, 250). (**d**) Simulation environment type IV with source at (40, 500).

Table 2. Parameters that produced figure 2a–e.

Area	Parameters					
	$\{Q_1, Q_2, Q_3, Q_4\}$ (mg/s)	$\{X_1, X_2, X_3, X_4\}$	$\{Y_1, Y_2, Y_3, Y_4\}$	u (m/s)	Environment type	Figure
50 m × 50 m	{0.5, 0.3, 0.6, 1}	{5, 5, 8, 4}	{10, 15, 12, 18}	3	V	2(a)
50 m × 50 m	{0.5, 0.3, 0.6, 1}	{5, 5, 8, 4}	{10, 15, 12, 18}	1.5	VI	2(b)
50 m × 50 m	{0.5, 0.3, 0.6, 1}	{5, 5, 8, 4}	{10, 15, 12, 18}	4.5	VII	2(c)
50 m × 50 m	{0.5, 0.3, 0.6, 1}	{2, 3, 8, 4}	{8, 5, 30, 25}	3	VIII	2(d)
50 m × 50 m	{0.3, 1, 0.6, 0.5}	{5, 5, 8, 4}	{10, 15, 12, 18}	3	IX	2(e)

environment pertaining to wind velocity, arrangement of odor sources and their release rates are furnished in table 2. It is to be noted that $H_s = 0$ for all cases. Generated figure 2(a)–(e) is marked S1, S2, S3 and S4 as the odor source locations. Their concentrations are also shown with the help of filled contour plots.

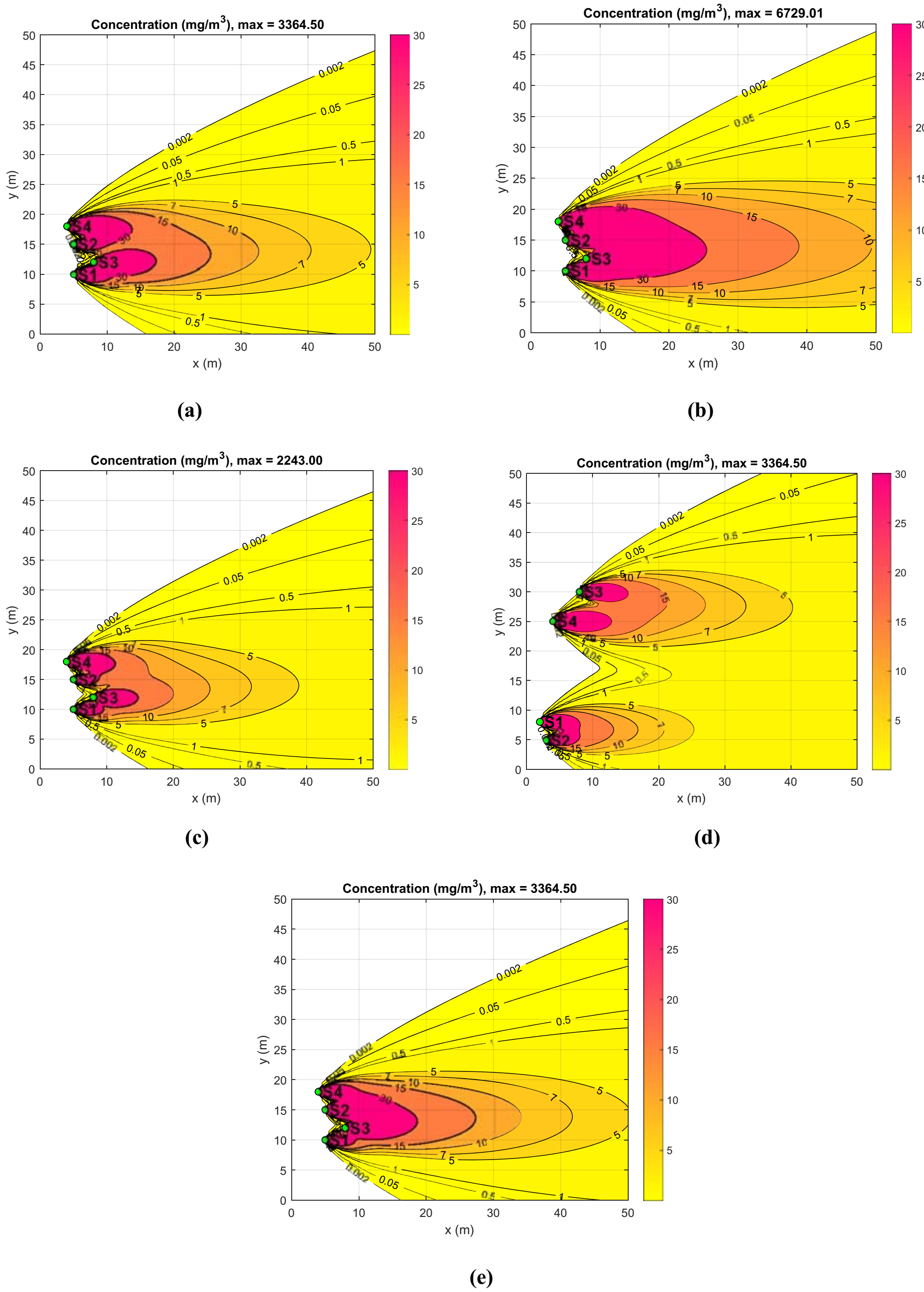


Figure 2. Simulation environment type V, VI, VII, VIII and IX shown in (**a**), (**b**), (**c**), (**d**) and (**e**) respectively with multiple odor sources in green dots (S1, S2, S3 and S4).

3. Brief description of implemented algorithms

Odor source localization may be considered as an optimization problem. To address this optimization problem, suitable heuristic algorithm is required. Therefore, in this section, the notion and implementation of the optimization algorithms used in this study are presented. The three optimization algorithms used are namely teaching–learning-based optimization (TLBO), particle swarm optimization (PSO) and hybrid-teaching learning particle swarm optimization (HTLPSO). It is worth mentioning that HTLPSO is an ensemble of two well-established algorithms, namely, TLBO and PSO. Therefore, following discussion is divided into three subsections which are TLBO, PSO, and HTLPSO.

3.1 *TLBO*

Teaching–learning based optimization is a population-based algorithm. It does not require parameter tuning which makes it implementation simplest among all algorithms [37]. This algorithm is based on the class teaching–learning philosophy. The class consists of learners and a set of courses is assigned to each learner in which grades are awarded. In TLBO, the class, learner, a set of courses, and numeric grades are analogous to population, population size, design variables, and values of design variables, respectively. In addition, learners result is identical to the fitness function value of any nature-inspired algorithm. The algorithms maintain a right balance between exploration and exploitation. It works in two phases, namely, teaching and learning phases. The completion of a teaching–learning cycle completes one iteration. A detailed illustration on implementation of TLBO can be found in [37, 43].

3.2 *PSO*

PSO is another population-based nature-inspired algorithm that is inspired from the simulation of environmental conditions. It simulates the natural and unpredictable bird flocking choreography [44]. It starts with the random population initialization followed by search space exploration by updating the population. In this algorithm, particles are analogous to the potential solutions. The coordinates of the particle are extracted from the search space corresponding to the best fitness solution. The best solution obtained so far is termed as 'pbest' whereas the location of overall best solution is called 'gbest.' The obtained 'pbest' and 'gbest' values are used to update the velocity in each step which helps in pushing the solution towards 'pbest' and 'gbest' coordinates. Then following equations are used for updating the velocity and position.

$$V_{i+1} = wV_i + c_1 rand_1 (pbest_i - Y_i) + c_2 rand_2 (gbest_i - Y_i) \tag{6}$$

$$Y_{i+1} = Y_i + V_{i+1} \tag{7}$$

In which V_{i+1} represents updated velocity for each particle based on its previous velocity, Y_{i+1} denotes the particle's updated position, $rand_1$ and $rand_2$ are two random numbers taken in the range [0, 1], w is inertia weight, c_1 and c_2 are the acceleration constants. A detailed discussion on PSO can be found in [44].

