# Performance Analysis of Energy Efficient Optimization Algorithms for Cluster Based Routing Protocol for Heterogeneous WSN

**Kamini Maheshwar, S. Veenadhari, and S. Almelu**

## 1 Introduction

Wireless sensor network consists of wireless sensor nodes which stores information and used to exchange the information for the communication process. These networks are playing very significant role as they are used in numerous fields like monitoring or particular area which includes health care monitoring, industrial monitoring, pollution monitoring, detecting threats, traffic management and control and many more. Wireless sensor networks are heterogeneous and homogenous, heterogeneous networks wireless sensor networks are comprised of sensing nodes with enhanced configuration for complicated tasks like clustering, routing etc. [1–3]. These wireless sensor networks store energy in their nodes which is consumed in performing the communication between the nodes [4]. Consumption of energy takes place in the sensor nodes by, sensing the data, processing it and finally exchanging it. Thus, it is necessary that wireless sensor networks should be energy efficient so that lifetime of the networks can be enhanced by using multiple techniques. One of the most significant problems in prolonging the life of a WSN is developing an energy-efficient routing protocol [5, 6]. Network scale can have an impact on lifetime; the network's stability becomes heavily essential as the scale grows. Grouping is one of the most effective ways to improve energy efficiency and the network's lifetime. K-means clustering separates information into K-clusters with more resemblance inside groupings but less similarities across clusters, and is one of the most widely used data clustering methods. CH is a node that collects information from sensor nodes in the cluster and delivers it to the base station. Clustering has shown to be one of the most effective strategies for boosting scalability and developing an energy-efficient WSN routing algorithm [7–11]. Several sensors can even con-serve energy

K. Maheshwar (✉) · S. Veenadhari · S. Almelu
Department of CSE, RNTU, Bhopal, M.P, India
e-mail: kaminimaheshwar@gmail.com



B. Unhelker et al. (eds.), *Applications of Artificial Intelligence and Machine Learning*, Lecture Notes in Electrical Engineering 925,
https://doi.org/10.1007/978-981-19-4831-2_51

by adjusting each node's sample rate. These techniques use quantitative optimization techniques or heuristic models to alter sample rates for topological modification, covering protection, or localization. Furthermore, as previously noted, model-based WSN management has several downsides. The effectiveness of sensor nodes implemented in the real world, on the other hand, is heavily dependent on the environment in which they operate. The quality of the obtained sensor data is directly affected by environmental conditions (e.g., location, etc.). Machine Learning (ML) methods are well-known for their self-experiencing characterized by the fact that they do not need reprogramming. Machine Learning is an effective technique that provides a computational method that is scalable, dependable, and cost-effective [12–15]. There are three forms of machine learning: Supervised learning, unsupervised learning, and reinforcement learning. It was noticed that techniques based on machine learning are beneficial in understanding the core issues of wireless sensor networks. The ML algorithm is effective in increasing the existence of the network, which, in turn, enhances the WSNs and how to make them appropriate for forecast the amount of energy that can be harvested in a given time frame. The WSNs' performance can also be increased by machine learning technique. WSNs need dynamic routing due to the variable nature of the sensor network. ML techniques can help with this and improve the system's efficiency.

