Comparative Study of PSO, GWO & SSA Energy Efficient Techniques in WSNs

Dr. BrahmPrakashDahiya
Assistant Professor, Computer Science, BLM Girls College, Punjab, India
E-mail: brahmprakashdahiya@gmail.com

Abstract: Wireless sensor network is collection of sensor nodes that use to collect information from the environment. In last few years, various swarm intelligence optimization techniques has implemented to resolve the problem of hotspots, sensor nodes deployment & localization problems in WSNs. These techniques play important roles to improve energy efficiency in WSNs. Here we present recent works that focus on hotspots, localization and nodes deployment issues. The low cost node deployment and localization model have been implemented to deploy the sensor nodes in wireless sensor networks. It works in low connectivity networks and gives good results in scant network. A probability-based technique has applied to collect the localization related data. Additionally, PSO has been implemented for feasible deployment of sensor nodes. The performance analysis has given better result and it's proved better performance.This paper presents comparative analysis of various energy efficient techniques to resolve node localization problem.The Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO) and Salp Swarm Optimization are analyzed to improve network lifetime on the basis of localization error, throughput and number for localized sensor nodes.
Keywords: PSO, GWO, SSA, WSNs and Node deployment.

1. Introduction

A wireless sensor network (WSN) is a congregation of many sensor nodes and having self-configuration capability. These nodes may wirelessly communicate with one another, i.e., through radio signals. The sensor nodes are installed in an area for sensing, monitoring, and understanding the real (physical world). Sometimes, sensor nodes are known as motes.
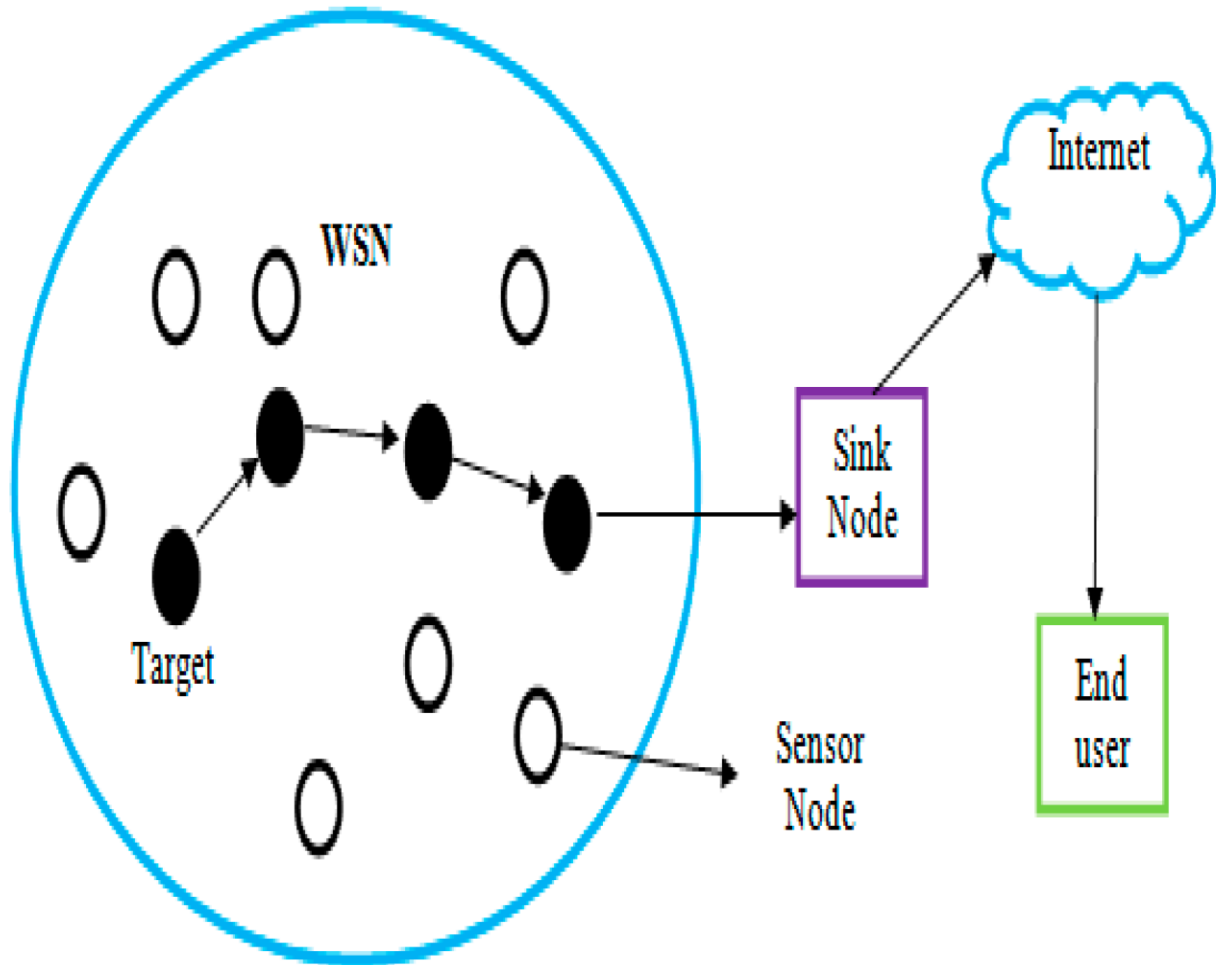
Figure-1 Wireless Sensor Network