3.3 *HTLPSO*

In HTLPSO, teaching phase of TLBO is merged with the PSO and the best solutions are retained while maintaining the size of initial population. The schematic of HTLPSO is presented in figure 3 [38]. The algorithm begins with the random population initialization for an even population size. The generated population is considered for both the TLBO and PSO and objective functions are computed. Thereafter, the best half of the population obtained after PSO is merged with the best half of the population obtained after the teaching phase of the TLBO. This assures that size of the population remains same after merger between TLBO and PSO. The population so obtained is used in the learning phase of TLBO. The completion of learning phase marks the end of first iteration of HTLPSO algorithm. Eventually, the population obtained after learning phase is considered for the next iteration. The hybridization of TLBO with PSO, helps to improve the computation speed and efficiency of the algorithm. A detailed discussion on HTLPSO can be found in [38].

4. Experimental procedures

Under this section, the whole experimental setup has been described. As discussed earlier, there are two types of cases considered in this paper. The first being localization of a SOS and second one to localize MOS. Simulation experiments have been broadly classified in these two categories with their results presented in the same order under section 6.

Environment types for SOS (I–IV) and MOS (V–IX) are separately discussed in section 2. Under two categories namely SOS and MOS, these distinct environments have different characteristics. As a testing platform for adopted algorithms these environments are used. In other words, HTLPSO, TLBO and PSO have been applied in each environment of SOS and MOS. For a selected environment and algorithm (e.g., HTLPSO in Type I of SOS), the mobile agents or virtual agents (VAs) are varied in every new experiment termed as 'set'. As there are different number of VAs in a group ranging from {3, 15}, there are 13 sets for the selected case where VAs team size of 3 belongs to set 1, VAs team size of 4 belongs to set 2 and likewise. These VAs are assumed particles with no weight and mass in experiments. These VAs are working in collaboration which are invoked by chemical concentration gradient and try to converge towards maximum concentration consequently, declaring the source location. An experimentation 'set' for the selected case has 100 simulations runs to collect the faithful data. The same procedure has been extended to MOS while implementing all three algorithms. A schematic to illustrate this experimental procedure has been shown in figure 4. Finally, results of HTLPSO are compared with PSO and TLBO, based on the evaluation tools discussed later in section 5. MATLAB® R2018a software package (Mathworks Inc.) has been used to carry out all simulation experiments on a system having an Intel Core

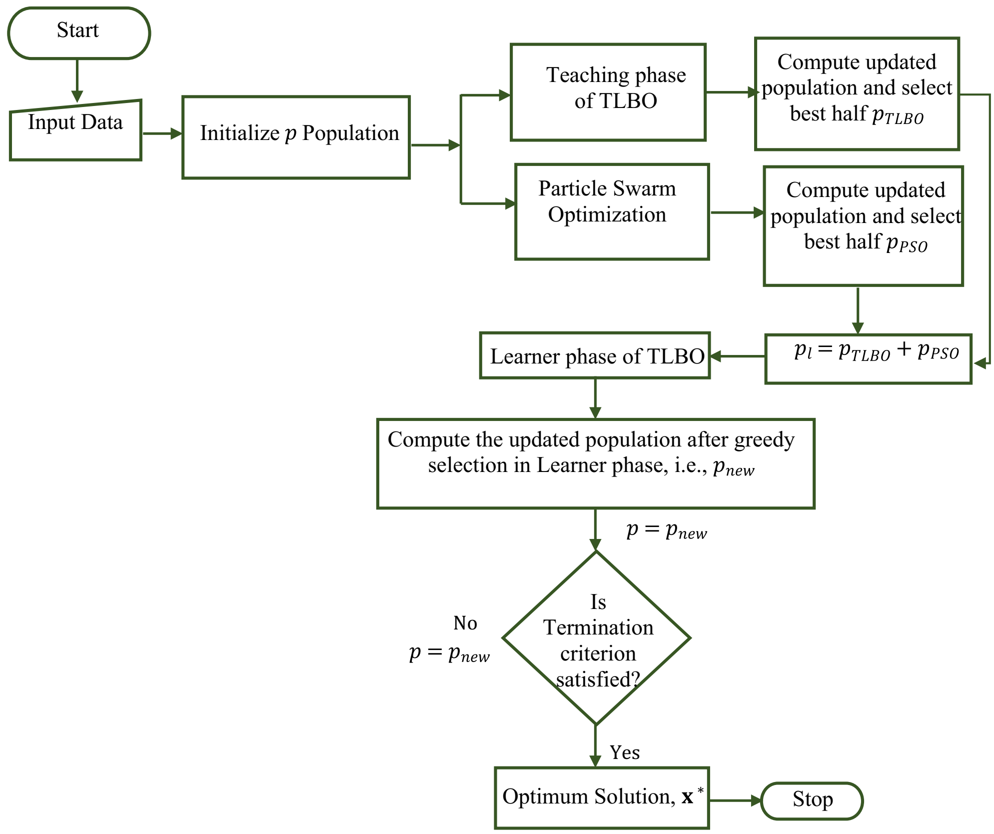


Figure 3. Flowchart of HTLPSO algorithm.

i5-3230M CPU with 4 GB RAM. Simulated results have been generated and compiled in MATLAB® and MS Excel only.

5. Performance and evaluation tools

This section deals with different tools to evaluate performance and comparison of all three algorithms. It also helps in analyzing results and find suitability of an algorithm to an environment type of an experiment category. Performance metrics of the applied algorithms in OSL problem relies on two factors. First one is the success rate i.e. out of 100 simulation experiments, the total number of source declaration/identification activity and second one is source declaration/identification with a smaller number of VAs for minimum number of iterations. This is valid for both the cases, namely SOS and MOS. Especially for MOS, one more factor i.e. maximum source declaration (MSD) is defined. As there are four odor sources, these need to be

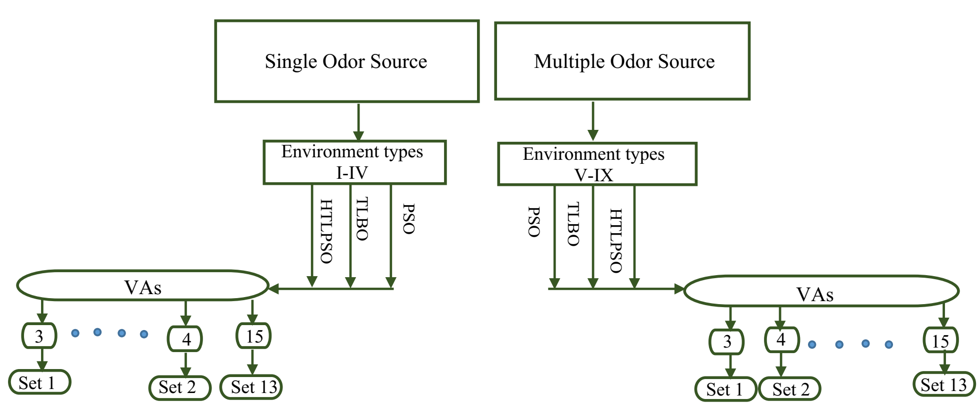


Figure 4. Experimental procedures under two broad categories viz. SOS and MOS.

Table 3. SDET for SOS with all environment types.

Area	Parameters		
	SDET (m)	Source Position (x′, y′)	Environment type
20 m × 20 m	0.02	(5, 12)	I
100 m × 100 m	0.3	(20, 50)	II
500 m × 500 m	0.3	(40, 250)	III
1000 m × 1000 m	1	(40, 500)	IV

Table 4. Success rate with different virtual agents for environment type I.