## 2 Related Work

YuchaoChang [4] proposed a model termed as MLPGA algorithm that is based on determining optimal number of chromosomes in evolutionary algorithm. The model is designed in two-tier architecture. The clustering is done using k-mean clustering. Shashi Bhushan [5] the proposed method introduces a new concept called hybridization of population initialization. To cluster WSN, a hybrid method combining GA (as stated in Algorithm 3) and K-means is suggested in this paper. To ensure high-quality CHs, GA's initial population is seeded with K-means. The fitness module is based on factors such as intra-cluster distance, inter-cluster distance, and cluster number. Deyu Lin [9] focused on two main factors for energy efficiency: One is reducing energy consumption and second is managing energy consumption. The clustering algorithm is based on game theory. Dual cluster heads are formed in this algorithm for energy efficiency. JunfengXie [11] attempted to give readers a basic grasp of how machine learning algorithms work and when they can be applied to SDN challenges. Serious research difficulties and regarding the study paths in ML-based SDN include elevated quality training datasets, decentralized multi-controller platforms, increasing network security, cross-layer network optimization, and progressively implemented SDN. Sahoo et al. [12] suggested a particle swarm optimization (PSO) approach paired through energy efficient clustering and sinking (PSO-ECSM) to deal with the CH selection difficulty and the sink mobility issue. The efficiency of the PSO-ECSM is determined using comprehensive simulations. As per simulation results was performed on stability period, partially node dead, lifetime of the network, and performance, respectively. Nigam et al. [13] presented an upgraded algorithm dubbed ESO-LEACH to overcome the difficulties with LEACH, such as the non-uniformity of the number of cluster heads and the disdain for the nodes' residual energy. In this paper, meta-heuristic particle swarm augmentation is used to cluster the sensor nodes at first. In this paper, meta-heuristic particle swarm augmentation is used to cluster the sensor nodes at first. In the presented ESO-LEACH, the idea of upgraded nodes and an updated set of rules for CH election are employed to reduce the algorithm's randomness. Khatoon et al. [14] leverages the multiagent randomized parallel search approach of particle swarm optimization to construct a clustering algorithm that addresses both mobility and energy efficiency issues. Using particle swarm optimization, a multi-objective fitness function is used to build clusters. Nayyar et al. [15] represented an interesting energy-efficient ACO-based multipath routing technique for WSNs in this investigation, i.e., IEEMARP. Maheshwari et al. [16] used a combination of BOA and ACO to reduce total energy consumption and networking longevity. Wang et al. [17] proposed an algorithm termed as GECR to compute the total energy consumed by all sensor nodes throughout, where the technique integrates a clustering scheme and a routing approach in the same chromosomes. To find the ideal number of clusters and cluster heads, Bhushan et al. [18] suggested protocol uses range among clusters, length inside clusters, and a number of cluster heads. To lengthen the network's survival time, a fuzzy expanded grey wolf optimization algorithm-oriented threshold sensitive energy efficient clustering protocol is considered by Mittal et al. [19]. Daneshvar et al. [20] described a new clustering algorithm that uses the grey wolf optimizer to choose CHs. Zivkovic et al. [21] augmented GWO swarm intelligence metaheuristics to solve the clustering issue in WSNs in the research that will be conducted. Oluwasegun Julius Aroba [22] proposed a machine learning algorithm-based model termed as DEEC GAUSS for optimizing positioning and energy efficiency in wireless sensor network nodes. B. R. Al-Kaseem et al. [23] proposed a system that produced clusters based on heuristic data via sensor nodes, and this study proposes an efficient route optimization strategy focused on it. Abidoye and Kabaso [24] suggested as a fog-based technique for WSNs termed as EEHFC. EEHFC demonstrated a hierarchical routing framework for data transfer via fog nodes from typical sensor nodes to data centers. Vially Kazadi Mutombo [25] presented an EER-RL, an EER-based energy-efficient IoT routing protocol relying on reinforcement learning. Seyyedali Hosseinalipour [26] presented fog learning, a new approach for distributing machine learning model training across massive networks of heterogeneous devices.

## 3 Methodology

Clustering has proven to be one of the most powerful methods for increasing network scalability and designing a WSN routing protocol that is energy efficient. Moreover, model-based WSN management has some drawbacks, as mentioned herein. The routing algorithm is designed to follow various QoS criteria to provide better efficiency and to increase the lifetime of WSN challenges and problems considered by the network. This section, therefore, discussed about some optimization algorithms that contributes in energy efficiency of WSN and to provide application-specific assurance for Quality of Service (QoS).

## 3.1 Network Model

The following is the model-based presumption employed in this study:

N sensor nodes are placed at random throughout the sensing region, which is A = N * N in size. Both the sensor nodes and the base stations are situated random.

Every node in the network has a unique ID identifier and the similar beginning energies. The nodes have a definite amount of energy, but the Base Station has an endless amount.

The connection is symmetric. Depending on the acquired signal strength, the node can estimate the span between the transmitter and itself.

Every node only requires one primetime to connect with its parent node, and in that timeframe, every node can only accept or transmit one data packet and accompanying control packet.

The transmit power of the node can be adjusted based on the interaction distance.

