Journal of Science and Technology
ISSN: 2456-5660 Volume 5, Issue 6, Nov-December 2020

www.jst.org.in *DOI: https://doi.org/10.46243/jst.2020.v5.i6.pp80-86*

Three Swarm Intelligence Algorithms for Wireless Sensor Network Applications: A review

Himanshu Jahagirdar[1], Pratik Bobade[2],Vilas Dhuri[3], Rajani Mangala[4]
[1, 3, 4](Department of Electronics Engineering, V.E.S.I.T., Mumbai University)
[2](Department of Computer Science Engineering, V.I.T, Mumbai University)
[3]Corresponding Author: vilasrks11@gmail.com

To Cite this Article
Himanshu Jahagirdar, Pratik Bobade, Vilas Dhuri and Rajani Mangala, "Three Swarm Intelligence Algorithms for Wireless Sensor Network Applications: A review", Journal of Science and Technology, Vol. 05, Issue 06, Nov-December 2020, pp80-86

Article Info
Received: 28-06-2020 Revised: 25-09-2020 Accepted: 01-10-2020 Published: 05-10-2020

Abstract: *Wireless Sensor Networks (WSNs) are increasingly realizing applications in IoT, smart grids, healthcare, security, swarm robotics, etc. Swarm Intelligence is used to optimize performance parameters associated with WSNs including localization, coverage, network lifetime, energy efficiency to name a few. The scope of this paper is restricted to a survey on Stochastic Diffusion Search, Genetic Algorithm and Particle Swarm Algorithm with respect to their organization and capacity to optimize these network parameters and their current as well as potential applications in WSNs.*

Keywords*: Wireless Sensor Networks (WSNs), Stochastic Diffusion Search****,*** *Genetic Algorithm, Particle Swarm Optimization, LEACH.*

I. Introduction

Swarm intelligence or SI is a branch of artificial intelligence that derives inspiration from certain biological systems, which collectively solve problems much bigger than themselves. SI consists of a population of agents that optimize a defined search space to obtain a good solution. The biggest application of SI algorithms has been in swarm robotics. Wireless Sensor Networks or WSNs, on the other hand, are spatially distinct sensors wirelessly interconnected to share information for necessary analytics of the sensor data to further monitor and solve complex physical problems. The biggest usage of the principles of WSNs has been in the Internet of Things (IoT).

The most popularly used SI algorithm is Ant Colony Optimization(ACO) that studies the behavior of ants (that release 'pheromones' to collectively navigate a path to their destination) to solve complex computational problems like the travelling salesman problem. This paper discusses three other SI algorithms that have their unique advantages and limitations, each based on a different biological system- Stochastic Diffusion Search (SDS) on ants, Genetic Algorithm(GA) on chromosomes and Particle Swarm Optimization(PSO) on birds. This paper further surveys the implementations as well as potential applications of these SI algorithms in WSNs and the performance delivered by these algorithms to solve common problems associated with WSNs like localization, clustering, etc.

II. SI Algorithms IN WSN

A. Stochastic Diffusion Search

A.1 Introduction

Stochastic Diffusion Search (SDS) came into existence to solve computational problems under swarm intelligence. The mining game example is used to highlight the working [4]- A group of gold miners should dig a potential hill range to find gold. They must all dig around the richest seams, the location of which are unknown, to maximize individual earnings. Initially, each miner chooses a hill to mine (hypothesis) at random. In the evening, every unhappy miner randomly selects another miner to communicate. If chosen miner is also unhappy, the miner repeats the dig on another random hill on the next day. However, if chosen miner is happy, he shares the location and both work collectively on the good seam, thus sharing their hypothesis. This organization will ultimately lead all agents towards the gold (global optima).

SDS presents a unique approach to distributed computing, wherein time taken to converge to optimal hypothesis position is undefined. However, the spatial concerns of the target model are addressed and available to every agent. The combination of positive feedback and partial evaluation of the objective function result in a powerful and robust architecture as opposed to algorithms that generate full evaluation. The workflow of the algorithm goes as below [5] [6] [10]-

1. Initialization phase*:* Agents are initialized as inactive and map themselves on the search space by selecting a hypothesis position, which implies that at least one agent must map the best hypothesis.