In recent past, WSNs have become a great source of interest to research and scientific community. Though WSNs are different from traditional wireless networks, and therefore pose many challenges to solve such as limited battery energy that restricted the network lifetime etc. WSN consists of hundreds or thousands of small wireless sensor nodes equipped with data computing and communicating capabilities. A sensor node senses the physical environment, and therefore the information obtained is converted into data packets then transmitted to BS. Energy constraint is one among the foremost significant issues for WSNs, because the battery of every sensor node can't be easily replaced or recharged in harsh environment. Therefore, all embedded batteries of deployed sensor nodes

need to be managed, so as to prolong the network lifetime. WSNs are prejudiced by several challenging influences as précised below [1-3]. It is projected that wireless sensors will play a superior and superior role in our everyday's' life in the near future of new types of applications. It is connected with number of devices and send/receive processed data to/from other sensing nodes. We are well on the way towards a hundred of billions-wireless sensor are available in market [4]. This development is ongoing the wireless sensors (Figure 1.1) becoming an ever-present component of our life in homes, vehicles, traffic, healthcare, education, production and monitoring & controlling our daily activities. It is an important element in this advancement that participate by low-cost hardware and resource-efficient solutions in software development.

Dense Node Deployment: SNs are compactly deployed in the area. The ratio of sensor nodes are deployed is higher as compare to a MANET.

Battery: Sensor nodes are battery operated electronic devices. They are installed in a harsh environment, where it is difficult to trace, change or recharge the embedded batteries.

Severe Energy, Computation and Storage Constraints: Sensor nodes have limited battery energy, less processing or computation and storage capability.

Self-Configurable: Once sensor nodes are randomly deployed over a given network area, they have to autonomously configure themselves accordingly.

Application Specific: It is deployed for a selected application. The design metrics of a WSN alteration consistent with its application.

Unreliable Sensor Nodes: Due to physical damages and environmental hazards sensor nodes are prone to failure and hence network becomes unreliable.

Frequent Topology Change: Due to node energy depletion, node damage, node addition and channel fading the network topology changes frequently.

No Global Identification: The global addressing scheme is impossible to build for a WSN, because the large number of sensor nodes would introduce high overheads for the identification maintenance.

Other sections are structures as: section 2 represents literature reviews which have been performed in this area. The experimental setup and results comparisons are discussed in section 3. In last section 4 represents the conclusion and future work.

2. **Literature Review**

In last few years, various swarm intelligence optimization techniques has implemented to resolve the problem of hotspots, sensor nodes deployment& localization problems in WSNs [6]. These techniques play important roles to improve energy efficiency in WSNs.