## 3.2 Energy Consumption Model

The data exchange consumes the amount of energy consumed by sensor nodes. In this research, we solely consider the energy usage cost of data transmitting and merging information. The energy usage of transmitting and receiving is formalized in the calculations below in Eq. (1) [16]:

$$E_{tx}(m, s) = \begin{cases} mE_{selects} + m\varepsilon_{fs}s^2, & s < s_0 \\ mE_{selects} + m\varepsilon_{amp}s^4 & s \geq s_0 \end{cases} \tag{1}$$

$$E_{rx}(m) = mE_{selects} \tag{2}$$

where, m = data length, s = data transmission distance or span, Eselects = energy usage during transmitting and receiving of unit length data, $\varepsilon_{fs}$ *and* $\varepsilon_{amp}$ = amplifier energy usage of free space model and multiple path attenuation model.

The free space model is employed when the length s between the transmission and receiving nodes is smaller than the energy usage model cutoff, and the transmission range is attenuated as $s^2$. Instead, the multi-path attenuation framework is employed, using $s^4$ as the transmitted power. The energy needed for nodes to merge m-length information is calculated as follows:

$$E_u(m) = mE_{da} \tag{3}$$

where, $E_{da}$ = The amount of energy it takes to merge a unit length of information.

## 3.3 Bio-inspired Optimization Algorithms

Cluster optimization is one of the very useful technique in wireless sensor network that was introduced to optimize the cluster size and selection of optimal candidate of cluster head. The bio-inspired algorithms are used to evaluate the optimal parameters for cluster head selection that is based on intelligence and capabilities. The fundamental challenge in a wireless sensor network is sensor node deployed, covering capability, and movement plan; yet, the connectivity challenge in a wireless sensor node is dependent on a deployment sensor node. Even as scale of the problem grows larger, the optimizing strategies increase dramatically. As a consequence, an optimization algorithm which uses minimal memory and processing while producing excellent results is preferable, particularly for sensor network implementations. Traditional analytic procedures are substantially inefficient; thus, bioinspired optimization techniques offer a good alternative. General architecture of bio-inspired algorithm is presented in Fig. 1. Some of bio-inspired algorithms are discussed below:

Particle swarm optimization-based clustering algorithm: This algorithm automatically compute the optimal number of cluster without much intervention. It employs a swarm of agents (particles) that move around in the search space in search of the optimum answer. In search space, each particle changes its “flying” based on its own flying experience as well as that of other particles and hence the name “Particle swarm optimization based clustering algorithm”.

Ant colony optimization-based clustering algorithm: A way to solve optimisation problems based on the way that ants indirectly communicate directions to each other. In this algorithm some random solutions are generated first represent the word ant and the ant path represent the solution.

Genetic optimization-based clustering algorithm: Genetic based algorithm technique based on the principle of genetic and natural selection. It is frequently used to find the optimal and near optimal solutions to difficult problem which otherwise would tale a lifetime to solve.

Gray wolf optimization-based clustering algorithm: This algorithm predicts the solution based on the mathematical model in which a particle or object has better knowledge about the solution. In this algorithm, best solutions are saved and used to update other particle’s position for search optimal results.

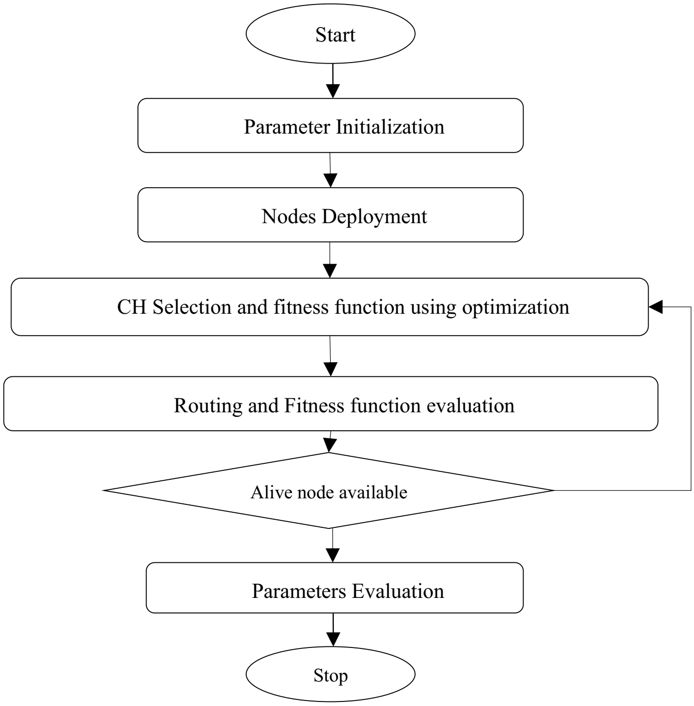


**Fig. 1** General flowchart of bio-inspired optimization algorithms

### 3.4 Parameters for Designing Bio-Inspired Optimization Algorithm

***Residual Energy of the CH:*** Inside a system, the cluster head conducts a variety of functions such as data collection from regular sensors and transfer of data to the base station. Because the cluster head takes a huge amount of energy therefore the nodes with the highest residual energy is selected to be a cluster head. The remaining energy ($F_1$) is expressed mathematically below in Eq. (4).

