IAES International Journal of Robotics and Automation (IJRA)
Vol. 13, No. 3, September 2024, pp. 255~263
ISSN: 2722-2586, DOI: 10.11591/ijra.v13i3.pp255-263

A hybrid gradient climbing algorithm for a swarm robot-based gas leak detector

Adeola Erastus Adegunsoye[1], Brendan Ubochi[1], John Macaulay[2], Kayode Francis Akingbade[3]
[1]Department of Electrical/Electronic Engineering, School of Engineering and Engineering Technology, Federal University of Technology, Akure, Nigeria
[2]Cardiff School of Technologies, Cardiff Metropolitan University, Cardiff, United Kingdom
[3]Department of Information and Communication Technology, School of Engineering and Engineering Technology, Federal University of Technology, Akure, Nigeria

Article Info

Article history:

Received Dec 11, 2023
Revised May 16, 2024
Accepted Jun 17, 2024

Keywords:

Convergence time
Firefly agents
Gas leakage detection
Gradient climbing
Opportunistic agents
Path length
Swarm intelligence
Swarm robotics

ABSTRACT

Methane emissions from leak sources can have a negative climate impact, in addition to contributing to the risk of explosions in urban environments. These risks can be minimized by developing systems that provide for an accurate and timely detection and localization of a gas leakage point. This research used a swarm of robots to detect and locate a leakage point. The localization algorithm derives from further optimization of the gradient climbing algorithm using fireflies acting as opportunistic agents. Firefly agents are characterized by their bioluminescent communication which guides them to dynamically adjust their positions and intensities based on the quality of the gradient information available to them. The proposed research focuses on enhancing gas leak detection through the development of a hybrid gradient climbing algorithm. This algorithm integrates gradient climbing techniques with swarm intelligence, utilizing the strengths of both approaches. This simulation resulted in the hybrid algorithm leading to a reduced convergence time and path lengths when compared to the swarm without opportunistic agents. The suggested approach can be important especially in gas distribution systems or in areas where human intervention is considered to be unsafe.

Corresponding Author:

John Macaulay
Cardiff School of Technologies, Cardiff Metropolitan University
Cardiff, United Kingdom
Email: JMacaulay@cardiffmet.ac.uk

1. INTRODUCTION

Gas leak incidents occurring either at homes, gas distribution systems, or in an industrial environment constitute a severe environmental health hazard. It was revealed that natural gas leakages otherwise known as fugitive emissions at individual leak points in the gas distribution systems in Metro Boston, Massachusetts, can range from between $4.0 - 2.3 \times 10^4 g\ CH_4\ day^{-1}$ with fifteen percent of surveyed leaks characterized as potentially explosive [1], [2]. While these methane emissions due to gas leakages can have a negative climate impact, they also constitute a risk to explosions in urban environments [2], [3]. In Nigeria, there were around 2,346 reported cases of domestic fire accidents between 2010 and 2014, a majority of these accidents have been attributed to the widespread leakages from liquefied natural gas (LPG) cylinders [4], [5].

The early detection and localization of a gas leak can have profound implications on human safety, industrial operations, and environmental preservation [6]. The main objectives of any gas monitoring system are the detection and localization of a gas leak. Previous monitoring systems have relied mostly on sensor-based technologies that are placed at fixed pre-determined locations and sometimes incorporate communication devices for remote data transmission over the Internet of things (IoT) [7], [8]. Recently, mobile robot-based monitoring systems have been suggested especially for outdoor monitoring of gas pipelines [9], [10]. While these systems are generally less expensive than most of the fixed-sensor based systems, they may suffer from longer detection and localization times. Consequently, multi-robot systems have been developed in configurations such as the alpha-follower, that aim to improve the detection and localization times [11]–[13]. These approaches are, however, hampered by their accuracy and reliability since these parameters depend disproportionately on the swarm leaders/explorers.

The accuracy can improve if each robot in a swarm contributes guidance information allowing the swarm to collectively detect and locate gas leaks more effectively. A popular technique known as gradient climbing utilizes shared information within the swarm that relates to the measured gas concentration gradient in the air as a function of the distance away from the source [14]. Gradient climbing is implemented such that each robot measures a local gradient, which represents the direction of the steepest increase in the intensity of a particular signal, such as light, odor plume, or temperature [15]. Robots then use this information to adjust their own movements, moving in the direction of the steepest gradient until they reach the target location or object. The main problem with the gradient climbing algorithm is that it often gets stuck in a local optimum, making it difficult to find the global optimum [16]. Additionally, it may converge towards a point in the search space that is neither a local nor global optimum [17].