Environment type I with success rate						
VAs	3	4	5	6	7	{8–15}
HTLPSO	23	72	96	100	100	100
TLBO	8	41	77	95	99	100
PSO	59	89	100	100	100	100

identified/declared according to monotonically decreasing emission rate. Out of four, an odor source having maximum emission rate is expected to be declared mostly followed by other odor sources having lower emission rates.

5.1 *Source declaration error (SDE) and success rate*

Authors would like to define here the term known as "source declaration error" (SDE). In an experiment when the VAs are close to the source but declare/identify it nearby other than the actual location, at that time Euclidean distance from the global best agent to the target location is computed. It is termed as source declaration error (SDE). In this work, the source position is fixed for different environment types in SOS. Therefore, relative to its position SDE is calculated which eventually decides the accuracy in declaring the source successfully.

In contrast to SOS, in MOS, global best VA position is calculated w.r.t each source location as they tend to

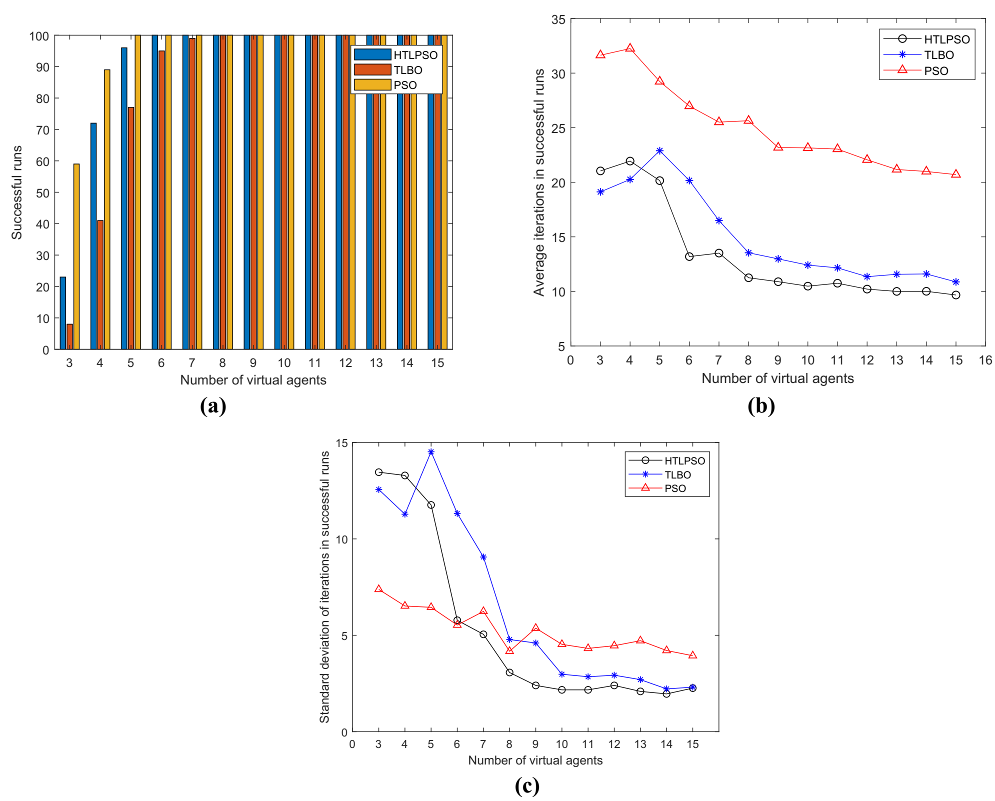


Figure 5. For adopted three methods with number of virtual agents in simulation environment type I, (**a**) Success rate, (**b**) Average iterations in successful runs and (**c**) Standard deviation of iterations in successful runs.

converge unequally or their convergence to one source location (which may be highest emission) is not permanent. It will be discussed in detail later in section 6.3.

Successful run can be defined in two ways. First the VAs exactly identify/declare the source of odor and second they reach close to the vicinity of the source. In this work, second case is adopted, considering this scenario to be practical. In first case if the maximum number of iterations in a simulation run is predefined in which exactly zero value of SDE can be achieved then source localization is considered to be successful [23, 32]. However with the latter successful experiment can be defined as the closest reach of the global best agent to the odor source. To find the closest reach, SDE is taken as a base value to calculate successful run in all simulation experiments. If SDE is less than a threshold hereafter defined as source declaration error threshold (SDET), then a simulation run is termed as successful provided that maximum number of iterations are 60 only. Therefore, SDET is defined beforehand for each environment type for both cases i.e. SOS and MOS to find the successful run.

Hence success rate can be found by the following equation

$$S = \frac{R}{T} \tag{8}$$

where R = successful runs, T = Total runs.

Table 5. Success rate with different virtual agents for environment type II.

Environment type II with success rate						
VAs	3	4	5	6	7	{8–15}
HTLPSO	24	75	95	100	100	100
TLBO	17	52	81	97	99	100
PSO	36	76	98	99	100	100

The proposed values of SDET has been tabulated in table 3.

5.2 *Need for minimum number of virtual agents with less average iterations*

This subsection highlights the need of minimum number of VAs in team size looking out for an odor source. It is an important factor to decide the performance of an algorithm. For example, VAs team size of 3 is better than VAs team size of 5 for a particular algorithm. Even for intra-algorithm comparison it forms an underlying factor. This is because as per the practical aspects are concerned more number of VAs may lead to self-collision and exit from the task. Hence for an arena in SOS or MOS, it is an attempt to

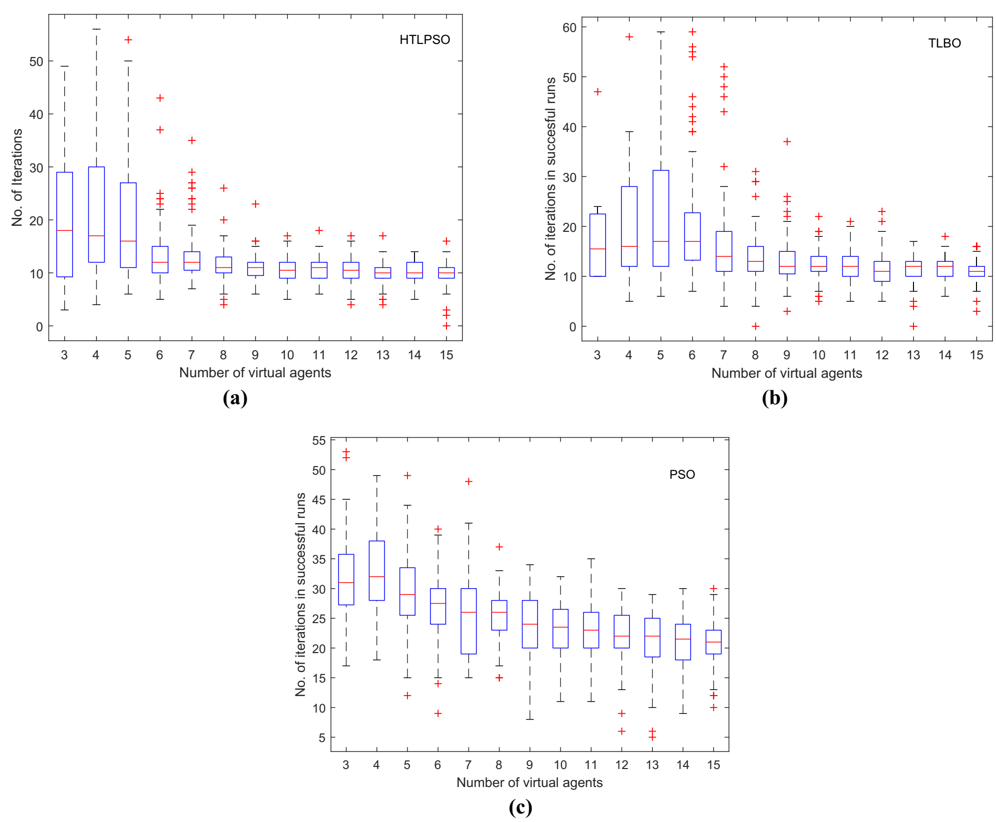


Figure 6. Number of iterations in successful runs with number of virtual agents in environment type I (**a**) HTLPSO, (**b**) TLBO, (**c**) PSO.

