Parametric Analysis on Cluster Head Selection using Hybrid Optimization Framework

Kale Navnath Dattatraya†, S. Ananthakumaran††

†Research Scholar, Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, India
††Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, India

Abstract

Clustering and Routing are the most important issues in Wireless Sensor Networks (WSNs) as these factors hold a significant role in data transmission. In clustering, cluster heads (CH) are overloaded with heavy traffic than other nodes of cluster. This leads to the hotspot issues. Therefore, it is essential to choose a suitable CH in a cluster oriented routing model. This paper introduces a novel CH selection model to increase the energy efficiency and life span of network. In addition, this work deploys Fitness based Glowworm swarm with Fruit fly Algorithm (FGF) for the optimal selection of CH. At last, parametric analysis is carried out to prove the supremacy of the presented approach with respect to cost analysis, energy analysis and alive node analysis by varying the count of neighbors and sensor ranges.

Key words:
Routing; Cluster Head; FGF Algorithm; Clustering; Sensor range.

Nomenclature

Abbreviation	Description
APTEEN	Adaptive Threshold Energy Efficient sensor Network
CH	Cluster Heads
EE	Energy Efficiency
FGF	Fitness based Glowworm swarm with Fruit fly Algorithm
FF	Firefly
GSO	Glowworm swarm
HSO	Harmony Search Optimization
HABC-MBOA	Hybrid Artificial Bee Colony and Monarchy Butterfly Algorithm
HML	Hierarchical Maximum Likelihood
LEACH	Low-Energy Adaptive Clustering Hierarchy
MOFPL	Multi-objective fractional particle lion algorithm
OWSN	Optical WSN
PSO	Particle Swarm optimization
Taylor KFCM	Taylor kernel fuzzy C-means
WSNs	Wireless Sensor Networks

Manuscript received December 5, 2020
Manuscript revised December 20, 2020
https://doi.org/10.22937/IJCSNS.2020.20.12.11

1. Introduction

WSN includes a number of sensors that are connected to the wireless medium. The sensed data from sensor nodes is typically forwarded to BS, where the data is collected, analyzed and certain actions are carried out accordingly [9] [6] [7]. The WSN is deployed in several appliances like weather monitoring, field surveillance, meteorological data collection, transportation, and health-care [8] [9]. However, the nodes in WSN don't include any rechargeable storage device or any researchable batteries. However, it should support any system with efficient power utilization.

Clustering is a well-known technique to make the data transmission more effectual with respect to energy and power utilization. Each cluster in network has unique CH, which is accountable for transferring data to other sensor nodes in its cluster. Furthermore, the communication to BS is done only through this CH. In this scenario, major role is to select the optimal CH under varied constraints such as less energy utilization, delay and so on [10] [11] [12] [13]. By forming the clusters, the energy efficiency of network will be increased as the amount of data send to BS is significantly minimized [14] [15].

Accordingly, the cluster-based protocols are engaged in extending the network lifetime [20]. The most commonly employing algorithms are "APTEEN, LEACH", and so on. Further, LEACH operates in the distributed manner that elects the CH depending on the predetermined probability [15] [16]. Based on the meta-heuristic algorithms, various centralized cluster based protocols have been introduced so far. Some of the familiar algorithms are PSO, HSO etc. Still, challenges exist in designing the routing protocol with higher network lifetime, EE and QoS. This paper carries out the parametric analysis of proposed FGF algorithm in selecting the optimal CH selection by varying the sensor range and number of neighbours.

Rest of the paper is arranged as follows: Section II analyses the reviews. Section III explains the optimal cluster head selection in WSN. Section IV described the parameters considered for optimal CH selection. Section V and VI explains the results and conclusion.

2. Literature Review

In 2019, Reeta and Dinesh [1] have designed a multi-objective fitness function depending on distance, traffic rate, energy, cluster density and delay. The energy-aware routing was carried out based on the proposed MOFPL. This model has recognized the optimal CH from numerous CH nodes in WSN and consequently, the optimal path was also determined. Furthermore, the outcomes established from the designed model have ensured effectual CHS with higher network energy.

In 2019, Bandi *et al.* [2] have presented a new HABC-MBOA model for optimal selection of CH in WSN. Here, the implemented model has enhanced the global search capability and it has also eliminated the feasibility of CH being overloaded with numerous sensor nodes that causes rapid death of nodes while deploying ineffective CHS process. At last, the outcomes have revealed the betterment of presented method in terms of count of alive nodes.