In this study, the firefly algorithm has been selected to further optimize the gradient climbing algorithm. The attributes of some of the robots in the swarm are modified by the firefly algorithm thereby characterizing them as opportunistic agents [18]. Opportunistic agents can take advantage of random events and changes in the environment to improve their performance and thus enhance the optimization process [19]. By integrating fireflies as opportunistic agents, the swarm can dynamically adapt its composition and optimize gradient climbing to improve detection accuracy and response time. Swarm coordination techniques, such as consensus algorithms or distributed control strategies, are implemented to ensure synchronized and efficient behavior of the swarm [11]. In the simulations, the dispersion of gas has been modeled using the Gaussian plume model [20] since it offers advantages such as its analytical tractability and computational efficiency. Also, path planning algorithms are integrated into the swarm robot system to optimize the trajectories during gradient climbing [21]. The potential field method is used to guide the movement of swarm robots towards the gas leakage point and it is defined by combining the attractive and repulsive forces [22]. Whereas the attractive forces pull the swarm toward the gas leakage point, the repulsive forces prevent them from colliding with one another and with obstacles in the environment.

2. METHOD

The first objective of this study is to model gas leak concentration in a constrained environment. The mathematical formulation used to model this is the Gaussian Plume [19]. It is used to estimate the concentration of gas at different locations within the environment in the vicinity of the gas emitting source. The model assumptions include i) the gas dispersion occurs in three-dimensional space; ii) the gas release is continuous and from a single-point source; and iii) the gas is well-mixed and behaves as a passive scalar and the influence of obstacles and topography on the dispersion is neglected.

The Gaussian Plume model estimates the concentration of gas at a specific location (x, y, z) in the environment using (1) [23],

$$C_{(x,y,z)} = \frac{Q}{2\pi u \sigma y_i \sigma_{Zi}} exp - \frac{(y_1-y_0)^2}{2{\sigma_y}^2} [\exp - \frac{(Z_i-h_0)^2}{(2\sigma_{zi})^2} + \exp - \frac{(z_i+h_o)^2}{(2\sigma_{zi})^2}] \tag{1}$$

where $C_{(x,y,z)}$ represents the 3-D gas concentration at position with coordinates x, y, and z; Q is the emission rate of the gas (amount of gas released per unit time) (kgs^{-1}); u is the wind speed at the location of interest (ms^{-1}); (y_0, z_0) denotes the coordinates of the gas release point; σ_y *and* σ_z represent the standard deviations of the gas plume in the y and z directions, respectively. The concentration gradient is estimated from the partial derivative of the Gaussian Plume model and is given in (2) to (4) [24].

$$\frac{\partial c}{\partial x} = 0 \tag{2}$$

$$\frac{\partial c}{\partial y} = \left(\frac{Q}{(\pi u \sigma_y \sigma_z)}\right) * (\mathrm{y} - y_0) \times \exp\left(-\left(\frac{(y-y_0)^2}{2\sigma_y^2} - \left(\frac{(z-z_0)^2}{2\sigma_z^2}\right)\right)\right) / {\sigma_y}^2 \tag{3}$$

$$\frac{\partial c}{\partial z} = \left(\frac{Q}{(\pi u \sigma_y \sigma_z)}\right) \times (z - z_0) \times \exp\left(-\left(\frac{(z-z_0)^2}{2\sigma_y^2} - \left(\frac{(z-z_0)^2}{2\sigma_z^2}\right)\right)\right) / {\sigma_z}^2 \tag{4}$$

The gradient of gas concentration is represented by the vector (5).

$$\nabla C = [\partial C/\partial x, \partial C/\partial y, \partial C/\partial z] \tag{5}$$

To ensure that the gradient of gas concentration is positive-definite, constraints or normalization techniques are applied to the gradient vector ∇C. This is achieved by scaling the concentration values to between 0 and 1 and ensuring that the gradient remains positive or zero. This normalization process ensures that the swarm robots follow the direction of increasing gas concentration toward the leak point, avoiding any non-physical or contradictory movements. The swarm updates its position with the agent's position closest to the gas source. This is illustrated in Figure 1. However, the movement of the swarm towards the gas leak point is modelled by attractive and repulsive forces given in (6) and (7), respectively.