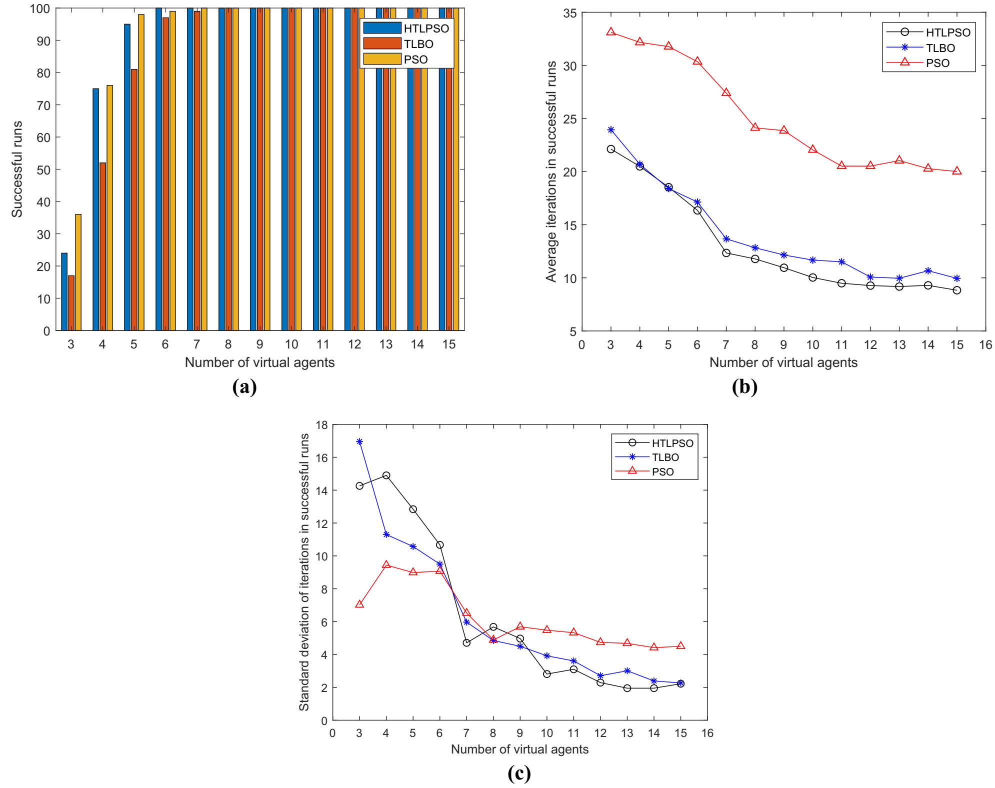


Figure 7. For three adopted methods with number of virtual agents in simulation environment type II (**a**) Success rate. (**b**) Average iterations in successful runs. (**c**) Standard deviation of iterations in successful runs.

comment on the minimum number of VAs required to carry out the successful run.

In addition to that average iterations are an important consideration and their separate discussions are furnished in each subsection of results and discussions. As per initial runs of HTLPSO, it was found that convergence is very fast [38] and VAs are able to detect the source of odor in SOS as well as in MOS. Keeping this as the basic idea the maximum number of iterations are limited to 60 only. Therefore, for a set having a group of three VAs, 60 iterations are allowed in each run with a total of 100 simulation experiments. Above mentioned factors are expected to be minimum.

Table 6. Success rate with different virtual agents for environment type III.

Environment type III with success rate								
VAs	3	4	5	6	7	8	9	{10–15}
HTLPSO	7	60	91	99	100	100	100	100
TLBO	6	32	62	87	97	99	100	100
PSO	11	34	68	81	97	100	98	100

6. Results and discussions

6.1 *Single odor source*

For SOS, performance of HTLPSO, TLBO and PSO has been evaluated in all the simulation environment types I–IV and VAs with team size varying from {3–15} are deployed to search the odor source.

6.1a *Environment type I:* Results of environment type I are discussed here whose SDET value is 0.02 as per table 3. Its other characteristics such as dimensions and source position can also be referred from table 1. Also, its source position is marked at (5, 12). Table 4 gives the success rate information using three methods namely HTLPSO, TLBO and PSO for environment type I. Here PSO is the winner with success rate 59 and 89 for VAs team size of 3 and 4, respectively. For other group size of VAs, its success rate is 100%. In comparison with PSO, HTLPSO stands at second place with success rate 23, 72, and 96 for VAs team size 3, 4 and 5, respectively. Thereafter it is 100%. However, TLBO performance is poor with success rate 8, 41, 77, 95 and 99 for VAs team size 3, 4, 5, 6 and 7, respectively. It gives 100% success rate only after team size of 8 or greater. Figure 5(a) shows the success rate in three methods adopted with number of VAs.

In addition, performance comparison based on average iterations in successful runs is also performed and shown in

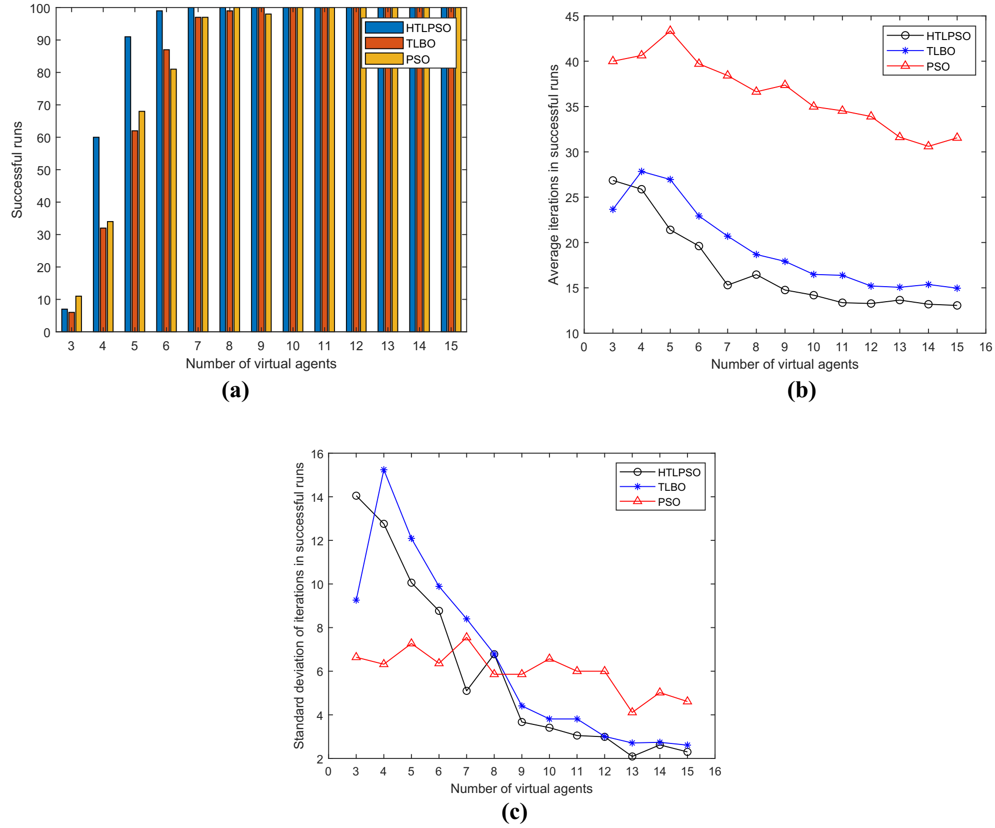


Figure 8. For three adopted methods with number of virtual agents in simulation environment type III (**a**) Success rate. (**b**) Average iterations in successful runs. (**c**) Standard deviation of iterations in successful runs.