Here we present recent works that focus on hot-spots, localization and nodes deployment issues.The low cost node deployment and localization model have been implemented to deploy the sensor nodes in wireless sensor networks. It works in low connectivity networks and gives good results in scant network. A probability- based technique has applied to collect the localization related data [6]. Additionally, PSO has been implemented for feasible deployment of sensor nodes. The performance analysis has given better result and it's proved better performance [7]. Hybrid node localization has introduced to reduce node deployment issue and reduce the overhead burden. It is very beneficial in node deployment. Further, the connectivity based geometrical algorithm has employed to deploy sensor nodes in wireless sensor networks. The comparative analysis gave better results in term of computational cost and localization error [8].The self-adaptive artificial bee colony (SAABC) node deployment algorithm has proposed to deploy optimal node localization based on dynamic topology. The SAABE gave better results in wireless sensor networks with heterogonous and dynamic topological structure [9]. An integration approach of bacterial foraging and particle swarm has been proposed to improve the energy efficiency and to get optimal node deployment in the wireless sensor networks. The integration of PSO and BFA enhances the convergence rate. The proposed algorithm has more capability to search global optima in the given search area. The results analysis gave better performance in term of node deployment cost [10].The plant growth simulation algorithm (PGSA) has been proposed for sensor nodes deployment. It works based on intelligent optimization.It has enhanced convergence time and performs optimal sensor nodes localization. The performance of PGSA has proved better as compared to simulated annealing algorithm based on computational time and sensor nodes deployment [11].

The genetic algorithm (GA) has been introduced to resolve environmental issues in the wireless sensor networks.It works on improve the energy efficiency in WSNs. It has given best results in localization with high computational speed and fewer errors[12].Additionally cuckoo search (CS) optimization algorithm has been proposed for calculate the sensor nodes coordinates in WSNs. It has global

optima capability to find optimal solution.The experimental results have proved that PSO gave better results in term of computational speed and sensor nodes localization [13].On the other hand PSO two phase algorithm has proposed to improve energy efficiency in WSNs. First phase performs optimal sensor nodes deployment and resolve flip problem. The second phase performs error correction and boost up network convergence [14].The gravitational search algorithm (GSA) has proposed to resolve non-linear optimization problem.It works on sensor nodes deployment and optimizes the flip ambiguity issues. The experimental results have given better performance during node deployment in wireless sensor networks [15].The Hybrid Distance Vector Hop approach has proposed to improve convergence rate and reduces localization error. It alsoperforms hop distance calculation.The distance vector hop approach has integrated with genetic algorithm. The proposed algorithm has improvedlocalization correctness in WSNs [16]. Furthermore, a hybrid received signal strength– parallel firefly algorithm (RSS-PFA) has proposed to handles sensor nodes deployment. It works on non-linear unconstrained optimization issues to improve objective function. It is also calculated the coordinates of sensor nodes. The RSS-PFA has proved better than GA, PSO, GA, RSS and PFA based on computational cost, node deployments and node localization [17].

A firefly optimization algorithm-mobile anchor positioning (FOA-MAP) has been proposedto select optimal node localization. It performs two phases operation. The coordination distance of sensor nodes are calculated in first phase using range free localization technique. The localization errors are eliminated in second phase by parallel firefly algorithm. The MAP has proved better results as compare to modify cuckoo search (MCH), bat optimization technique (BOT) [18]. A particle swarm optimization algorithm (MOPSOLA) has offered to resolve multi-objective problems.It works based on the geometric topology constraints and space distance in WSNs. It performs dynamic node deployment. The experimental setup has given best results to enhance convergence rate and localization accuracy [19]. The fireworks algorithm (FWA) has introduced to reduce node deployment issues.It works to enhance convergence range and reduce computational errors. It gives better results as compare to particle swarm optimization [20].Improved node localization for WSNs has proposed to improve convergence range. It increases the number of deployed nodes. It has been compared with existing algorithms like genetic algorithm, particle swarm PSO,