$$F_1 = \sum_{i=1}^{M} \frac{1}{E_{ch(i)}} \tag{4}$$

where $E_{ch(i)}$ is the i$^{th}$ remaining energy of the cluster head.

***The Range Among Sensor Nodes:*** It specifies the spacing in between standard sensor nodes as well as its own cluster head. The spacing of the transmitting link has the greatest impact on the node's energy loss. Once the selected node has a shorter transmission range to the base stations, the node's energy usage was reduced. The Eq. (5) expresses the range between the regular sensors and cluster head ($F_2$).

$$F_2 = \sum_{j=1}^{M}\left(\sum_{i=1}^{Ij}\frac{range\left(R_i, CH_j\right)}{I_j}\right) \tag{5}$$

Here, the range between the sensors (i) and cluster head $CH_j$ is represented as $range\left(R_i, CH_j\right)$, and the quantity of sensor nodes that belongs to cluster head is denoted as $I_j$.

***The Range Among the Cluster Head and Base Station:*** It specifies the range between the cluster head and the base station. The node's energy usage is proportional to the range travelled along the transmission link. For example, if the base station is located far off the cluster head, it will consume more energy for information transfer. As a result, the rapid decrease of cluster head might occur as a result of rising energy usage. As a result, throughout transmission, the node closest to the base station is favored. The objective function ($F_3$) of range in between cluster head and the base station is expressed by the following Eq. (6).

$$F_3 = \sum_{i=1}^{M} range\left(CH_j, BS\right) \tag{6}$$

***The Degree of the Node:*** It specifies the quantity of sensor nodes assigned to each cluster head. Cluster heads with fewer sensor-nodes are chosen as cluster heads with more cluster members incur losses in a shorter period of time. Equation (7) expresses the node degree ($F_4$).

$$F_4 = \sum_{i=1}^{M} I_i \tag{7}$$

***The Centrality of Nodes:*** Node centrality ($F_5$) expresses how far a node is from its neighbors and is stated in Eq. (8).

$$F_5 = \sum_{i=1}^{M}\frac{\sqrt{\sum_{j\in N} Range^2(i, j)\Big/ N(i)}}{Dimension\,of\ Network} \tag{8}$$

Here, N(i) is the quantity of nodes in neighborhood of $CH_i$.

**Table 1** Simulation scenario for WBAN

| Simulation scenario | Values |
|---|---|
| Area | 100 * 100 m |
| WBAN sensor nodes | 100 |
| Initial energy of network | 0.5 J |
| Packet size | 2000, 4000 |

# 4 Discussion

## *4.1 Simulation Scenario*

The simulation scenario is deployed with sensor nodes in area of 100 * 100 m as mentioned in Table 1. For energy evaluation, energy consumption model/radio model is considered to analyze some bio-inspired algorithms. The main objective of this paper is to evaluate and reduce the overall energy consumption of each node in the network. So, the cluster-based routing is developed with bio-inspired optimization based cluster head selection and routing between the nodes. The inputs given to bio-inspired optimization for better CH selection are residual energy, node degree, distance to the neighbors, distance to the BS, etc. For performance evaluation of the proposed model, the paper presents the simulated the scenario on the MATLAB platform under different conditions and with different parameters. These parameters are discussed below.

Throughput: Another important parameter is the throughput that is calculated on the successful delivery of data packets to the sink node at a particular time. The routing protocols of WBAN are dedicated to maximizing the throughput.

Network Longevity: In WBAN routing algorithms, the most important parameter is network longevity as sensor nodes are battery-operated. This is evaluated by counting the alive and dead nodes after every round or after a particular period.