Table 7. Success rate with different virtual agents for environment type IV.

Environment type IV with success rate									
VAs	3	4	5	6	7	8	9	10	{11–15}
HTLPSO	20	62	88	96	100	100	100	100	100
TLBO	10	31	63	85	98	100	100	100	100
PSO	5	34	57	72	92	98	99	99	100

figure 5(b). It depicts that average iterations required for PSO is maximum, thereafter decreases for TLBO and least required for HTLPSO. It can be inferred that HTLPSO is performing better in simulation runs to find and declare the odor source. For HTLPSO, if the team size is 3 then average iterations required are 21.04 but with team size of 15 it requires 9.67. It is also observed that average iterations are nearly constant for a team size of 6 and higher for HTLPSO. In comparison with HTLPSO, TLBO requires 19.12 average iterations for a team size of 3 and 10.87 average iterations for a team size of 15. It is higher than HTLPSO. Average iterations required are almost constant for TLBO for a team size of 8 or bigger. Even though PSO enjoys high success rate but it is worst performer in context to average iterations. PSO requires much higher number of average iterations for team size of 3 i.e. 31.64 and 20.7 for team size of 15. Average iterations are nearly constant for team size of 9 or higher. Figure 5(c) shows standard deviation plot of iterations in successful runs. It can be observed that there is a certain dip for team size of 6 in case of HTLPSO and 8 for TLBO. However, in case of PSO it is not easy to visualize but with a team size of 9 standard deviation decreases significantly.

Figures 6(a)–(c) show the box plot of iterations only in successful runs for all the VAs team size i.e., {3–15}. It is clearly observed that iterations for all the successful runs are minimum in HTLPSO and maximum for PSO.

6.1b *Environment type II:* Like discussion about success rate in previous section, success rate for environment type II has been summarized in table 5. From collected data, it can be observed that there is no substantial improvement in success rate for HTLPSO whereas TLBO seems to be gaining and its success rate for all the team size has improved. PSO has suffered in this simulation environment type in terms of success rate with drop recorded specially with team size of 3 and 4. But overall, again in this arena PSO has the highest success rate, followed by HTLPSO and TLBO. Except in one case, where team size is 6, HTLPSO success rate is 100 and that of PSO is 99 which is almost

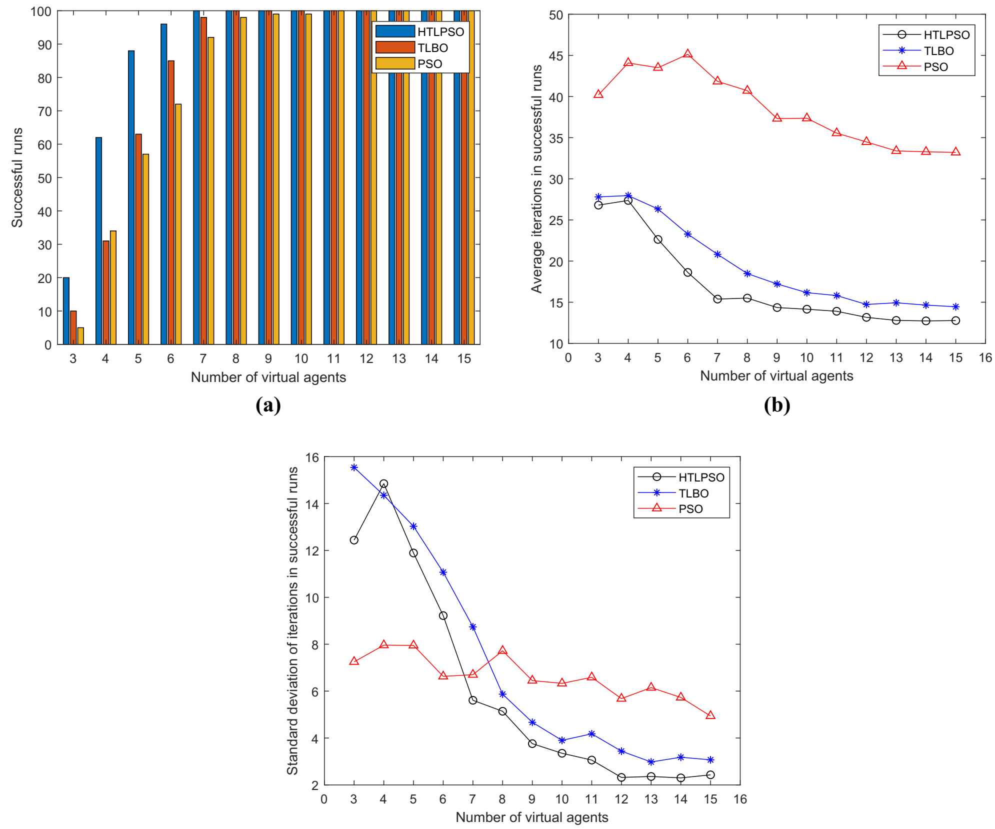


Figure 9. For three adopted methods with number of virtual agents in simulation environment type IV (**a**) Success rate. (**b**) Average iterations in successful runs. (**c**) Standard deviation of iterations in successful runs.

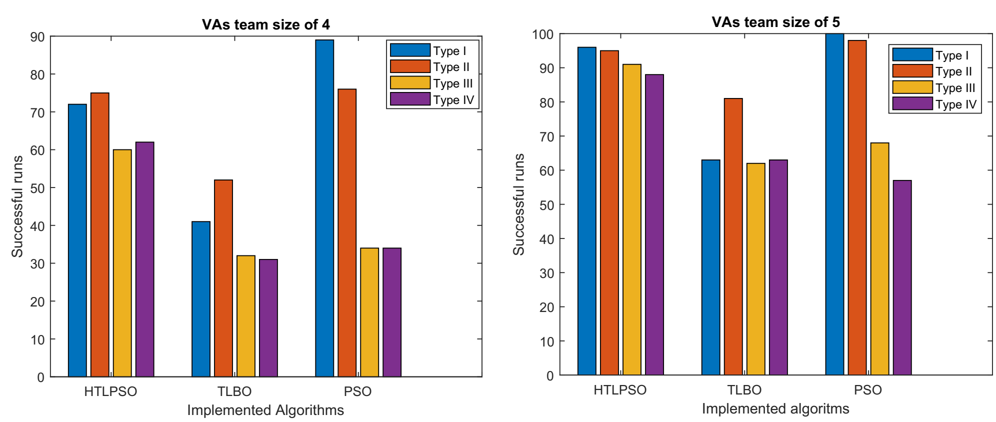


Figure 10. Success rate of HTLPSO, TLBO and PSO in simulation environment type I, II, III and IV with VAs (**a**) team size of 4, (**b**) team size of 5.

comparable. Reduced success rate in PSO is probably due to its lack in exploitation capability and which is again a factor of improvement in TLBO. Figure 7(a) shows the success rate of three methods for the present case.

As far as the average iterations are concerned as shown in figure 7(b) the trend continues to be same as for type I. PSO has the highest number of average iterations maximum being 33.11 for team size of 3 and minimum as 20.01. Average iterations of TLBO is higher than HTLPSO when team size is greater than 6. Up to team size 6 average iterations of both TLBO and HTLPSO are comparable. It means TLBO has matched its performance to HTLPSO. Alternatively, convergence is poor for TLBO with large number of VAs. Figure 7(c) shows the standard deviation plot of iterations for all three methods and clearly validates the above point mentioned for average iterations.