In 2019, Kale and Raghava [3] have introduced a novel CHS selection scheme for improving the life span and EE in WSN. Moreover, this work has exploited the FGF for selecting the optimal CH in WSN. In the end, the performance of the developed technique was revealed in terms of energy and cost function.

In 2020, Augustine and Ananth [4] have offered an enhanced approach for CHS based on Taylor KFCM that was modified from the kernel fuzzy model. The presented model has elected the CH by means of "acceptability factor" that was computed based on trust, distance, and energy. Further, the supremacy of the designed technique was confirmed in terms of maximal energy and higher trust.

In 2019, Goswami *et al.* [5] have developed a cluster formation model using FF model and HML model in OWSN for enhancing the EE. Here, the issues in FF model were overcome by integrating the concept of HML with it. At the end, the simulation analysis has exposed the enhancement of the adopted model in terms of EE and cost function.

3. Optimal Cluster Head Selection in WSN

Consider WSN with n^C clusters, where the cluster is signified as cl_i, $\left(i = 1,.......n^C\right)$. In this, B_{ij} refers to the nodes in cluster, in which $i = 1,2,.......M$ and $j = 1,2,........L$. From the cluster nodes, the cluster head CH_i is selected that acts as the head for all nodes in the cluster. The CH directly communicates with BS D_S. Moreover, a novel hybrid algorithm is used for electing the optimal CH by considering the constraints such as energy, distance and delay [19].

A. Fitness Function Evaluation

For optimal CH selection, the constraints such as energy, distance and delay are to be considered. In addition, this work considers the QoS constraint as the main factor for the proficient performance of network. Eq. (1) illustrates the objective of this work, in which β refers to constant with a value of 0.3. In Eq. (2), γ^1, γ^2 and γ^3 points out the constraints of distance, energy and delay, in that order and $\| B_r - D_S \|$ in Eq. (3) refers to the distance among the node and BS.

$$OF = \beta \times f^2 + (1-\beta) f^1 \ ; 0 < \beta < 1 \tag{1}$$

$$f^1 = \gamma^1 * f_i^{dist} + \gamma^2 * f_i^{energy} + \gamma^3 * f_i^{delay} \tag{2}$$

$$f^2 = \frac{1}{n^C} \sum_{r=1}^{n^C} \| B_r - D_S \| \tag{3}$$

4. Parameters considered for Optimal Cluster Head Selection

The parameters that are defined in this work is mathematically modelled as follows:

Energy: It is determined in Eq. (4), in which $E(B_i)$ and $E(CH_j)$ refers to the energy of i^{th} normal node and energy of j^{th} CH, in that order.

$$f^{energy} = \frac{f^{energy}(q)}{f^{energy}(p)} \tag{4}$$

$$f^{energy}(q) = \sum_{j=1}^{M} uE(j) \tag{5}$$

$$uE(j) = \sum_{\substack{i=1 \\ i \in j}}^{M} \left(1 - E(B_i) * E(CH_j)\right); \ 1 \le j < L \tag{6}$$

$$f^{energy}(u) = L * \underset{i=1}{\overset{M}{Max}}\left(E(B_i)\right) * \underset{j=1}{\overset{L}{Max}}\left(E(CH_j)\right) \tag{7}$$

Distance: It is computed as per Eq. (8), where $f^{dist}(q)$ refers to the distance among normal nodes and CH and between CH and BS as specified in Eq. (9) and $f^{dist}(p)$ refers to the distance amongst two normal nodes as specified in Eq. (10). Here, the value of $f^{distance}(q)$ lies among [0, 1].

$$f^{dist} = \frac{f^{dist}(q)}{f^{dist}(p)} \tag{8}$$

$$f^{dist}(q) = \sum_{i=1}^{M} \sum_{j=1}^{L} \left\| B_i - CH_j \right\| + \left\| CH_j - D_s \right\| \tag{9}$$

$$f^{dist}(p) = \sum_{i=1}^{M} \sum_{j=1}^{L} \left\| B_i - B_j \right\| \tag{10}$$

Delay: The delay among nodes is shown in Eq. (11), and it lies between [0, 1]. If the number of nodes in a cluster minimizes, the delay also gets reduced considerably. In Eq. (11), CH_j refers to the CH in WSN and M refers to the total node count.

$$f^{delay} = \frac{\underset{j=1}{\overset{L}{Max}}\left(CH_j\right)}{M} \tag{11}$$

Quality of Service: QoS encompasses all the constraints mentioned above. All those constraints must be satisfied to define higher QoS.