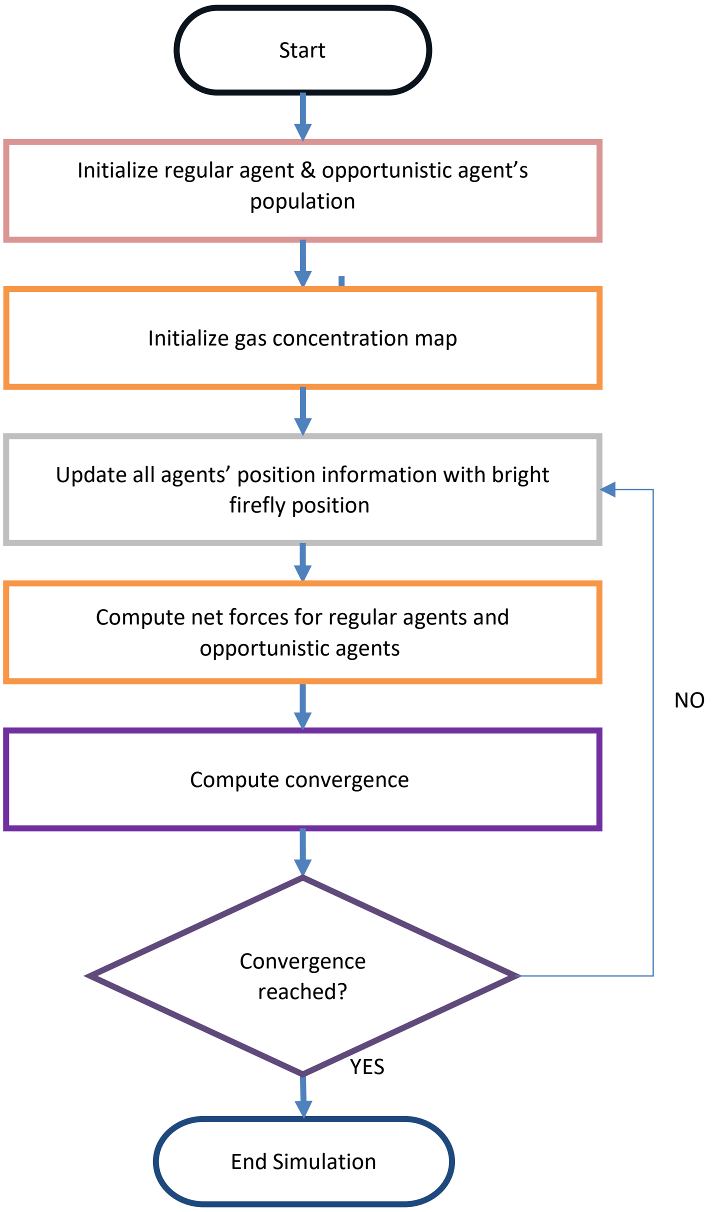

Figure 1. Flowchart for the simulation of swarm robot's gas leak detection with regular and opportunistic agents

$$F_{att} = K_a \times \frac{\nabla}{r} \quad (6)$$

$$F_{Rep} = \sum_{i=1}^{N} k_r \times \frac{p_{r-} p_O}{D^2} \quad (7)$$

Here, F_{att} and F_{Rep} are the attractive and repulsive forces respectively; K_a and k_r are constant scalar controlling the strength of attraction and repulsion.; ∇ is the normalized vector pointing from the robot's position to the gas leakage point and r is the Euclidean distance between the robot's position and the gas leakage point; N is the total number of robots or obstacles; $p_{\ r}$ is the position vector of the robot; p_O is the position vector of the obstacle. By summing the attractive and repulsive forces, the net force acting on each robot is determined. This force is then used to update the robot's velocities and guide its movement towards the gas leakage point.

2.1. Gradient climbing with opportunistic agents

Each regular swarm robot is modelled as a point mass with position, p_i, and velocity, v_i, where "i' represents the robot index. The dynamics of the regular swarm robots can be described by (8) and (9) [25].

$$p_i(t + \Delta t) = p_i(t) + v_1(t) \times \Delta t \quad (8)$$

$$v_i(t + \Delta t) = v_i(t) + \frac{F_i(t)}{m} \times \Delta t \quad (9)$$

Here, Δt represents the time step, F_i is the net force acting on the i^{th} regular swarm robot, and m is the mass of each robot. Similar to the regular swarm robots, each opportunistic agent is also modelled as a point mass with position p_{op} and velocity v_{op}. The dynamics of the opportunistic agents can be represented by (10) and (11).

$$p_{op}(t + \Delta t) = p_{op}(t) + v_{op}(t) \times \Delta t \quad (10)$$

$$v_{op}(t + \Delta t) = v_{op}(t) + \frac{F_{op}(t)}{m_{op}} \times \Delta t \quad (11)$$

Here, F_{op} is the total force acting on the opportunistic agent, and m_{op} represents its mass.