6.1c *Environment type III:* Results observed in this case, point out that success rate has declined for all three methods, may be owing to larger dimension of the simulation environment. Success rate results for this case have been tabulated in table 6. Interestingly, HTLPSO has the best success rate as compared to TLBO and PSO except for team size 3 which PSO exceeds the success rate of HTLPSO by 4. Figure 8(a) shows the bar graph of the success rate for three methods. For VAs team size of 4, HTLPSO registers 60 successful runs as compared to PSO with 34 and TLBO only 32 runs. This trend continues for even bigger team size of VAs making HTLPSO the highest scorer in all cases.

Average iterations required for HTLPSO is minimum except for team size of three VAs when compared to TLBO. For team size of 4 VAs, HTLPSO requires 25.88 iterations on an average whereas 27.84 iterations are required for TLBO and 40.64 iterations for PSO. This suggests that HTLPSO is an efficient algorithm in comparison with TLBO and PSO requiring less iterations, ultimately, consuming less time for runs. Figure 8(b) shows the plot for same. Variation of standard deviations with iterations is shown in figure 8(c) shows the plot. It is constant for VAs team size of 9 or bigger and nothing can be deduced about PSO due to high number of iterations.

6.1d *Environment type IV:* As compared to environment type III, in this arena improvements are noticed in case of HTLPSO but no significant improvement in TLBO (except for VAs team size of 4) and further decrement in PSO. Variations in success rate can be observed till VAs team size of 10. Table 7 gives summary of the success rate for environment type IV. Here HTLPSO has achieved success rate of 20, 62, 88 and 96 with VAs team size of 3, 4 5 and 6, respectively. Similarly, PSO has lost in terms of success rate while having only 5, 34, 57, 72 and 92 with VA team size of 3, 4, 5, 6 and 7, respectively. Figure 9(a) shows the bar graph in which HTLPSO has the best success rate is visible.

HTLPSO consumes 26.8 iterations for VAs team size of 3 and 12.77 for team size of 15 whereas, TLBO on the other hand utilizes 27.8 and 14.45 iterations on an average in successful runs respectively. PSO takes maximum number of iterations on an average to be successful as shown in figure 9(b). Standard deviation is higher for both HTLPSO and TLBO but low for PSO as shown in figure 9(c).

6.2 *HTLPSO, TLBO and PSO performance in different environments based on team size*

It is very important to note that how the algorithms performed for a particular team size of VAs. Two cases are considered (with VAs team size of 4 and 5) based on which success rate has been shown with respect to environment in which they are applied. Figure 10(a) shows for environment type I and II, PSO is performing better but for higher dimensions i.e. type III and IV, HTLPSO outperformed PSO. TLBO performance is not up to the mark and lags both HTLPSO and PSO. Similarly results of VAs with a team size of 5 are shown in figure 10(b). It is readily observed that success rate of HTLPSO and PSO is now easily comparable in environment type I and II, whereas for

Table 8. Success rate with different virtual agents for environment type V.

Environment type V with success rate

	Methods														
	HTLPSO					TLBO					PSO				
VAs	S1	S2	S3	S4	Total	S1	S2	S3	S4	Total	S1	S2	S3	S4	Total
3	7	7	14	12	40	14	2	18	11	28	0	2	38	15	55
4	5	8	42	28	83	19	2	43	12	77	4	1	59	22	86
5	11	11	49	28	99	16	6	54	15	89	4	3	78	14	99
6	8	5	56	29	98	21	4	54	18	97	5	3	64	27	99
7	11	7	51	30	99	19	3	58	19	99	0	3	67	30	100
8	14	2	45	38	99	16	5	51	28	100	6	4	62	28	100
9	10	6	43	41	100	12	6	58	24	99	0	2	68	30	100
10	10	3	55	32	100	10	5	62	23	100	3	5	67	25	100
11	7	2	47	44	100	10	3	58	29	98	2	6	57	35	100
12	9	3	53	35	100	7	2	61	30	100	1	7	59	33	100
13	8	6	51	35	100	9	6	60	25	100	2	5	60	33	100
14	8	8	43	41	100	9	3	60	28	100	9	2	62	27	100
15	8	1	55	36	100	13	3	59	25	100	4	5	63	28	100

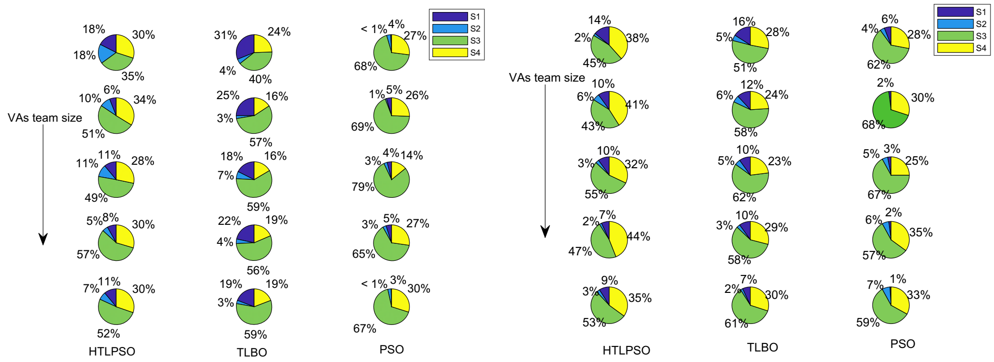


Figure 11. Success rate of HTLPSO, TLBO and PSO in percentage of all odor sources for environment type V (**a**) for VAs team size of {3–7} from top to bottom and (**b**) is {8–12}.

Table 9. Success rate with different virtual agents for environment type VI.

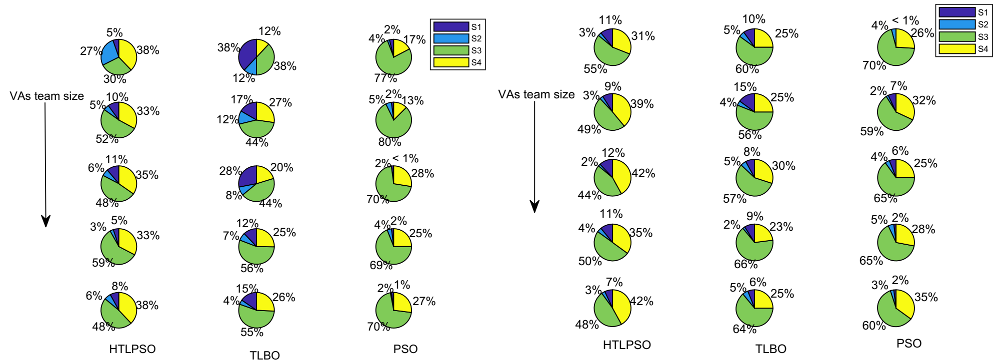
Environment type VI with success rate												
	Methods											
	HTLPSO				TLBO				PSO			
VAs	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4
3	2	10	11	14	19	6	19	6	2	1	40	9
4	8	4	41	26	11	8	29	18	2	5	77	12
5	11	6	47	34	25	7	39	18	2	0	69	27
6	5	3	58	32	12	7	55	25	2	4	69	25
7	8	6	48	38	15	4	53	25	2	1	70	27
8	11	3	55	31	10	5	60	25	0	4	70	26
9	9	3	49	39	15	4	56	25	7	2	59	32
10	12	2	44	42	8	5	57	30	6	4	65	25
11	11	4	50	35	9	2	66	23	2	5	65	28
12	7	3	48	42	6	5	64	25	2	3	60	35
13	3	1	55	41	9	3	67	21	7	6	57	30
14	9	3	50	38	6	2	70	22	7	5	56	32
15	10	3	50	37	6	0	64	30	3	4	62	31

type III and IV HTLPSO has higher success rate than PSO. TLBO as in the previous case is much lower than HTLPSO.