brain storm optimization, grey wolf optimizer and firefly algorithm based on computational rates and node deployment correctness [21].The dragonfly algorithm (DA) has been proposed to deploy sensor nodes in wireless sensor networks.It is applied to identify the sensor nodes coordinates which are dynamically distributes in networks. The experimental results have given better performance than PSO based on computational speed, convergence rates [23].The multi-objective firefly algorithm has introduced to calculate sensor nodes position in WSNs. It used two constraints such as distance and geometric topology. The results have proved better performance based on computational speed, convergence rate and localization correctness [24].The butterfly optimization technique (BOT) has offered to deploy nodes in wireless sensor network (WSNs). The Gaussian Noise (GN) is used for distance calculation to deploy the nodes in wireless sensor networks.The experimental comparative analysishas proved that the proposed node deployment algorithm is gave good performance than particle swarm intelligence and firefly algorithms on the bases of deployment correctness and convergence rates [25].Additionally, the whale optimization algorithm (WOA) has proposed to deploy nodes in wireless sensor networks. A hybrid localization algorithm has proposed to localize sensor nodes in WSNs. It works on eliminates the square error calculation and estimated the position of sensor nodes to improve the localization in WSNs. The proposed algorithm gives the better performance as compare to existing algorithms [26].A hybrid flower pollination algorithm (HFPA) has offered to optimize energy efficiency of wireless sensor networks. It is swarm intelligence technique that use to enhance convergence rate and node deployment in WSNs. The proposed algorithm has compared with PSO, GWO and firefly algorithm on the base of computational time, sensor nodes deployment, correctness. The proposed algorithm has proved better results as compare to existing algorithms [27].As per our survey, the hybridsalp swarm optimization integration with particle swarm optimization was never implemented for the sensor nodes deployment/ localization issues. The main focus of this paper is to proposeHSSA to resolve nodes deployment/localization problems in wireless sensor networks. The detail description about proposed HSSA and swarm intelligence are mentioned in coming sections.

3. Comparative Analysis of Node Deployment Techniques

The PSO [26], GWO [37] and SSA [39] optimization algorithms have implemented to evelute the performance of the algorithms in different scenarioson the basis of computational time and localization accuracy.The performance analysis of the different algorithms has been performedin MATLAB R2018B with 8 GB RAM, Window 8 and Intel core i3 CPU.

Table 1: Simulation setup in WSNs

Parameters	Values
Sensor nodes	Value change on $\sum_{i=1}^{6} i * 25$
Anchor nodes	Value increment on i=i+5
TransmissionRange	Thirty m
Deployment Area Range	100m * 100m
Maximum number of rounds	100

The simulation setup configured central nodes and target nodes randomly during node deployment. This network has anchor, localized and target nodes. The anchor nodes have known location in the network. The localized nodes have estimated position in network. The target nodes have unknown position. Thecomparative analysis of PSO [26], GWO [37] and SSA [39] based on computational time, localization error and number of localization nodes. The comparative analysis results of proposed algorithm and existing algorithms are derived in table-2. In various rounds the proposed algorithms has improved number of iteration, localized nodes ratio, computational time and decrease the localization error.   The numbers of iteration are directly proportional to

computational time. The optimal solution and computational speed depend on higher number rounds.

Table 2: Comparative analysis of localization algorithms in WSNs

Target Nodes	Anchor Nodes	No of Rounds	PSO			GWO			SSA		
			AL(m)	T(s)	NT	AL(m)	T(s)	NT	AL(m)	T(s)	NT
25	10	25	0.818	0.40	16	0.744	0.22	20	0.465	0.35	22
		50	0.812	0.40	15	0.741	0.41	21	0.462	0.35	23
		75	0.803	0.41	18	0.741	0.54	21	0.458	0.36	23
		100	0.792	0.41	18	0.740	0.79	23	0.451	0.37	24
50	15	25	0.419	0.71	41	0.690	0.42	44	0.477	0.67	43
		50	0.426	0.73	47	0.688	0.63	45	0.472	0.69	47
		75	0.429	0.76	46	0.686	0.81	46	0.468	0.69	48
		100	0.434	0.76	48	0.682	0.98	48	0.464	0.70	50
75	20	25	0.735	1.31	73	0.641	0.72	72	0.519	0.90	69
		50	0.728	1.32	74	0.641	0.95	72	0.513	0.92	72
		75	0.728	1.33	74	0.638	1.3	73	0.504	0.95	73
		100	0.724	1.35	75	0.635	1.4	74	0.503	0.96	75
100	25	25	0.661	2.10	97	0.611	1.1	95	0.511	1.31	98
		50	0.658	2.16	97	0.606	1.5	97	0.509	1.33	98
		75	0.642	2.17	99	0.602	1.8	98	0.502	1.36	99
		100	0.641	2.20	100	0.602	2.1	98	0.504	1.37	100
125	30	25	0.754	4.87	120	0.589	1.5	122	0.529	1.67	123
		50	0.748	4.86	121	0.580	2.2	123	0.524	1.68	124
		75	0.750	4.89	122	0.580	2.8	123	0.522	1.70	125
		100	0.752	4.95	125	0.572	3.3	125	0.522	1.72	125