A. Solution Encoding

For optimal selection of CH, this paper exploits the FGF algorithm. The input solution given to FGF is shown in Fig 1, where CH_n refers to the total number of cluster heads.

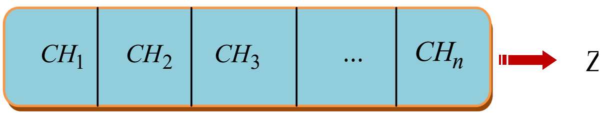


Fig. 1. Solution Encoding

B. FGF Algorithm

FGF algorithm is the hybrid version of both FFOA and GSO algorithms. In fact, the hybrid optimizations are reported to be capable for solving search issues [22] [3]. As per FGF algorithm [19], the evaluation of fitness is done initially and then the fitness is sorted. After sorting, choose the best five fitness (choose the index). If the index number is lesser than five, GSO update is carried out. In GSO [17], the glowworms express a luminous quantity called "luciferin". Moreover, they take their own decisions with respect to decision domain $G_e^g\left(0 < G_e^g \le G_u\right)$. Let us consider g glowworms, and w be the neighbouring glowworms.

Initialization: The glowworms are arbitrarily distributed in the searching space. Consequently, the glowworms include identical luciferin intensity with identical decision domain G_0.

Luciferin-Update: Generally, the luciferin intensity is very much related to the location's fitness. If the intensity value is better, the best position can be attained and it is said to be the best target value. Or else, the target is regarded as poor. The g glowworm position at t time is $Z_g(t)$ and the related objective value at g^{th} glowworm position at t is $J(Z_g(t))$. Further, convert $J(Z_g(t))$ to $U_g(t)$, which is the luciferin level associated to g glowworm at t and it is shown in Eq. (12), wherein υ refers to the luciferin decay constant, η points out the constant variable.

$$U_g(t) = (1-\upsilon)U_g(t-1) + \eta\left(J\left(Z_g(t)\right)\right) \tag{12}$$

Movement: During this phase, g glowworm moves towards w neighbor that initiates from $H_g(t)$ with a committed probability $P_{gj}(t)$, and it is modelled as specified in Eq. (13).

$$P_{gj}(t) = \frac{U_w(t) - U_g(t)}{\sum_{l \in Y_g(ti)} U_l(t) - U_g(t)} \tag{13}$$

Once the g glowworm moves, the position will be updated and the evaluation of position update takes place as specified in Eq. (14), wherein $size$ points out the step size.

$$Z_g(t+1) = Z_i(t) + size * \left(\frac{Z_w(t) - Z_g(t)}{\| Z_w(t) - Z_g(t) \|} \right) \tag{14}$$

On the other hand, if the index number is higher than five, FFOA update [18] [21] is carried out as shown in Eq. (15) and (16). In FFOA model, the fruit flies are dispersed randomly as Z_axis and W_axis and $index^{best}$ points out the higher component and its respective indices.

$$Z\_axis = Z\left(index^{best}\right) \tag{15}$$

$$W\_axis = W\left(index^{best}\right) \tag{16}$$

5. Results and Discussion

A. Simulation setup

The proposed model for CH selection in WSN was implemented in MATLAB and the results were noticed. Here, the nodes were distributed with area $100m \times 100m$ with BS at center. The initial energy E^{In} was set as 0.5J, the energy of free space model E^{fr} was $10\,pJ/bit/m^2$. In addition, the power amplifier energy $\left(E^{power}\right)$ was fixed as $0.0013\,pJ/bit/m^2$, the transmitter energy E^{tr} was fixed as $50nJ/bit/m^2$, and the data aggregation energy E^{Da} was fixed as $5nJ/bit/signal$. Furthermore, the analysis was performed by varying the count of neighbors of GSO from 1, 2, 3, 4 and 5. Moreover, the sensor range of GSO was varied from 0.2×10^{13}, 0.4×10^{13}, 0.5×10^{13}, 0.6×10^{13}, and 1×10^{13} and the results were taken for 2000 rounds.