6.3 *Multiple odor source (MOS)*

For MOS, simulation environments are generated with parameters listed in table 2 with Eqs. (3)–(5). Figure 2(a)–(e) show the layout of the simulation environment. In this case, three methods have been applied namely HTLPSO, TLBO and PSO to compile the results based on success rate and average number of iterations. SDET in all the simulation environment types V–IX has been taken as 0.3 meters. As discussed earlier, VAs team size of {3–15} has been taken into consideration for search and identification of the source.

6.3a *Environment type V for MOS:* There are four odor sources kept at positions (5, 10), (5, 15), (8, 12) and (4, 18) with the emission rate {0.5, 0.3, 0.6, 1} mg/s respectively. Source kept at (4, 18) i.e., S4 as shown in figure 2(a) has the highest emission rate followed by S3 (8, 12), S1 (5, 10) and S2 (5, 15). It is expected that success rate out of 100 runs for all the odor sources may be in the sequence S4 > S3 > S1 > S2. As per table 8 declaration of odor source S3 and S4 is prominent. S3 is second highest emitting source, however, VAs may encounter S3 prior to S4 due to its location and direction of wind. S4 is kept a little bit before S2 and S1 and emitting at the highest rate. Even chances of locating S1 is higher because it enjoys the third highest emission rate. However from table 8 it can be observed that S3 and S4 declarations are as desired for PSO but S1 declarations are comparatively lower than S2. As S1 is at a little bit more distance than S2 (it is closer to S4) PSO algorithm is unable to detect. As far as TLBO is concerned, S1 declarations are greater than S2 whereas S4 and S3 declarations are as desired. In contrast, HTLPSO has equally performed well for S4 and S3, but S1 and S2 are comparable. However, declarations of S3 are greater than S4 in all three algorithms while S1 greater than S2 in HTLPSO and TLBO only. Therefore, it is not easy to compare these algorithms for MOS. Hence figure 11(a) can be referred which shows that for VAs team size of 3, S4 declarations/identification are 30%, 24% and 27% in HTLPSO, TLBO and PSO respectively. Taking in consideration figure 11(b) in all the cases of VAs team size of {3–12} HTPSO declares S4 with highest percentage (except for VA team size of 7 where HTLPSO is equal to PSO i.e., 30%) as compared to TLBO and PSO. It is desired as per the given conditions. Thereafter, PSO is in the list which exceeds TLBO except the case of VAs team size of 5 (here PSO is 14% and TLBO is 16%) and 8 (both are equal). S3 declarations are undesired and can be a factor for choosing one out of three algorithms. Here it is observed that HTLPSO has the least percentage of S3 declarations (except VAs team size of 6 in which HTPSO is 57% and



(a) (b)

Figure 12. Success rate of HTLPSO, TLBO and PSO in percentage of all odor sources for environment type VI (**a**) for VAs team size of {3–7} from top to bottom and (**b**) is {8–12}.

Table 10. Success rate with different virtual agents for environment type VII.

Environment type VII with success rate												
	Methods											
	HTLPSO				TLBO				PSO			
VAs	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4
3	2	5	25	11	14	6	20	6	5	2	35	15
4	11	9	30	31	13	7	37	20	3	4	68	14
5	8	5	49	33	23	7	47	12	4	8	62	23
6	10	3	57	30	15	2	56	24	2	1	72	24
7	8	2	52	37	11	3	53	31	4	3	59	34
8	7	5	49	39	14	1	64	21	4	4	59	33
9	9	5	53	33	10	3	68	19	0	3	58	39
10	19	2	45	34	18	1	55	25	5	5	63	27
11	4	3	54	39	9	6	61	24	1	7	57	35
12	7	3	59	31	12	2	59	27	7	3	57	33
13	4	8	49	39	9	3	77	11	4	5	64	27
14	12	6	44	38	12	1	59	28	1	6	59	34
15	10	5	53	32	10	3	59	28	3	4	58	35

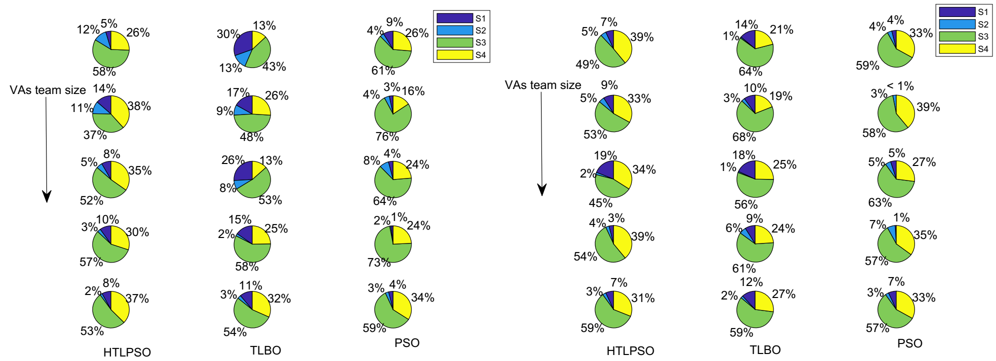
TLBO is 56%). Even after that TLBO has the lesser declaration percentage for S3, and PSO suffers drastically on this aspect (except for VAs team size of 11 and 12). Therefore, total collective declarations for S1, S2, S3 and S4 are highest for PSO but it can't be selected due to above reasons. The optimum choice will be HTLPSO for highest declaration percentage for S4 and comparatively less declarations for S3.

6.3b *Environment type VI and VII for MOS:* In this section results for environment types VI and VII have been presented. Environment type VI and VII has been generated with modified parameter of wind speed. To study the effect of wind on performance of algorithms first the wind speed has been reduced to 1.5 m/s which corresponds to type VI. It has been further increased to 4.5 m/s which corresponds to type VII. Other all parameters have been kept same with no change as listed in table 2. Success rate results have been tabulated in table 9 for type VI. It is observed that HTLPSO performs best for all team size of virtual agents. Figure 12 can also be referred for the same where odor source wise declaration percentage has been shown for environment type VI. As the sequence remains same as that of previous case i.e. S4 > S3 > S1 > S2 this has been well maintained by HTLPSO again. For type VII, results with success rate have been shown in table 10.

Here it can be observed that for environment type VII, HTLPSO performance has been affected with increased wind speed. HTLPSO has performed best except for the VAs team size of 9 and 12. With these VAs team size PSO has outperformed other two algorithms. Figure 13 can also be referred for the same where odor source wise declaration percentage has been shown for environment type VII.

6.3c *Environment type VIII for MOS:* Environment type VIII is very similar to that of environment type V. There are few noticeable changes regarding placement of odor sources. This particular environment has been generated to study the effect of placement of odor sources on the success rate of algorithms. More details regarding this environment is available in table 2. As per table 11, it is interesting to know that TLBO has surpassed the values of HTLPSO and PSO in terms of success rate. Figure 14 gives the better picture. In all team size of VAs, TLBO performance is best followed by HTLPSO. This brings important highlight about its percentage in declaring the odor sources in the sequence S4 > S3 > S1 > S2. It is observed best in TLBO. The reason behind this is the placement of odor sources which are scattered in space as compared to environment type V. Exploration is the advantage for TLBO hence it gets maximum benefit in locating the four odor sources in desired sequence.