Let $F_{att,op}$ denote the attractive force on opportunistic agents towards the gas leakage point and $F_{rep,op}$ represent the repulsive force from both regular and opportunistic agents within the repulsive radius. The attractive force for the opportunistic agents is given by (12),

$$F_{att,op} = K_{att,op} \times (p - p_{op}) \quad (12)$$

where $K_{att,op}$ is a proportionality constant, p is the gas leakage point, and p_{op} is position of opportunistic agent.

The repulsive forces are computed based on the inverse squire law, where $K_{rep,op}$ is a proportional constant and r_{rep} is the repulsion radius as given in (13),

$$F_{rep,op} = -k_{rep,op} \sum_{i=1}^{n} \left(\frac{P_{op} - P_{ag} i}{\|P_{op} - P_{ag} i\|^2} \right) \times fa_{rep}\left(\|P_{op} - P_{ag} i\|\right), r_{rep}$$
$$fa_{rep}(d, r_{rep}) = \begin{cases} 1, & if\ d < r_{rep} \\ 0, & x \geq otherwise \end{cases} \quad (13)$$

where P_{ag} is the position of regular agent and fa_{rep} is the repulsive factor.

The net force acting on each regular swarm robot (F_i) is computed by considering attractive and repulsive forces; the attractive force ($F_{att,i}$) directs the regular swarm robots towards the gas leak, while the repulsive force ($F_{rep,i}$) helps them avoid collisions with obstacles and other robots. This net force is given by (14).

$$F_i = F_{att,i} + F_{rep,i} \quad (14)$$

2.2. The proposed hybrid system

This proposal leverages the strengths of both the swarm and firefly agents to improve gas leak localization and concentration estimation. The attractiveness, $\beta(r)$, of fireflies is proportional to their light intensities $I(r)$ seen by adjacent fireflies [26], and is given in (15).

$$I(r) \propto \beta(r) \tag{15}$$

This is given by (16) to (19),

$$I(r) = k\,\beta(r) \tag{16}$$

$$\beta(r) = \beta_0 e^{-\gamma r^2} \tag{17}$$

$$I(r) = i_0 e^{-\gamma r^2} \tag{18}$$

$$i_0 = k\beta_0 \tag{19}$$

where i_0 is the original light intensity, k is the constant of proportionality, β_0 is the attractiveness at $r = 0$, γ is the coefficient of light absorption, and r represents the Euclidean distance. The distance between any two fireflies s_i and s_j is expressed as the Euclidean distance between them expressed as (20).

$$r_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{20}$$

The movement of a firefly i towards another more attractive (brighter) firefly j is determined by (17),

$$x_i = x_i + \beta_0 e^{-\gamma r^2} ij\left(x_j - x_i\right) + \alpha(rand - \tfrac{1}{2}) \tag{21}$$

where the second term is due to the attraction, while the third term is randomization with α being the randomization parameter, and $r\ and$ i is a vector of random numbers drawn from a Gaussian distribution. These firefly agents act as opportunistic members within the swarm to further enhance the system's performance.

2.3. Computation of convergence

Lastly, in order to evaluate the performance of the developed model, the convergent rate is considered. The convergence, c_t, for ‘n’ swarms at every iteration t, is obtained by summing the distance of all agents to the gas leak point. The convergent point is thus determined by numerically differentiating the curve where time corresponding to the zero value indicates the convergence time.

2.3.1. Swarm path length

The cumulative distance traveled by individual robots or agents within the swarm while executing the leakage detection can be estimated. It is a measure of the total distance covered by the agents until convergence has been met. The path length is a fundamental metric that provides insights into the overall swarm convergence performance and the effectiveness of swarm communication. The distance traveled by each agent is calculated by multiplying the number of steps taken to converge with the step length [27]. The algorithm is implemented and simulated in MATLAB with an Intel(R) Core(TM) i5-10210U CPU @ 1.60GHz 2.11 GHz processor and 8GB RAM computer. This is implemented in a flowchart in Figure 1.