2. Test phase: Agents evaluate their test functions at respective positions. This partial evaluation determines if agents are set as active or inactive. An agent is active if the evaluation is successful, otherwise they remain inactive.

3. Diffusion phase**:** Agents exchange their hypothesis function via:

Passive Recruitment: If the other agent is active, then the agent adopts its location and goes back to test phase.

Active Recruitment: If the other agent is active, the current agent is removed from the model.

In either case, if the randomly selected agent is also inactive, then both agents are again initialized to other random search points.

4. Termination Phase*:* An initial activation threshold is set, in sync with the defined stability criteria, and the system is allowed to operate until the threshold is achieved, after which, the system is observed to minimize error.

A.2 Performance and Applications

SDS has been used to solve N-P problems like finite Markov chains, no free lunch problem, or computer vision-based object tracking [10] etc. In this section, we discuss SDS applied to wireless sensor networks and its future possibilities.

Site selection forms an important part of setting up a wireless sensor network as we need to maximize the possible number of receive points in space. In [25], through its distributed computing ability, SDS minimized the time to calculate the number and position of sites required and also the coverage percentage for given total radial distance. The minimum coverage threshold was 80%, with a few experiments resulting in as much as 96% coverage.

In the letter [6], for stable convergence of SDS, value of minimum test score α_{min} for test function in a search space retains a cluster for $\alpha < \alpha_{min.}$ The letter demonstrated the relationship between optimal cluster size and background noise ratio for 5000 iterations among 10,000 agents. The higher ratios do not minimize the resulting cluster to a usable optimum, while the lower ratios are successful in doing so, making SDS relatively immune to low background noise.

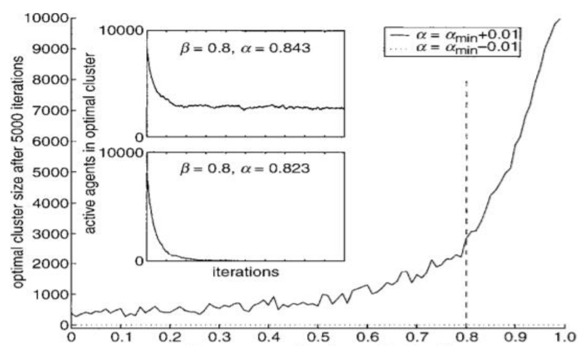


Fig. 3 *Graph showing cluster size after 5000 iterations for values of* $\alpha = \alpha_{min} \pm 0.01$

. Insets: Evolution of optimal cluster size for $\beta = 0.8$, $\alpha = \alpha_{min} \pm 0.01$

Minimum stable convergence criteria for SDS [6]

Clustering is extremely important to energy conservation in WSNs and it also improves the network lifetime. In 2015, SDS was compared with nine other clustering algorithms (including k-means, PSO, etc.) [27]. SDS outperformed all of these algorithms in clustering the iris dataset being highly recommended for high-dimensional problems and suitable for real-world applications.

A study was conducted under J.M. Bishop in comparison with RANSAC (Random Sample Consensus) algorithm [14], an important algorithm used in WSNs. The study reinforces the understanding that SDS works better under low-medium noise conditions. CSDS(Coupled) was introduced and proven to outperform RANSAC with variable population sizes in convergence per iteration rate (however with increase in number of dimensions n, the agent size required becomes n^3, and SDS will not work as efficiently with too many agents). This paper advocates the usage of SDS in swarm intelligence and computer vision applications, which are one of the most essential elements in a robotic WSN.

In 2011, SDS and PSO were merged to study creative swarm intelligence, with the dynamic diffusion by SDS assisting the localization and tracking by PSO [28]. A real-world swarm using fish was mentioned to discuss the possibilities of artificial aesthetic using a sensor network.

Diffusion time is the parameter responsible for ease of information spread, which is a desirable feature in WSNs. Random and lattice mobility models of WSNs were tested for diffusion time with and without SDS in [26], for four population sizes. The probability of these models being unsuccessful when used without SDS was high in magnitude. Further, the positive feedback from SDS resulting from diffusion of information led to higher stability in a dynamic search space.