6.3d *Environment type IX for MOS:* This environment was created to study the impact of emission rate of odor



(a) **(b)**

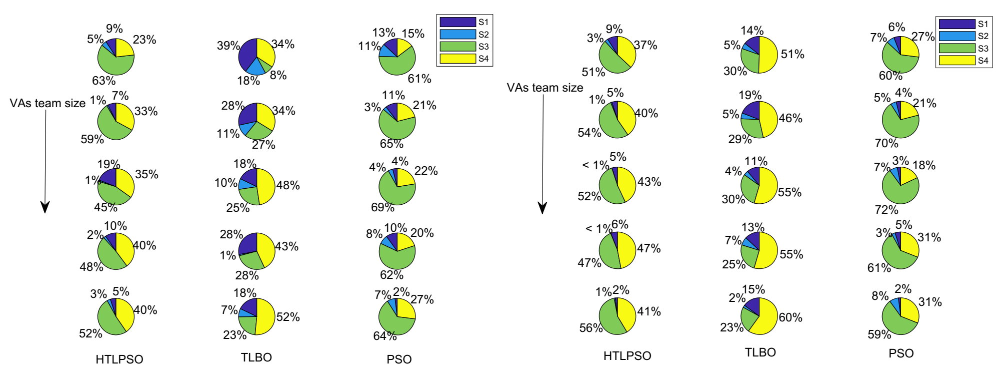
Figure 13. Success rate of HTLPSO, TLBO and PSO in percentage of all odor sources for environment type VII (**a**) for VAs team size of {3–7} from top to bottom and (**b**) is {8–12}.

Table 11. Success rate with different virtual agents for environment type VIII.

Environment type VIII with success rate												
	Methods											
	HTLPSO				TLBO				PSO			
VAs	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4
3	4	2	27	10	15	7	3	13	8	7	37	9
4	6	1	48	27	21	8	20	25	10	3	62	20
5	17	1	40	31	15	8	21	40	4	4	68	22
6	9	2	45	37	26	1	26	40	10	8	62	20
7	5	3	51	40	17	7	22	49	2	7	64	27
8	9	3	51	37	14	5	29	49	6	7	60	27
9	5	1	53	40	19	5	29	46	4	5	70	21
10	5	0	52	43	11	4	30	54	3	7	72	18
11	6	0	47	47	13	7	25	54	5	3	61	31
12	2	1	55	41	15	2	23	60	2	8	59	31
13	7	2	49	42	10	2	32	56	6	4	60	30
14	5	3	54	38	14	0	28	58	8	1	70	21
15	5	0	52	43	8	4	36	52	4	7	63	26

Table 12. Success rate with different virtual agents for environment type IX.

Environment type IX with success rate												
	Methods											
	HTLPSO				TLBO				PSO			
VAs	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4
3	2	15	16	6	15	13	15	4	2	12	44	3
4	4	31	47	8	4	22	47	3	0	11	71	6
5	2	34	53	5	6	29	51	3	2	8	84	3
6	3	37	50	8	1	36	61	2	3	14	78	5
7	2	44	46	8	4	44	48	4	1	18	78	3
8	1	38	51	10	3	49	46	2	0	17	78	5
9	3	51	44	1	4	42	52	2	0	23	72	5
10	1	53	43	2	0	44	54	2	1	21	75	3
11	1	50	47	2	1	40	58	1	1	22	70	7
12	2	50	43	5	0	44	54	2	1	18	76	5
13	0	48	49	3	0	45	53	2	1	25	65	9
14	2	54	42	2	1	51	46	2	0	33	60	7
15	2	51	45	2	1	42	54	3	0	33	65	2



(a) **(b)**

Figure 14. Success rate of HTLPSO, TLBO and PSO in percentage of all odor sources for environment type VIII (**a**) for VAs team size of {3–7} from top to bottom and (**b**) is {8–12}.

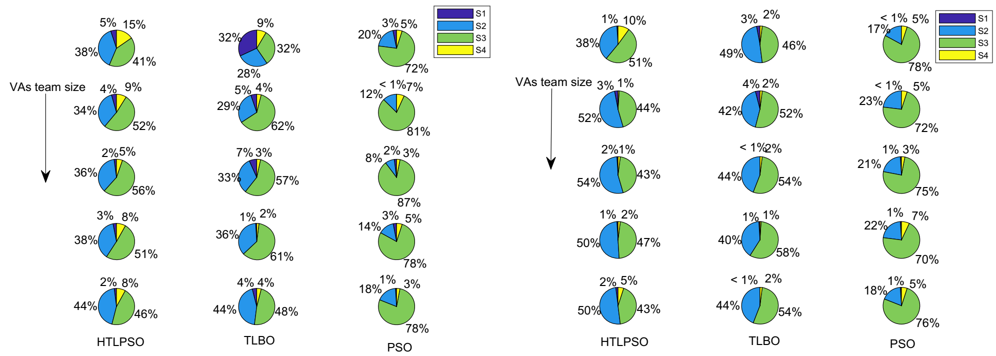


Figure 15. Success rate of HTLPSO, TLBO and PSO in percentage of all odor sources for environment type IX (**a**) for VAs team size of {3–7} from top to bottom and (**b**) is {8–12}.

sources on algorithms. As the odor source locations are similar to environment type V but their emission rates have been reshuffled as {0.3, 1, 0.6, 0.5} mg/s. So, keeping the same locations but changing their emission rates will change the expected outcome of declaration as S2 > S3 > S4 > S1. It is important to note that the earlier sequence was S4 > S3 > S1 > S2 for environment type V in which HTLPSO was the best performer. As per table 12 it can be observed that HTLPSO remains at the same level of success outperforming TLBO and PSO. A better pictorial representation can be seen in figure 15. There are only two cases where HTLPSO success percentage is either equal or less than TLBO. It is for VAs team size of 7 and 8 respectively. For VAs team size of 7 both HTLPSO and TLBO are equal to 44% for S2. It is 38% and 49% for HTLPSO and TLBO respectively for VAs team size of 8. From figure 15 it can be inferred that PSO has performed very badly. So, the optimum choice would be HTLPSO again.

7. Conclusions

In the present work, odor source localization problem has been addressed with adopted optimization-based algorithms. There were two cases taken into consideration. In the first case, only a single odor source was emitting chemical gas whereas in second the chemical concentration at a point is cumulative effect of multiple odor sources. Gaussian plume model was used to simulate the environments. For the first case i.e. SOS there were four distinct environments generated in terms of layout as well as other environmental factors such as diffusion constant and wind velocity. On the other hand, for MOS there were five distinct environments with the same layout but different factors such as emission rates, placement of odor sources and wind velocity. The analysis of results points out that for SOS, environment type I, PSO has outperformed HTLPSO and TLBO when number of VAs are in the team size of {3–5}. Success rate of PSO is highest, whereas HTLPSO stands second and TLBO is third. When the number of agents in the group was increased, it improved the success rate of HTLPSO to 100% equal to that of PSO. Pertaining to TLBO, it had success rate of 95% and 99% for team size of 6 and 7 respectively and then becomes 100% for bigger team size. For environment type II, success rate was almost consistent for HLTPSO whereas for PSO it had decreased. There was increase in success rate for TLBO, even then its lower than PSO and HTLPSO. Therefore, in this environment, HTLPSO ranked first, PSO second and TLBO third even though its success rate had improved. In environment type III, performance of all three algorithms had reduced but significantly for TLBO and PSO. HTLPSO in environment type III had performed better than TLBO and PSO. For the last environment type IV, HTLPSO success rate for the last simulation environment remained unchanged (almost as that of type III) except for improvement with VAs team size of 3. However, no improvements or decrements were observed in TLBO. For PSO it further reduced. As the dimensions were increased for single odor source, it was found that HTLPSO had outperformed both TLBO and PSO. It had optimally utilized both the characteristics of exploration and exploitation in higher dimensions of simulation environment.

For MOS, all the environment types had the arena layout of 50 m × 50 m. Some other factors such as wind velocity, odor sources placement and emission rate were changed. Impact of these three was studied on the implemented algorithms. It was found that in the presence of weak/strong wind flow, performance of HTLPSO was not affected and gave best result of the success rate (environment types V, VI and VII). Needless to mention in these environmental conditions odor sources were placed very close to each other. When these odor sources were scattered (environment type VIII) TLBO emerged as a winner. Even if the emission rates were reshuffled, HTLPSO remained the best performer (environment type IX). Overall HTLPSO may be the optimum choice for the arenas in consideration. Further, these algorithms may be tested on MOS in larger dimensions which is not considered in this study.

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