150	35	25	0.625	5.41	145	0.559	2.8	148	0.511	2.12	149
		50	0.622	5.42	146	0.547	3.6	149	0.509	2.14	149
		75	0.619	5.44	148	0.523	4.3	150	0.504	2.16	150
		100	0.616	5.45	150	0.523	4.8	150	0.504	2.18	150

Table 3: Comparative analysis (mean) of localization algorithms in WSNs

Target Nodes	Anchor Nodes	PSO			GWO			SSA		
		AL(m)	T(s)	NT	AL(m)	T(s)	NT	AL(m)	T(s)	NT
25	10	0.79	0.40	18	0.74	0.54	21	0.45	0.35	24
50	15	0.43	0.76	46	0.69	0.81	46	0.46	0.69	48
75	20	0.72	1.35	75	0.64	0.95	72	0.50	0.96	73
100	25	0.65	2.16	100	0.60	2.1	98	0.51	1.35	100
125	30	0.74	4.90	123	0.58	2.8	123	0.52	1.70	125
150	35	0.62	5.43	149	0.52	4.3	150	0.50	2.15	150

The table-2 represents comparative analysis of PSO, GWOand SSAwith different target and anchor nodes. The simulator results have proved that SSA gave less localization error during sensor nodes deploymentas compare to other existing localization algorithms.Therefore SSA has proved superiority to other existing algorithms.The table-3 represents comparative analysis of PSO, GWO and SSA with different target and anchor nodes. The simulator results have proved that SSA took less computational time during sensor nodes deployment as compare to other existing localization algorithms. Therefore SSA has proved superiority to other existing algorithms.The table-3 represents comparative analysis of PSO, GWO and SSA with different target and anchor nodes. The simulator results have proved that SSA has large number of localized nodes

during sensor nodes deployment as compare to other existing localization algorithms. Therefore SSA has proved superiority to other existing algorithms.

4. Conclusion:

In last few years, various swarm intelligence optimization techniques has implemented to resolve the problem of hotspots, sensor nodes deployment & localization problems in WSNs. These techniques play important roles to improve energy efficiency in WSNs. Here we present recent works that focus on hotspots, localization and nodes deployment issues. The low cost node deployment and localization model have been implemented to deploy the sensor nodes in wireless sensor networks. It works in low connectivity networks and gives good results in scant network. A probability- based technique has applied to collect the localization related data.The comparative analysis performed with PSO, GWO and SSA on the basis of localization error, throughput and number of localized sensor nodes. The comparative analysis has proved that SSA is superior to the existing localization algorithms in term of computational time, number of localized sensor nodes and localization error. In future, SSA algorithm can be integrated with other swarm intelligence technique to improve network lifetime.

References

1. R. V. Kulkarni, G. K. Venayagamoorthy, and M. X. Cheng, "Bio-inspired node localization in wireless sensor networks," in Proceedings of IEEE International Conference in Systems, Man, and Cybernetics (SMC), pp. 205–210, San Antonio, TX, USA, October 2009.

2. D. Lavanya and S. K. Udgata, "Swarm intelligence-based localization in wireless sensor networks," in International Workshop on Multi-Disciplinary Trends in Artificial Intelligence, pp. 317–328, Springer, Berlin, Germany, 2011.

3. J. Wang, R. K. Ghosh, and S. K. Das, "A survey on sensor localization," Journal of Control Aeory and Applications, vol. 8, no. 1, pp. 2–11, 2010.

4. J. Aspnes, T. Eren, D. K. Goldenberg et al., "A theory of network localization," IEEE Transactions on Mobile Computing, vol. 5, no. 12, pp. 1663–1678, 2006.

5. S. Goyal and M. S. Patterh, "Modified bat algorithm for localization of wireless sensor network," Wireless Personal Communications, vol. 86, no. 2, pp. 657–670, 2015.

6. M. M. Ahmed, E. H. Houssein, A. E. Hassanien, A. Taha, and E. Hassanien, "Maximizing lifetime of wireless sensor networks based on whale optimization algorithm," in International Conference on Advanced Intelligent Systems and Informatics, pp. 724–733, Springer, Berlin,

Germany, 2017.