## *4.2 Result Analysis*

Heterogeneous WSN areas are simulated for multiple sensor nodes in a particular area. The configuration of the simulation is presented in Table 1. Random location of sink node is selected with unlimited energy whereas sensor nodes are deployed with limited energy with different energy levels. The proposed scheme is implemented for variable rounds of iterations for different packet sizes (2000 and 4000). In this paper, we have presented the comparative analysis of optimization algorithms. So, Tables 2 and 3 represents the result analysis under 2000 packet size and 4000 packet size respectively of some well-known bio-inspired optimization algorithms such as PSO [12], ACO [16], GA [12] and GWO [21].

**Table 2** Comparative performance analysis with 2000 packet size

| | Network Longevity (in rounds) | Throughput (packets) |
|---|---|---|
| LEACH [16] | 1500 | 40,000 |
| PSO-ECSM [12] | 19,071 | 637,880 |
| ICRPSO [12] | 17,360 | 568,457 |
| PSOBS [12] | 15,222 | 486,712 |
| DEEC [16] | 1700 | 40,000 |
| ACO [16] | 8500 | 350,000 |
| DCH-GA [12] | 10,466 | 308,695 |

**Table 3** Comparative performance analysis with 4000 packet size

| Algorithms | Network Longevity (in rounds) | Throughput (packets) |
|---|---|---|
| LEACH | 1570 | 13,000 |
| LEACH-PSO [21] | 3,880 | 20,000 |
| LEACH-EEGWO [21] | 3900 | 21,000 |

From Fig. 2 it can be concluded that the PSO optimized cluster routing protocols outperforms better as compared to others. In PSO [12], the network lifetime was observed to be 19,071 rounds, GA [12] achieves 10,466 rounds of lifetime and ACO [16] achieves 8500 rounds of network lifetime. Similarly, from Fig. 3 it was observed that PSO [12], GA [12] and ACO [16] achieved 637880 packets, 308695 packets and 350,000 packets of throughput respectively. So, from this analysis it can be said that there is future research scope with PSO optimization algorithm because by using PSO optimization maximum output can be achieved. Another analysis is presented on 4000 packets and its result is shown in Table 3. From Figs. 4 and 5 shows another comparison between PSO and GWO optimization algorithms. The result analysis shows just similar results of PSO and GWO. Therefore, from this analysis it can be concluded that PSO and GWO can be opted in future as an optimization algorithm for routing in cluster based WSN.