In 2014, SDS backed swarm intelligence was employed for medical imaging applications to identify potential chance of ruptured aortic aneurysms (AA) and localization in NG tube procedures [16]. The lead researcher further proposed an advanced swarm ingestible pill type robotic system backed by SDS, capable of endoscopic exploration and identification of pre-cancerous growth in gastrointestinal lumen [24].

In [29], unsupervised algorithms for WSNs to reduce feature set and exploit spatial correlation were studied. SDS also offers a similar feature selection capability, both independently and as a hybrid algorithm [30], working well with high dimensional dataset and features greater than ten and enhancing classification accuracy. The future scope mentioned involved optimizing final data set size and the feature values.

B. Genetic Algorithm

B.1 Introduction

Genetic Algorithm is a heuristic algorithm that estimates optimal solution by generating different individuals [1]. It uses the fitness function to determine the best population. In nature, the fitness determines the individual’s ability to pass on the genetics from one organism to the other. It includes traits such as the ability to reproduce and to survive. The fate of an individual depends on this fitness value, the higher the value, the better the chance of survival. Genetic Algorithm provide solutions for the biological problems that are similar to the natural problems [2].

Workflow of Genetic Algorithm [3]:

1. Initialization: The population consists of a set of individuals known as chromosomes. Each chromosome is defined by a binary set of 0’s and 1’s.

2. Fitness: For each chromosome, the fitness function has a score assigned to it which depends on their qualification. Based on this score, it gives further idea for reproduction.

3. Selection:The selection between the previous generation and the new generation is developed by adopting the current generation members to mate which is decided by the fitness function.The individuals with high score have a greater chance for being selected.

4. Crossover:The crossover or reproduction process results in a new generation with desirable traits that replaces current population. Crossover is often accompanied by mutation (new solutions) and selection operators and many of these operations take place, each with different objectives.

B.2 Performance and Applications

*Genetic algorithm is used to minimize the communication distance and maximize the lifetime of a network. GA is an optimization-based algorithm which has three operator’s selection, crossover, and mutation. During each iteration, these operators generate new population. This helps to improve efficiency and lifetime of the network [33].

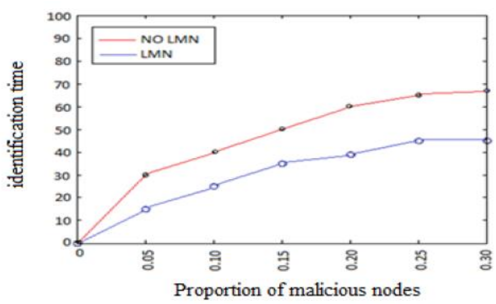
LEACH defined as the Low-Energy Adaptive Clustering Hierarchy is a cluster-based energy-efficient protocol [20] which uses an optimal thresholding probability for cluster formation. A set-up phase for cluster head (CH) selection and a steady state phase for time-slot scheduling and transmission is created. With the help of these phases, the sensor nodes then independently decide whether the other nodes will be CH or not.

A two-dimensional chromosome representation was used in [21]. It was mapped to the actual node layout of the deployment area. The genes value zero indicated non-existing node, or one for sensor node or two for CH. It used the result of LEACH as an initial condition to GA algorithm. It started with an initial population of chromosomes, then assessed the structures which recreated the chromosome from the poor arrangements. The correctness was characterized from the present population and new chromosome created from the desired qualities, which can be numerical, double, image or character based as per requirement. The chromosome is divided into sectors, and crossover is performed by exchanging sectors between parents which ensures that the genes move within their neighbors to the next generation [22]. GA is used to calculate the optimum number of clusters, cluster selection and cluster layout [23]. *The ability for discovering different paths of the LEACH protocol are enhanced that finds the best path which has less intricacy, low information movement and least misfortune.

Localization is known as the process of determining the positioning of node in the network. It is an efficient method for computing the positions of the nodes in low-cost sensor networks [31]. To obtain the node location, the communication between localized and delocalized nodes is estimated by localization for determining geometrical position using distance and angle between nodes [32].