3. RESULTS AND DISCUSSION

The simulations consist of three routine iterations: i) simulations of 25 regular swarms (Case 1); ii) simulations of 15 regular swarms and 10 swarms with opportunistic behavior (Case 2); and iii) simulations of 15 regular swarms and 10 fireflies (Case 3) to determine convergence time and the calculated path lengths of the three scenarios. Also, the combination of fireflies and regular agents was varied to ascertain the best combinational ratio between the swarms. Figure 2 shows the normalized plots of the simulations of 3 scenarios. It can be observed that the combination of regular agents and fireflies gives a better convergence than the other two. This suggests that the addition of opportunistic agents, having more effective search strategies, aids in reaching the desired state faster.

Figure 3 shows a comparison of different combinations of swarms- regular agents and fireflies. From the result, the combination of 15 regular agents and 10 fireflies gives the best result among the selected configurations for converging toward the gas leakage point. This result suggests that for a given swarm size consisting of a combination of regular and opportunistic agents, the optimum combining ratio is required to be determined in order to achieve an improved convergence. Figure 4 compares the path lengths of the three different swarms. The swarm of regular agents alone has a total path length of 935.98 m; the combination of regular and opportunistic agents is 892.74 m, while the path length for a combination of regular agents and fireflies is 846.83 m. Although the firefly agents (16-25) have longer individual path lengths, their contribution to determining the optimum route to the leakage point results in a reduction in the overall swarm path length. Longer swarm path lengths typically indicate that agents are taking longer routes to reach their destinations and this inefficiency could be due to suboptimal navigation strategies.

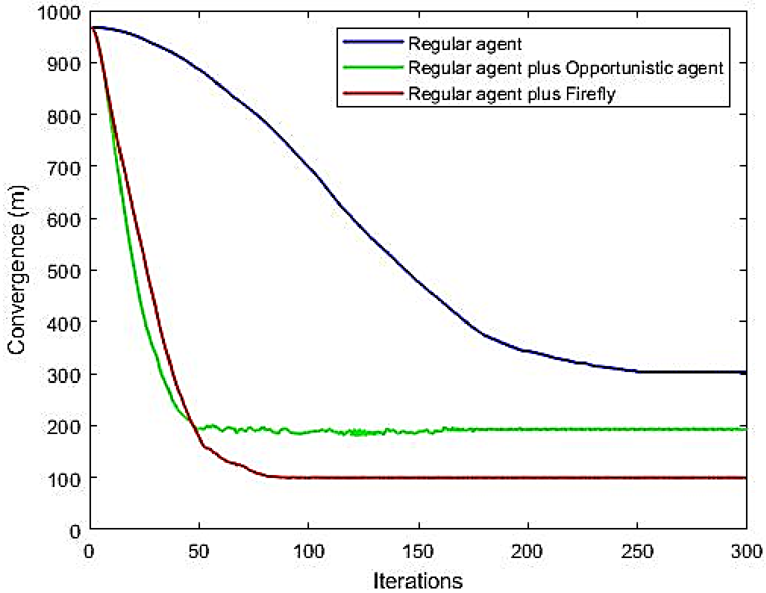

Figure 2. Comparison of three convergence plots: regular agents, regular and opportunistic agents and regular agents and fireflies

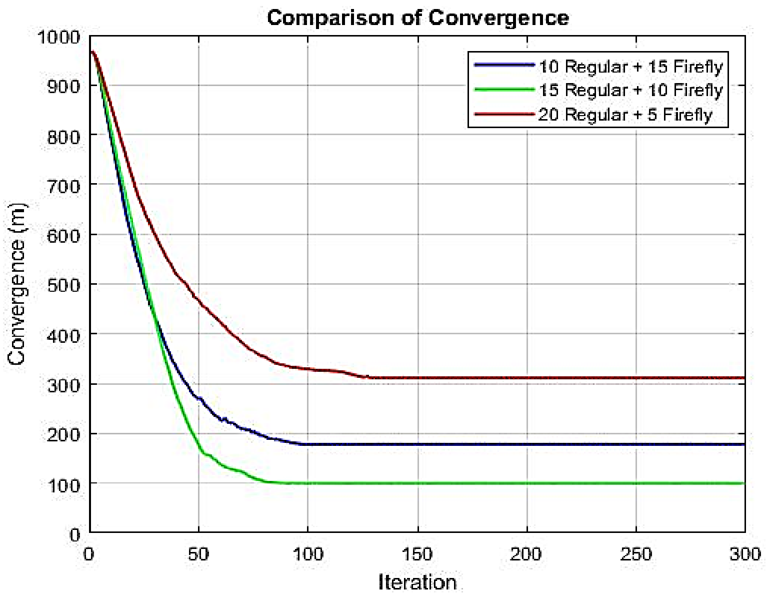

Figure 3. Convergence plots for different combination of regular agents and fireflies