B. Statistical Analysis

Table I and Table II demonstrates the analysis of presented work by varying the count of neighbors and sensor range. The analysis was carried out with respect to alive nodes and normalized energy under mean, median and standard deviation scenarios. On examining the results from Table I, the presented work has attained a higher energy of 0.31845 at mean case scenario, when the sensor range is at 0.6×10^{13}. For other sensor ranges, the energy attained by the presented work is comparatively low. Moreover, higher count of alive nodes (100) is attained when the sensor range is at 0.4×10^{13}, 0.5×10^{13}, $0.6\times10^{13}$and 1×10^{13} under median case scenario. Similarly, from Table II, higher energy (0.45081) is attained by the presented work under mean case scenario when the count of neighbours is 5. Thus, the analysis shows the efficiency of the proposed algorithm in selecting the optimal CH.

TABLE I. TATISTICAL ANALYSIS OF PROPOSED MODEL IN TERMS OF NORMALIZED ENERGY AND ALIVE NODES BY VARYING THE SENSOR RANGE

Sensor range	Mean		Median		Standard deviation	
	Normalized energy	Alive nodes	Normalized energy	Alive nodes	Normalized energy	Alive nodes
0.2×10^{13}	0.27345	68	0.22479	99	0.25308	43.994
0.4×10^{13}	0.31345	69	0.26479	100	0.25308	43.093
0.5×10^{13}	0.30345	69.4	0.25479	100	0.25308	42.553
0.6×10^{13}	0.31845	69.8	0.26979	100	0.25308	42.014
1×10^{13}	0.30845	70.6	0.25979	100	0.25308	40.937

TABLE II. STATISTICAL ANALYSIS OF PROPOSED MODEL IN TERMS OF NORMALIZED ENERGY AND ALIVE NODES BY VARYING THE COUNT OF NEIGHBOURS

Count of neighbours	Mean		Median		Standard deviation	
	Normalized energy	Alive nodes	Normalized energy	Alive nodes	Normalized energy	Alive nodes
1	0.27523	69.8	0.22726	99	0.2508	42.252
2	0.45007	79.2	0.44463	89	0.30853	31.252
3	0.27345	79.2	0.22479	89	0.25308	31.713
4	0.45075	79.2	0.4448	89	0.30779	31.713
5	0.45081	79.6	0.44542	89	0.30831	30.843

C. Difference in CH distance

For all iterations, the CH fluctuates depending on distance as well as energy. Table III and Table IV show the distance among the CHs in clusters by proposed algorithm for varied neighbors count and sensor range. A minimal distance of 47.769 is attained under best case scenario when the sensor range is 0.2×10^{13}.

TABLE III. DISTANCE EVALUATION AMONG DIFFERENT CHS BY PROPOSED MODEL FOR VARYING SENSOR RANGE

Statistics	Sensor range= 0.2×10^{13}	Sensor range= 0.4×10^{13}	Sensor range= 0.5×10^{13}	Sensor range= 0.6×10^{13}	Sensor range= 1×10^{13}
Best	47.769	229.18	133.28	211.95	290.95
Worst	4816.7	4379.3	3917.7	4267.7	4294.4
Mean	1836.8	1716.5	1714.2	1725.8	1722.4
Median	1835.2	1669.9	1683	1657.5	1677.2
Standard deviation	800.99	627.57	638.56	642.89	633.91

TABLE IV. DISTANCE EVALUATION AMONG DIFFERENT CHS BY PROPOSED MODEL FOR VARYING NEIGHBOUR COUNT

Statistics	Neighbour count = 1	Neighbour count = 2	Neighbour count = 3	Neighbour count = 4	Neighbour count = 5
Best	13.349	66.273	28.604	11.073	10.673

Worst	4505.9	4906.3	4646.3	4838.4	4529.3
Mean	1590.1	1722	1676.2	1686.1	1699.6
Median	1533.9	1667.4	1597.7	1599.6	1655.4
Standard deviation	789.95	769.47	769.28	771.38	786.68

D. Convergence Analysis

The convergence analysis (cost) of presented work is analysed in this section. The analysis is carried out by varying the count of neighbors and sensor range with respect to varied iterations that ranges from 0, 2, 4, 6, 8 and 10. On noticing Fig. 2 (a), the implemented work has attained a minimal cost of 6×10^{-3} at iteration 10, when the count of neighbour is 5. That is, the cost of presented model at count of neighbour= 5 is 8.33%, 33.33%, 13.33% and 13.33% better than the cost values attained when the count of neighbours is 1, 2, 3 and 4 respectively. Thus, the cost analysis of the presented model is proved from the analysis.