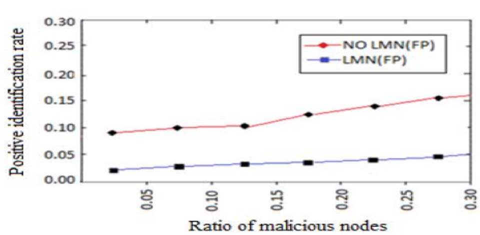
In [37], the comparative study between the traffic count (no. of nodes that collect different data) vs no. of base stations showed that the traffic count increased rapidly with traditional approach whereas for the optimized approach with GA, it does not increase much. This is because the distance between the base stations and nodes was greater without the application of GA. Thus, the study concluded that using GA resulted in effective optimization of the sensor localization problem in coverage area.

Intrusion Detection algorithm are used to identify malicious attacks. It is an effective and powerful mechanism for WSNs to optimize their limited battery processing resources and detect the malicious nodes for which Local Monitoring Nodes (LMN) are used as trusted proxy agents. The base station offers an LMN to act as a cluster head. Nodes are placed randomly in different positions [34][36].



Average time of all nodes compromised as a function of the number of malicious nodes [34]

A graph was plot to vary the positive detection rate as a function of number of nodes. The study concluded that positive rate due to misdetection causes discrepancy in the integrity of the system and efficiency of routing and clustering algorithms [34][36]. For faster detection, reliability and identification time increase as the presence of compromised node increases.



The positive rate of detection as a function of the relative number of malicious nodes [34]

Another result as observed in this graph showed an increase in the positive rate due to misdetection of nodes that causes discrepancy and lowers the efficiency of the algorithm [34]. If the detection of malicious nodes is faster, reliability and the network lifetime of sensor nodes is increased in the presence of other nodes in the system. However, this method has one limitation. If the number of nodes are increased, the convergence time of genetic algorithm increases exponentially. For future work, scalability can be improved for a greater number of nodes.

C. Particle Swarm Optimization

C.1 Introduction

Particle Swarm Optimization (PSO) is an algorithm that mimics navigation of a flock of birds or a school of fish. PSO is a groundbreaking computational method developed by Kennedy and Eberhart in 1995. In this method each particle interacts with other members in the population to determine the optimal solution for a problem over a period of time [7]. Position and velocity are the two main properties of the particle. PSO stands different from other algorithm such that it makes few or zero assumptions of the given problem that needs to be optimized and searches for a global minimum of the objective function by searching in very large spaces of candidate solution. For large error applications genetic algorithm results in local minima, hence despite greater computational cost, PSO is preferred.

In large regions of interest, it is suggested that PSO algorithm in convergence with the Voronoi diagram results in good network coverage optimization for sensor within an appropriate computational time [17].

The following mentioned are the schemes used in PSO [8]:

1. Initialization:First a general population of particles is introduced and each particle here has its own position and velocity. At initial state the population is generated randomly and the new population is updated depending upon the most recently updated position and velocity of each particle.

2. Fitness**:** As the particles keep searching for the global minimum of a predetermined function, each time the fitness value is calculated it is compared with the previous personal best of each particle as well as the previous best of the whole swarm particle population. If the value is better than the previous best, then personal best and global best fitness values are updated where necessary.

3. Stopping:After the new fitness value are updated a termination criterion is checked and if the appropriate solution is met then termination of particle swarm takes place.

C.2 Performance and Applications

The main attractive feature that enables the use of PSO is that it requires very few or no parameter adjustments. Due to recent progress of PSO algorithm, it is being used in artificial neural networks [9]. PSO not only improves the network weights but also the whole network structure. The shortcomings of traditional neural networks such as backpropagation are eliminated by the implementation with PSO.

PSO is also used in in adaptive indoor localization of WSN system to reduce the distance error between each particle and the access points. A proposed algorithm using PSO in [18] yields significant improvements over other hybrid PSO algorithms. The results of the simulation in [18], for a 50m X 80m area, concludes that Hierarchical Particle Swarm Optimizer With Time-Varying Acceleration Coefficients (HPSO- TVAC) [19] minimizes the maximum error distances to 0.5 meters in NPC (Number of particles in a circle) of 100. Further it was inferred that the average distance error minimized for NPC=100 using HPSO-TVAC was 0.19 meters, far better than other hybrid PSO.