In summary, the addition of opportunistic agents can significantly improve the performance of swarms utilizing the gradient climbing algorithm in localization tasks. Firefly agents, known for their attraction-repulsion behavior inspired by firefly behavior in nature, seem to be particularly effective in improving the optimization process. Further experiments may provide additional insights into the optimal composition and behavior of the agent swarm for specific optimization tasks.

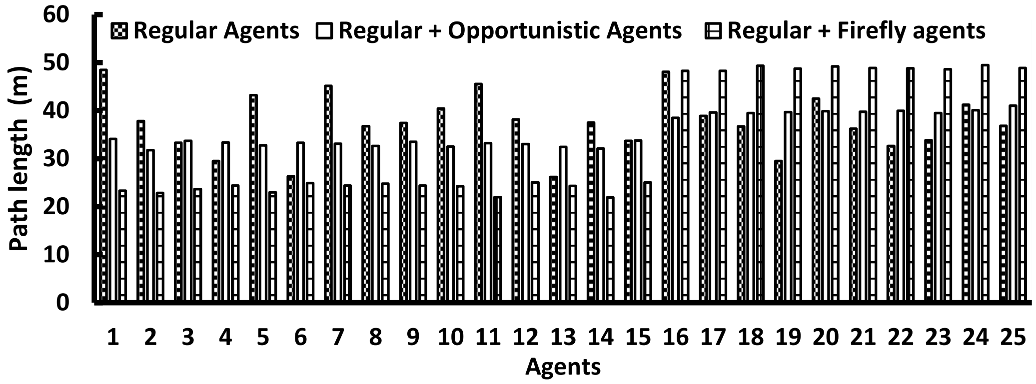

Figure 4. Path length to convergent of all the swarm

4. CONCLUSION

This study has proposed a hybrid algorithm consisting of gradient climbing and the firefly algorithms for swarm-based gas leak localization tasks. This has been implemented in a swarm of 25 agents by selecting the optimum combining ratio of regular agents (gradient climbing-based), opportunistic agents, and firefly agents. The results indicate that the swarm performance depends on the composition of the swarm and is significantly improved in terms of the time to convergence and the total path lengths when the opportunistic agents are included. The convergence time and the path lengths are 25 s and 936 m, 5.2 s and 892 m, and 8.2 s and 846 m for regular agents alone (Case 1), regular plus opportunistic agents (Case 2), and regular plus firefly agents (Case 3), respectively. Despite a slightly longer convergence time of Case 3 when compared to Case 2, the firefly-enhanced swarm exhibits greater resilience, attaining convergence with reduced path lengths. These results highlight the importance of the hybrid algorithm in swarm-based gas leak localization. This approach substantially improved the convergence time compared to using regular agents alone, demonstrating the benefits of a mixed-composition strategy for this task.

ACKNOWLEDGEMENTS

The first author would like to thank Dr. Okechi Onuoha for his discussions to improve the quality of the paper.

REFERENCES

[1] J. D. Albertson *et al.*, "A mobile sensing approach for regional surveillance of fugitive methane emissions in oil and gas production," *Environmental Science & Technology*, vol. 50, no. 5, pp. 2487–2497, Mar. 2016, doi: 10.1021/acs.est.5b05059.

[2] M. F. Hendrick, R. Ackley, B. Sanaie-Movahed, X. Tang, and N. G. Phillips, "Fugitive methane emissions from leak-prone natural gas distribution infrastructure in urban environments," *Environmental Pollution*, vol. 213, pp. 710–716, Jun. 2016, doi: 10.1016/j.envpol.2016.01.094.

[3] E. A. Grubert and A. R. Brandt, "Three considerations for modeling natural gas system methane emissions in life cycle assessment," *Journal of Cleaner Production*, vol. 222, pp. 760–767, Jun. 2019, doi: 10.1016/j.jclepro.2019.03.096.

[4] O. Belie, B. O. Mofikoya, I. O. Fadeyibi, A. O. Ugburo, A. Buari, and N. N. Ugochukwu, "Cooking gas explosions as cause of burns among patients admitted to a regional burn centre in Nigeria," *Annals of burns and fire disasters*, vol. 33, no. 1, 2020.