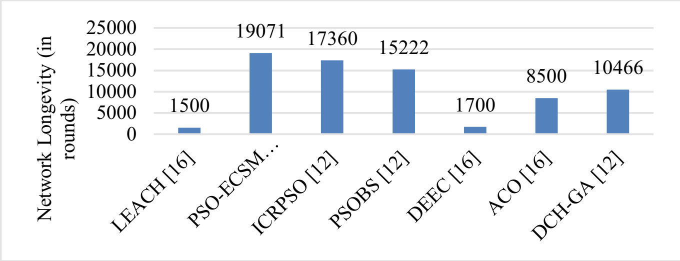


**Fig. 2** Network longevity analysis with 2000 packet size

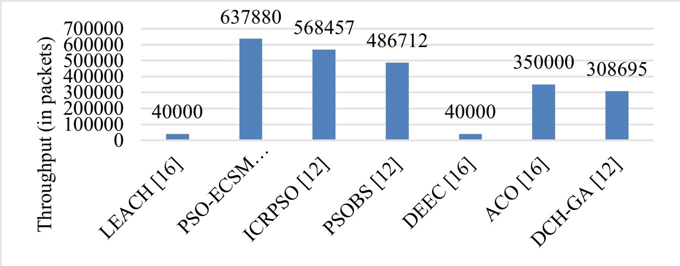


**Fig. 3** Throughput analysis with 2000 packet size

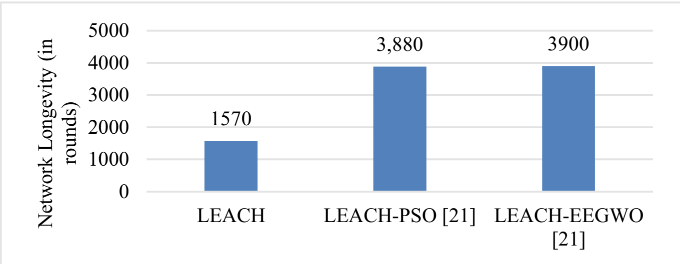


**Fig. 4** Network longevity analysis with 4000 packet size

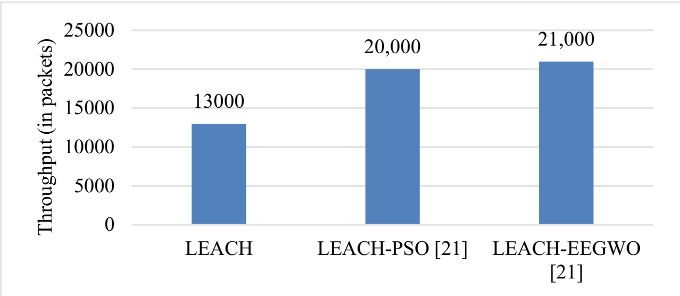


**Fig. 5** Throughput analysis with 4000 packet size

## 5 Conclusion

One of the most frequently used topologies for WSN is clustering for energy efficiency, load balancing and achieving quality of service (QoS). This paper summarizes the objectives for future research works in field of cluster-based routing for WSNs. This paper is dedicated to analyze the effectiveness of bio-inspired optimization algorithms for clustering of sensor nodes in WSN applications. The comparative analysis was performed in this paper among PSO, GA, ACO and GWO. Out of which PSO and GWO outperforms better as compared to others. So, for future research work, PSO can be used for designing more efficient routing protocol for WSN application such as Internet of things (IoT).

Recently, bio-inspired computing had attracted the interest of researchers due to its capabilities of intelligence and adaptive nature. Besides that, those technologies must be enhanced as well. For node mobility management, these novel models were based on bio-inspired computation must be implemented. There's also a function for node mobility, which aims to boost network coverage while simultaneously increasing network lifetime and improving data detail timeliness and dependability. Upcoming scientific investigations can look on how to reduce power usage for coverage options with gaps, as well as how to control sensor node tactical strategy to repair network coverage and extend lifetime of the network. Other factors, including an energy usage model for network nodes and their movement approach, must also be considered when constructing movement strategies.

## References


1. Gautam N, Vig R (2014) Energy efficient approach through clustering and data filtering in WSN. In: Proceedings 2014 international conference advanced computing communication informatics, ICACCI, pp 2142–2148. https://doi.org/10.1109/ICACCI.2014.6968467
2. Al-Aboody NA, Al-Raweshidy HS (2016) Grey wolf optimization-based energy-efficient routing protocol for heterogeneous wireless sensor networks. In: International symposium computing bus intelligence ISCBI, pp 101–107. https://doi.org/10.1109/ISCBI.2016.7743266
3. Yan J, Zhou M, Ding Z (2016) Recent advances in energy-efficient routing protocols for wireless sensor networks: a review. IEEE Access 4:5673–5686. https://doi.org/10.1109/ACCESS.2016.2598719
4. Chang Y, Yuan X, Li B (2019) Machine-learning-based parallel genetic algorithms for multi-objective optimization in ultra-reliable low-latency WSNs. IEEE Access 7:4913–4926. https://doi.org/10.1109/ACCESS.2018.2885934
5. Bhushan S, Pal R, Antoshchuk SG (2018) Energy efficient clustering protocol for heterogeneous wireless sensor network: a hybrid approach using GA and K-means. In: IEEE 2nd international conference data stream mining process DSMP, pp 381–385. https://doi.org/10.1109/DSMP.2018.8478538
6. Lata S, Mehfuz S (2019) Machine learning based energy efficient wireless sensor network. In: International conference power electron control automation ICPECA. https://doi.org/10.1109/ICPECA47973.2019.8975526