Clustering is another important application in WSN. Node deployment forms the first step where nodes are deployed in the sensing region. After that, the base station sends a message to all the nodes to collect the node information which includes position, velocity and energy and the values of them are updated to the base station. Then the base station requests the sensor nodes to perform clustering and this cluster formation is performed using PSO. Clustering takes place by considering the node with the maximum fitness value in the constructed network and the node with the maximum fitness value is the cluster head. This process is repeated until least or zero number of independent nodes remain in the network and then the cluster formation is stopped. Hence with the help of PSO clusters and cluster heads are selected and the residual nodes are eliminated [11][12].

Low Energy Adaptive Clustering Hierarchy (LEACH)[13] a powerful WSN clustering algorithm used today provides an efficient way of forming cluster heads and cluster network. As proposed in “The effectiveness of distance altering” by Khalil Bennani and Driss El Ghanami, PSO enables formation of optimal clusters by creating a central control algorithm which increases network life. In the proposed protocol (PSO-C), the algorithm is divided into rounds and each round has two phases - set-up phase and steady-phase.[15] The set-up phase includes cluster formation and development of cluster heads. The steady-phase involves collection of information from the node to the cluster heads. The cluster head performs data aggregation and passes on the data to the base station.

A simulation of this protocol was carried out in NS-2 along with LEACH-C for a total of 100 randomly deployed nodes in 100m X 100m network area. The other parameters included two base station- one inside the field, positioned (50,50) and other outside the field positioned (50,175). The number of clusters was set to K=5 and 20 PSO particles(Q) with initial energy of each node to 2J. For the network with the base station inside the field it was observed that in LEACH-C the first node's battery died at 360 while the other gradually died with the final node dying at 540. For PSO-C the first node's battery dies at 480 and the last nodes at 740. For the base station outside the field the first node dies at 340 for LEACH-C and at 440 for PSO-C.These observations led to the conclusion that the mentioned protocol improved the network lifetime by 30% as compared to LEACH-C (employed in majority applications) for WSN clustering. It was further inferred that if the base station distance from the cluster heads is decreased a considerable performance boost can be obtained [15].

PSO in combination with GA [1] i.e. hybrid PSO-GA is used in hierarchical WSN model, which consists of a single base station and one relay node for every single cluster. The hybrid PSO-GA algorithm is thus used for routing in WSN. This algorithm combines the merits of both PSO and GA - the high convergence rate of PSO and finding the fittest solution in a short period of time of GA. It is observed that for a large-scale network PSO-GA has the highest network lifetime as well as the highest packet delivery ratio in comparison with shortest path approach, standalone PSO or GA approach.[35]

III. Conclusion

This paper gives a brief account of three swarm intelligence (SI) algorithms- SDS, GA and PSO. SDS features a partial evaluation to reduce computational cost, provides stable convergence in noisy search spaces and reliable for dynamic search applications. GA is one of the fastest SI algorithms, falling short only in its expensive fitness function evaluation. In high error prone search spaces, GA may converge to local optima, so in those cases the most basic SI algorithm PSO is used. PSO and SDS can also be used for high dimensional search problems. The evaluation cost for PSO though, is very high, due to its simple architecture.

This paper focuses on the applications and potential usage of these biologically inspired algorithms for wireless sensor networks (WSNs). The performance associated with these algorithms is also discussed with respect to major WSN applications like localization, clustering etc.

References

[1] D. E. Goldberg, Genetic Algorithm in a Search Optimization and Machine Learning, Addison Wesley, 1989.