[5] Z. D. Weller, S. Im, V. Palacios, E. Stuchiner, and J. C. von Fischer, "Environmental injustices of leaks from urban natural gas distribution systems: patterns among and within 13 U.S. metro areas," *Environmental Science & Technology*, vol. 56, no. 12, pp. 8599–8609, Jun. 2022, doi: 10.1021/acs.est.2c00097.

[6] X. Zhang, X. Hu, Y. Bai, and J. Wu, "Risk assessment of gas leakage from school laboratories based on the Bayesian network," *International Journal of Environmental Research and Public Health*, vol. 17, no. 2, Jan. 2020, doi: 10.3390/ijerph17020426.

[7] N. Manjunathan, S. Muthulingam, and D. Jaganathan, "IoT based gas leakage detection system," in *2023 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS)*, Mar. 2023, pp. 1137–1142, doi: 10.1109/ICSCDS56580.2023.10105018.

[8] S. Gupta, V. Yadav, H. K. Jaiswal, S. Singh, and A. Shrivastava, "Underground gas leakage detection system," *Journal of Emerging Technologies and Innovative Research (JETIR)*, vol. 10, no. 5, pp. 4–12, 2023.

[9] J. Okoli and B. Ubochi, "Autonomous robot for gas pipeline inspection and leak detection," *International Journal of Computing and Digital Systems*, vol. 11, no. 1, pp. 811–820, Feb. 2022, doi: 10.12785/ijcds/110166.

[10] C. C. Nnokwe, B. C. Ubochi, and K. V Onwuzuruike, "Development of a gas leakage detection system," *Journal of Electrical Engineering, Electronics, Control and Computer Science – JEEECCS*, vol. 6, no. 2, pp. 23–28, 2020.

[11] Y. Tan and Z. Zheng, "Research advance in swarm robotics," *Defence Technology*, vol. 9, no. 1, pp. 18–39, Mar. 2013, doi: 10.1016/j.dt.2013.03.001.

[12] N. Sarma, A. Mittal, D. Choudhary, A. Chowdhury, and T. Ramya, "Augmented approach for gas leakage detection using swarm robotics," in *2019 International Conference on Vision Towards Emerging Trends in Communication and Networking (ViTECoN)*, Mar. 2019, pp. 1–5, doi: 10.1109/ViTECoN.2019.8899367.

[13] B. Ashokkumar, M. D. Frazer, and R. Imtiaz, "Implementation of load sharing using swarm robotics," *International Research Journal of Engineering and Technology (IRJET)*, vol. 3, no. 3, pp. 1855–1862, 2016.

[14] X. Chen and J. Huang, "Odor source localization algorithms on mobile robots: a review and future outlook," *Robotics and Autonomous Systems*, vol. 112, pp. 123–136, Feb. 2019, doi: 10.1016/j.robot.2018.11.014.

[15] E. Persson, "Robotic gas source localization in an industrial environment," 2010.

[16] M. Schranz, M. Umlauft, M. Sende, and W. Elmenreich, "Swarm robotic behaviors and current applications," *Frontiers in Robotics and AI*, vol. 7, Apr. 2020, doi: 10.3389/frobt.2020.00036.

[17] B. I. Schmitt, *Convergence analysis for particle swarm optimization*. FAU University Press, 2015.

[18] A. Sahoo and S. Chandra, "Multi-objective grey wolf optimizer for improved cervix lesion classification," *Applied Soft Computing*, vol. 52, pp. 64–80, Mar. 2017, doi: 10.1016/j.asoc.2016.12.022.

[19] J. Graham, J. A. Starzyk, and D. Jachyra, "Opportunistic behavior in motivated learning agents," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 26, no. 8, pp. 1735–1746, Aug. 2015, doi: 10.1109/TNNLS.2014.2354400.

[20] S. Chen, Yuval, and D. M. Broday, "Re-framing the Gaussian dispersion model as a nonlinear regression scheme for retrospective air quality assessment at a high spatial and temporal resolution," *Environmental Modelling & Software*, vol. 125, Mar. 2020, doi: 10.1016/j.envsoft.2019.104620.

[21] B. K. Patle, G. Babu L, A. Pandey, D. R. K. Parhi, and A. Jagadeesh, "A review: on path planning strategies for navigation of mobile robot," *Defence Technology*, vol. 15, no. 4, pp. 582–606, Aug. 2019, doi: 10.1016/j.dt.2019.04.011.