7. K. S. Low, H. A. Nguyen, and H. Guo, "A particle swarm optimization approach for the localization of a wireless sensor network," in Proceedings of IEEE International Symposium in Industrial Electronics (ISIE), pp. 1820–1825, Vancouver, Canada, June 2008.

8. D. Manjarres, J. Del Ser, S. Gil-Lopez, M. Vecchio, I. LandaTorres, and R. Lopez-Valcarce, "On the application of a hybrid harmony search algorithm to node localization in anchorbasedwireless sensor networks," in Proceedings of IEEE International Conference in Intelligent Systems Design and Applications (ISDA), pp. 1014–1019, Cordoba, Spain, No- ´ vember 2011.

9. M. Li, W. Xiong, and Q. Liang, "An improved abc-based node localization algorithm for wireless sensor network," in Proceedings of IEEE International Conference in Wireless Communications, Networking and Mobile Computing (WiCOM), pp. 1–4, Barcelona, Spain, September 2012.

10. A. Tamizharasi, R. Arthi, and K. Murugan, "Bio-inspired algorithm for optimizing the localization of wireless sensor networks," in Proceedings of IEEE International Conference in Computing, Communications and Networking Technologies (ICCCNT), pp. 1–5, Tiruchengode, India, June 2013.

11. C. Tang, R. Liu, and J. Ni, "A novel wireless sensor network localization approach: localization based on plant growth simulation algorithm," ElektronikairElektrotechnika, vol. 19, no. 8, pp. 97–100, 2013.

12. O. D. Jegede and K. Ferens, "A genetic algorithm for node localization in wireless sensor networks," in Proceedings of International Conference on Genetic and Evolutionary Methods (GEM), Ae Steering Committee of the World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp), pp. 1–7, Las Vegas, NV, USA, July 2013.

13. S. Goyal and M. S. Patterh, "Wireless sensor network localization based on cuckoo search algorithm," Wireless personal communications, vol. 79, no. 1, pp. 223–234, 2014.

14. L. Dan and W. Xian-bin, "An improved PSO algorithm for distributed localization in wireless sensor networks," International Journal of Distributed Sensor Networks, vol. 11, no. 7, Article ID 970272, 2015.

15. R. Krishnaprabha and A. Gopakumar, "Performance of gravitational search algorithm in wireless sensor network localization," in Proceedings of IEEE National Conference in Communication, Signal Processing and Networking (NCCSN), pp. 1–6, Palakkad, India, October 2014.

16. B. Peng and L. Li, "An improved localization algorithm based on genetic algorithm in wireless sensor networks," Cognitive Neurodynamics, vol. 9, no. 2, pp. 249–256, 2015.

17. V. O. Sai, C. S. Shieh, T. T. Nguyen, Y. C. Lin, M. F. Horng, and Q. D. Le, "Parallel firefly algorithm for localization algorithm in wireless sensor network," in Proceedings of IEEE International Conference in Robot, Vision and Signal Processing (RVSP), pp. 300–305, Kaohsiung, China, November 2015.

18. S. Sivakumar and R. Venkatesan, "Meta-heuristic approaches for minimizing error in localization

of wireless sensor networks," Applied Soft Computing, vol. 36, pp. 506–518, 2015.

19. Z. Sun, L. Tao, X. Wang, and Z. Zhou, "Localization algorithm in wireless sensor networks based on multiobjective particle swarm optimization," International Journal of Distributed Sensor Networks, vol. 11, no. 8, Article ID 716291, 2015.

20. A. Arsic, M. Tuba, and M. Jordanski, "Fireworks algorithm applied to wireless sensor networks localization problem," in Proceedings of IEEE Congress on Evolutionary Computation (CEC), pp. 4038–4044, Vancouver, Canada, July 2016.

21. C. S. Shieh, V. O. Sai, Y. C. Lin, T. F. Lee, T. T. Nguyen, and Q. D. Le, "Improved node localization for WSN using heuristic optimization approaches," in Proceedings of IEEE International Conference in Networking and Network Applications (NaNA), pp. 95–98, Hokkaido, Japan, July 2016.

22. J. Cheng and L. Xia, "An effective Cuckoo search algorithm for node localization in wireless sensor network," Sensors, vol. 16, no. 9, p. 1390, 2016.