[2] D. Goldberg, B. Karp, Y. Ke, S. Nath, and S. Seshan, Genetic algorithms in search, optimization, and machine learning. AddisonWesley, 1989

[3] A. Norouzi, F. S. Babamir, and A. H. Zaim, "A novel energy efficient routing protocol in wireless sensor networks," Journal of Wireless Sensor Network,vol3.,no.10,pp.1–10,2011

[4] al-Rifaie M.M., Bishop J.M., Blackwell T. (2011) Resource Allocation and Dispensation Impact of Stochastic Diffusion Search on Differential Evolution Algorithm. In: Pelta D.A., Krasnogor N., Dumitrescu D., Chira C., Lung R. (eds) Nature Inspired Cooperative Strategies for Optimization (NICSO 2011). Studies in Computational Intelligence, vol 387. Springer, Berlin, Heidelberg

[5] Williams, H.; Bishop, M. Stochastic Diffusion Search: A Comparison of Swarm Intelligence Parameter Estimation Algorithms with RANSAC. *Algorithms* 2014, *7*, 206-228.

[6]D. R. Myatt, J. M. Bishop and S. J. Nasuto, "Minimum stable convergence criteria for Stochastic Diffusion Search," in *Electronics Letters*, vol. 40, no. 2, pp. 112-113, 22 Jan. 2004.doi: 10.1049/el:20040096

[7] Kennedy J. (2011) Particle Swarm Optimization. In: Sammut C., Webb G.I. (eds) Encyclopedia of Machine Learning. Springer, Boston, MA.

[8]Kachitvichyanukul, Voratas. (2012). Comparison of three evolutionary algorithms: GA, PSO, and DE. Industrial Engineering and Management Systems. 12. 215-223. 10.7232/iems.2012.11.3.215.

[9]Eberhart, &Yuhui Shi. (n.d.). Particle swarm optimization: developments, applications and resources. Proceedings of the 2001 Congress on Evolutionary Computation (IEEE Cat. No.01TH8546). doi:10.1109/cec.2001.934374

[10]Bishop, John & Torr, Philip. (1992). The Stochastic Search Network. 10.1007/978-94-011-2360-0_24.

[11] J, RejinaParvin&Vasanthanayaki, C. (2015). Particle Swarm Optimization-Based Clustering by Preventing Residual Nodes in Wireless Sensor Networks. Sensors Journal, IEEE. 15. 4264-4274. 10.1109/JSEN.2015.2416208

[12]Bennani, K., & El Ghanami, D. (2012). *Particle swarm optimization based clustering in wireless sensor networks: The effectiveness of distance altering. 2012 IEEE International Conference on Complex Systems (ICCS).*doi:10.1109/icocs.2012.6458564

[13]W. R. Heinzelman, A. Chandrakasan and H. Balakrishnan, "Energy-efficient communication protocol for wireless microsensor networks," *Proceedings of the 33rd Annual Hawaii International Conference on System Sciences*, Maui, HI, USA, 2000, pp. 10 pp. vol.2-.doi: 10.1109/HICSS.2000.926982

[14]Williams, H.; Bishop, M. Stochastic Diffusion Search: A Comparison of Swarm Intelligence Parameter Estimation Algorithms with RANSAC. *Algorithms* 2014, *7*, 206-228.

[15]K. Bennani and D. El Ghanami, "Particle swarm optimization based clustering in wireless sensor networks: The effectiveness of distance altering," *2012 IEEE International Conference on Complex Systems (ICCS)*, Agadir, 2012, pp. 1-4.

[16]Al-Rifaie, Mohammad Majid & Aber, Ahmed & Collaboration, Monarc& Choke, Edward &Bown, Mathew. (2014). Deploying swarm intelligence in medical imaging. Proceedings - 2014 IEEE International Conference on Bioinformatics and Biomedicine, IEEE BIBM 2014. 14-21. 10.1109/BIBM.2014.6999242.

[17]N. A. B. A. Aziz, A. W. Mohemmed and M. Y. Alias, "A wireless sensor network coverage optimization algorithm based on particle swarm optimization and Voronoi diagram," *2009 International Conference on Networking, Sensing and Control*, Okayama, 2009, pp. 602-607.doi: 10.1109/ICNSC.2009.4919346

[18] Alhammadi, Abdulraqeb, Hashim, Fazirulhisyam, Fadlee, Mohd et al. (1 more author) (2016) An Adaptive Localization System Using Particle Swarm Optimization In A Circular Distribution Form. Jurnal Teknologi. pp. 105-110.

[19]Ratnaweera, A., Halgamuge, S., and Watson, H. C. 2004. Self-organizing Hierarchical Particle Swarm Optimizer With Time-Varying Acceleration Coefficients. IEEE Transactions on Evolutionary Computation. 8(3): 240-255.