[22] X. Lei, S. Zhang, Y. Xiang, and M. Duan, "Self-organized multi-target trapping of swarm robots with density-based interaction," *Complex & Intelligent Systems*, vol. 9, no. 5, pp. 5135–5155, Oct. 2023, doi: 10.1007/s40747-023-01014-6.

[23] S. Awasthi, M. Khare, and P. Gargava, "General plume dispersion model (GPDM) for point source emission," *Environmental Modeling & Assessment*, vol. 11, no. 3, pp. 267–276, Aug. 2006, doi: 10.1007/s10666-006-9041-y.

[24] J. M. Stockie, "The mathematics of atmospheric dispersion modeling," *SIAM Review*, vol. 53, no. 2, pp. 349–372, Jan. 2011, doi: 10.1137/10080991X.

[25] N. A. Atanasov, J. Le Ny, and G. J. Pappas, "Distributed algorithms for stochastic source seeking with mobile robot networks," *Journal of Dynamic Systems, Measurement, and Control*, vol. 137, no. 3, Mar. 2015, doi: 10.1115/1.4027892.

[26] O. Zedadra, A. Guerrieri, and H. Seridi, "LFA: a Lévy walk and firefly-based search algorithm: application to multi-target search and multi-robot foraging," *Big Data and Cognitive Computing*, vol. 6, no. 1, Feb. 2022, doi: 10.3390/bdcc6010022.

[27] P. Nandi, "Driven predictive modeling to enhance search efficiency of glowworm-inspired robotic swarms in multiple emission source localization tasks," Old Dominion University, 2023.

BIOGRAPHIES OF AUTHORS

Engr. Adeola Erastus Adegunsoye obtained the Bachelor of Engineering degree in Electrical and Electronics Engineering from the University of Ado Ekiti, now Ekiti State University, Ekiti State, Nigeria. He is currently pursuing a master's degree in control systems engineering at the Federal University of Technology Akure. His current research interests are in robotics, linear and non-linear control systems, multi-agent systems, system optimization, and artificial intelligence. He can be contacted at engrdola@yahoo.com.

Dr. Brendan Ubochi obtained the B.Eng. (2008), M.Sc. (2011), and Ph.D. (2018) degrees from The Federal University of Technology, Owerri, Nigeria, The University of Manchester, Manchester, United Kingdom and Swansea University, Swansea, United Kingdom, respectively. Since 2021, he has been a Senior Lecturer in the Department of Electrical and Electronics Engineering at the Federal University of Technology, Akure, focusing on the modeling and characterization of nano-electronic devices, circuit design, and embedded systems. He has presented scientific papers at international conferences and has more than 20 technical publications in conferences and journals such as the IEEE, IET, Elsevier, and IOP Science. Some of his more recent activities consider the development of AL-based assistive technologies for the visually impaired, pipeline monitoring robots, and AL-based adaptive lane allotment for road traffic management. He is COREN registered and is a member of several professional organizations such as the Nigerian Society of Engineers (NSE), the Institution of Engineering and Technology (IET), and the Institute of Physics (1OP). He can be contacted at brendan.ubochi@gmail.com.

Dr. John Macaulay is a lecturer in Power Electronics with the Department of Applied Computing and Engineering at Cardiff Metropolitan University. His research activities have been dedicated to the design, modeling, and control of power electronics converters and applications in renewable energy as well as the design and implementation of maximum power point tracking techniques for renewable energy generation systems. He can be contacted at JMacaulay@cardiffmet.ac.uk.

Kayode Francis Akingbade earned the M.Eng. and Ph.D. degrees in Electrical and Electronics Engineering (Communication Engineering Option) from the Federal University of Technology, Akure (FUTA), Nigeria, in 2003 and 2011, respectively. He is currently the Head of the Department of Information and Communication Technology in the School of Engineering and Engineering Technology, FUTA. He was promoted to the cadre of full Professor in Electrical Engineering (Communication and Control Engineering) in 2022. Kayode has published over 40 papers and reviewed papers and he is a chartered professional engineer. He has supervised over sixteen (16) master's students and has graduated as a Ph.D. student. Currently, he is supervising five (5) master's students and six (6) PhD students of which one is an international student. He is a fellow of the Massachusetts Institute of Technology Empowering the Teachers (MIT - ETT). His research interests are biomedical engineering, satellite communication engineering, radar systems and tracking, systems stability, control and automation, signal processing, and information theory. He can be contacted at kfakingbade@futa.edu.ng.