23. P. T. Daely and S. Y. Shin, "Range based wireless node localization using Dragonfly Algorithm," in Proceedings of IEEE International Conference in Ubiquitous and Future Networks (ICUFN), pp. 1012–1015, Vienna, Austria, July 2016.

24. T. T. Nguyen, J. S. Pan, S. C. Chu, J. F. Roddick, and T. K. Dao, "Optimization localization in wireless sensor network based on multi-objective firefly algorithm," Journal of Network Intelligence, vol. 1, no. 4, pp. 130–138, 2016.

25. S. Arora and S. Singh, "Node localization in wireless sensor networks using butterfly optimization algorithm," Arabian Journal for Science and Engineering, vol. 42, no. 8, pp. 3325–3335, 2017.

26. S. R. Sujatha and M. Siddappa, "Node localization method for wireless sensor networks based on hybrid optimization of particle swarm optimization and differential evolution," IOSR Journal of Computer Engineering, vol. 19, no. 2, pp. 07–12, 2017.

27. R. Kaur and S. Arora, "nature inspired range based wireless sensor node localization algorithms," International Journal of Interactive Multimedia and Artificial Intelligence, vol. 4, pp. 7–17, 2017.

28. A. Tarwat, E. H. Houssein, M. M. Ahmed, A. E. Hassanien, and T. Gabel, "MOGOA algorithm for constrained and unconstrained multi-objective optimization problems," Applied Intelligence, vol. 48, no. 8, pp. 2268–2283, 2017.

29. A. A. Ewees, M. AbdElaziz, and E. H. Houssein, "Improved grasshopper optimization algorithm using opposition-based learning," Expert Systems with Applications, vol. 112, pp. 156–172, 2018.

30. A. G. Hussien, E. H. Houssein, and A. E. Hassanien, "A binary whale optimization algorithm with hyperbolic tangent fitness function for feature selection," in Proceedings of Eighth International Conference on Intelligent Computing and Information Systems (ICICIS), pp. 166–172, Cairo, Egypt, December 2017.

31. B. Xue, M. Zhang, and W. N. Browne, "Particle swarm optimization for feature selection in classification: a multiobjective approach," IEEE Transactions on Cybernetics, vol. 43, no. 6, pp. 1656–1671, 2013.

32. S. Arora and S. Singh, "Butterfly algorithm with levy flights for global optimization," in Proceedings of IEEE International Conference in Signal Processing, Computing and Control (ISPCC), pp. 220–224, Waknaghat, India, September 2015.

33. S. Arora and S. Singh, "An improved butterfly optimization algorithm with chaos," Journal of Intelligent and Fuzzy Systems, vol. 32, no. 1, pp. 1079–1088, 2017.

34. R. B. Blair and A. E. Launer, "Butterfly diversity and human land use: species assemblages along an urban grandient," Biological Conservation, vol. 80, no. 1, pp. 113–125, 1997.

35. X. S. Yang and X. He, "Firefly algorithm: recent advances and applications," 2013, https://arxiv.org/abs/1308.3898.

36. X. S. Yang, "Firefly algorithms for multimodal optimization," in Proceedings of International Symposium on Stochastic Algorithms, pp. 169–178, Sapporo, Japan, October 2009.

37. S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," Advances in Engineering Software, vol. 69, pp. 46–61, 2014.

38. L. P. Madin, "Aspects of jet propulsion in Salps," Canadian Journal of Zoology, vol. 68, no. 4, pp. 765–777, 1990.

39. S. Mirjalili, A. H. Gandomi, S. Z. Mirjalili, S. Saremi, H. Faris, and S. M. Mirjalili, "Salp swarm algorithm: a bio-inspired optimizer for engineering design problems," Advances in Engineering Software, vol. 114, pp. 163–191, 2017.

40. P. A. Anderson and Q. Bone, "Communication between individuals in Salp chains. II. Physiology," Proceedings of the Royal Society of London. Series B. Biological Sciences, vol. 210, no. 1181, pp. 559–574, 1980.

41. H. T. Ibrahim, W. J. Mazher, O. N. Ucan, and O. Bayat, "Feature selection using salp swarm algorithm for real biomedical datasets," IJCSNS, vol. 17, no. 12, pp. 13–20, 2017.