[20] M. Al-Obaidy, A. Ayesh, and A. F. Sheta, “Optimizing the communication distance of an ad hoc wireless sensor networks by genetic algorithms,” Artificial Intelligence Review, vol. 29, no. 3, pp. 183–194, 2008.

[21] H.-S. Seo, S.-J. Oh, and C.-W. Lee, “Evolutionary genetic algorithm for efficient clustering of wireless sensor networks,” in Proceedings of the 6th IEEE Consumer Communications and Networking Conference, pp. 1–5, 2009.

[22]] N. LingaRaj.K, Aradhana.D, “Multiple mobile agents in wireless sensor networks using genetic algorithms,” International Journal of Scientific and Engineering Research, vol. 3, no. 8, pp. 1–5, 2012.

[23] M. Karimi, H. Naji, and S. Golestani, “Optimizing cluster-head selection in wireless sensor networks using genetic algorithm and harmony search algorithm,” in Proceedings of the 20th Iranian Conference on Electrical Engineering, pp. 706–710, 2012.

[24] al-Rifaie MM, Aber A, Raisys R (2011) Swarming robots and possible medical applications. In: International Society for the Electronic Arts (ISEA 2011), Istanbul, Turkey

[25]Hurley, S., & Whitaker, R. M. (2002). An agent based approach to site selection for wireless networks. Proceedings of the 2002 ACM Symposium on Applied Computing - SAC ’02.

[26] Abbas, N. H., & Rao, R. (2009). Notice of Violation of IEEE Publication PrinciplesSwarm intelligence stability based on stochastic diffusion search. 2009 Proceeding of International Conference on Methods and Models in Computer Science (ICM2CS).

[27]Al-Rifaie, Mohammad Majid & Joyce, Daniel &Shergill, Sukhi& Bishop, John. (2015). Investigating Stochastic Diffusion Search in Data Clustering. 10.1109/IntelliSys.2015.7361143.

[28]Al-Rifaie, Mohammad Majid; Bishop, Mark (J. M.) and Aber, Ahmed. 2011. Creative or Not? Birds and Ants Draw with Muscle. Proceedings of AISB'11 Computing and Philosophy, pp. 23-30. [Article]

[29]C.Alippi, G. Baroni, A. Bersani and M. Roveri, "Unsupervised feature selection algorithms for wireless sensor networks," 2009 IEEE International Conference on Computational Intelligence for Measurement Systems and Applications, Hong Kong, 2009, pp. 32-37.

[30]Alhakbani, Haya Abdullah and Mohammad Majid al-Rifaie. “Feature selection using stochastic diffusion search.” GECCO (2017).

[31]K.Muthukrishnan, M. Lijding, and P. Havinga, “Towards smart surroundings: Enabling techniques and technologies for localization”, in Proc. of the Int. Workshop on location and context awareness, volume 24,2005

[32]Nabil Ali Alrajeh, Maryam Bashir and Bilan Shams, “ Localization Techniques in WSN”,Volume2013,Hindawi,pp 1-9,2013

[33]Almuzaini, K.K. , “Localization in Wireless Networks Using Decision Trees and K-Means Clustering”, IEEE,PP 1-5,2012.

[34]G.Acs, and L. Buttyan, “Desiging a Secure Label-Switching Routing Protocol for Wireless Sensor Networks”, Telecommunications Budapest University of Technology and Economics, Hungary, Dec.22, 2008.

[35]Agnihotri, A., & Gupta, I. K. (2018). A hybrid PSO-GA algorithm for routing in wireless sensor network. 2018 4th International Conference on Recent Advances in Information Technology (RAIT).

[36]A.Modirkhazen, N. Ethnic, and O. Ibrahim, “Empirical Study on Secure Routing Protocols in Wireless Sensor Networks”, International Journal of Advancements in Computing Technology, Vol.2, No.5, Dec 2010.

[37] Abhinav Dhiman, Nishant (2016). “Genetic Algorithm for localization in WSN”. 10.15680/IJIRCCE.2016. 0407013.