7. Kang J, Kim J, Kim M, Sohn M (2020) Machine learning-based energy-saving framework for environmental states-adaptive wireless sensor network. IEEE Access 8:69359–69367. https://doi.org/10.1109/ACCESS.2020.2986507
8. Bharot N, Suraparaju V, Gupta S (2019) DDoS attack detection and clustering of attacked and non-attacked VMs using SOM in cloud network. In: Singh M, Gupta P, Tyagi V, Flusser J, Ören T, Kashyap R (eds) Advances in Computing and Data Sciences. ICACDS 2019. CCIS, vol 1046. Springer, Singapore. https://doi.org/10.1007/978-981-13-9942-8_35
9. Lin D, Wang Q (2019) An energy-efficient clustering algorithm combined game theory and dual-cluster-head mechanism for WSNs. IEEE Access 7:49894–49905. https://doi.org/10.1109/ACCESS.2019.2911190
10. Kumar N, Sandeep, Bhutani P, Mishra P (2012) U-LEACH: a novel routing protocol for heterogeneous wireless sensor networks. In: International conference communication information computing technology ICCICT. https://doi.org/10.1109/ICCICT.2012.6398214
11. Xie J, Richard YuF, Huang T (2019) A survey of machine learning techniques applied to software defined networking (SDN): research issues and challenges. IEEE Commun Surv Tutorials 21:393–430. https://doi.org/10.1109/COMST.2018.2866942
12. Sahoo BM, Amgoth T, Pandey HM (2020) Particle swarm optimization-based energy efficient clustering and sink mobility in heterogeneous wireless sensor network. Ad Hoc Networks 106:102237. https://doi.org/10.1016/J.ADHOC.2020.102237
13. Nigam GK, Dabas C (2018) ESO-LEACH: PSO based energy efficient clustering in LEACH. J King Saud Univ Comput Inf Sci. https://doi.org/10.1016/J.JKSUCI.2018.08.002
14. Khatoon N, Amritanjali (2017) Mobility aware energy efficient clustering for MANET: a bio-inspired approach with particle swarm optimization. Wirel Commun Mob Comput 2017:1–12. https://doi.org/10.1155/2017/1903190
15. Nayyar A, Singh R (2019) IEEMARP- a novel energy efficient multipath routing protocol based on ant colony optimization (ACO) for dynamic sensor networks. Multimed Tools Appl 79:35221–35252. https://doi.org/10.1007/S11042-019-7627-Z
16. Maheshwari P, Sharma AK, Verma K (2021) Energy efficient cluster-based routing protocol for WSN using butterfly optimization algorithm and ant colony optimization. Ad Hoc Netw 110:102317. https://doi.org/10.1016/J.ADHOC.2020.102317
17. Wang T, Zhang G, Yang X, Vajdi A (2018) Genetic algorithm for energy-efficient clustering and routing in wireless sensor networks. J Syst Softw 146:196–214. https://doi.org/10.1016/J.JSS.2018.09.067
18. Bhushan S, Pal R, Antoshchuk SG (2018) Energy efficient clustering protocol for heterogeneous wireless sensor network: a hybrid approach using GA and K-means. In: International conference data stream mining process DSMP, pp 381–385. https://doi.org/10.1109/DSMP.2018.8478538
19. Mittal N (2020) An energy efficient stable clustering approach using fuzzy type-2 bat flower pollinator for wireless sensor networks. Wirel Pers Commun 1122(112):1137–1163. https://doi.org/10.1007/S11277-020-07094-8
20. Daneshvar SMMH, Mohajer PAA, Mazinani SM (2019) Energy-efficient routing in WSN: a centralized cluster-based approach via grey wolf optimizer. IEEE Access 7:170019–170031. https://doi.org/10.1109/ACCESS.2019.2955993
21. Zivkovic M, Bacanin N, Zivkovic T et al (2020) Enhanced grey wolf algorithm for energy efficient wireless sensor networks. In: Zooming innovation consumer technology conference ZINC, pp 87–92. https://doi.org/10.1109/ZINC50678.2020.9161788
22. Aroba OJ, Naicker N, Adeliyi T (2021) An innovative hyperheuristic, gaussian clustering scheme for energy-efficient optimization in wireless sensor networks. J Sens 1–12. https://doi.org/10.1155/2021/6666742
23. AL-Kaseem BR, Taha ZK, Abdulmajeed SW, Al-Raweshidy HS (2021) Optimized energy efficient path planning strategy in WSN with multiple mobile sinks. IEEE Access 9:828833. https://doi.org/10.1109/access.2021.3087086
24. Abidoye AP, Kabaso B (2021) Energy-efficient hierarchical routing in wireless sensor networks based on fog computing. EURASIP J Wirel Commun Netw. https://doi.org/10.1186/s13638-020-01835-w

25. Mutombo VK, Lee S, Lee J, Hong J (2021) EER-RL: energy-efficient routing based on reinforcement learning. Mob Inf Syst. https://doi.org/10.1155/2021/5589145
26. Hosseinalipour S, Brinton CG, Aggarwal V, Dai H, Chiang M (2020) From federated to fog learning: distributed machine learning over heterogeneous wireless networks. IEEE Commun Mag 58(12):41–47. https://doi.org/10.1109/MCOM.001.2000410