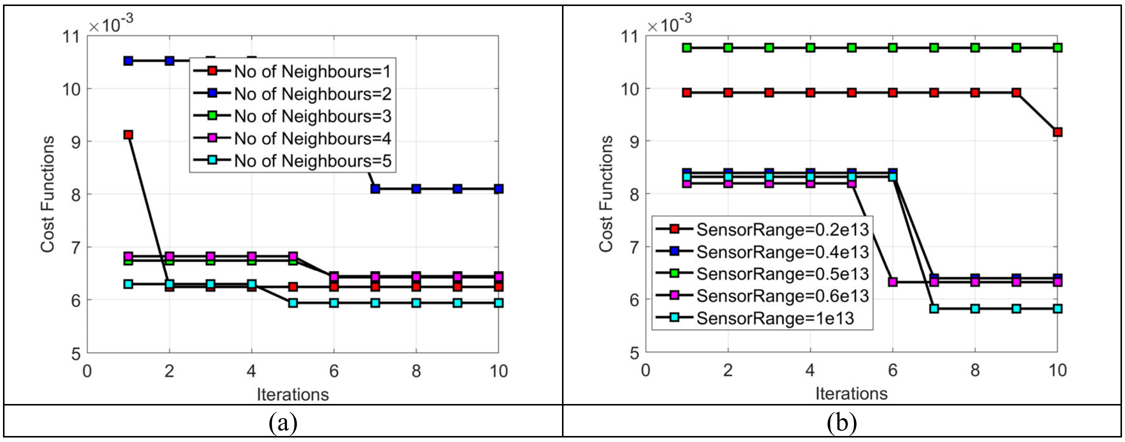


Fig. 2. Convergence analysis of proposed model by varying the (a) count of neighbours (b) sensor range

E. Alive Node Analysis

Fig 3 shows the analysis on alive nodes remains by the FGF model under the variation of count of neighbors and sensor ranges. Here, analysis is carried out for 2000 rounds and the results were observed. On observing the graphs, the presented approach has attained more alive nodes during the initial rounds, however, as the rounds increases; the count of alive nodes gets reduced. From Fig. 3(a), the presented model seems to include higher count of alive nodes when count of neighbour= 5 and it is 66.67%, 66.67%, 6.67% and 6.67% superior to the count of alive nodes attained when the count of neighbours is 1, 2, 3 and 4 respectively.

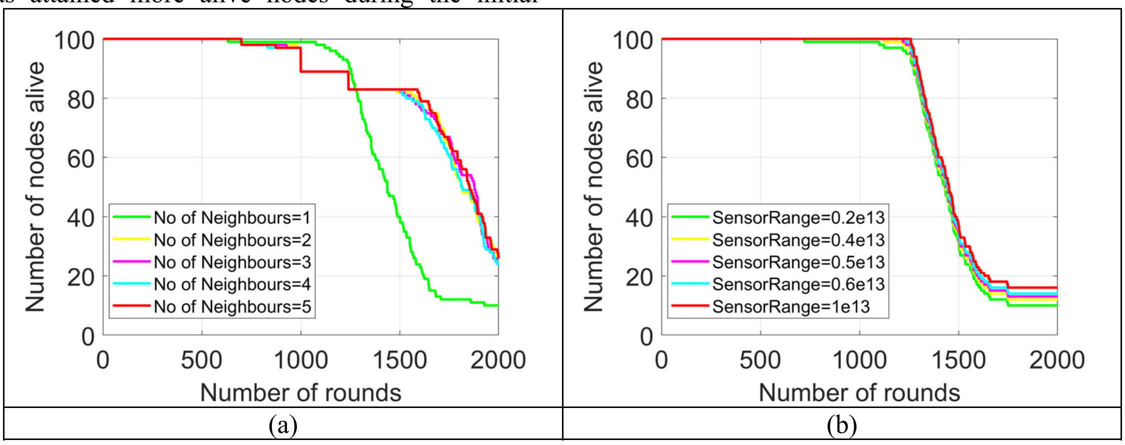
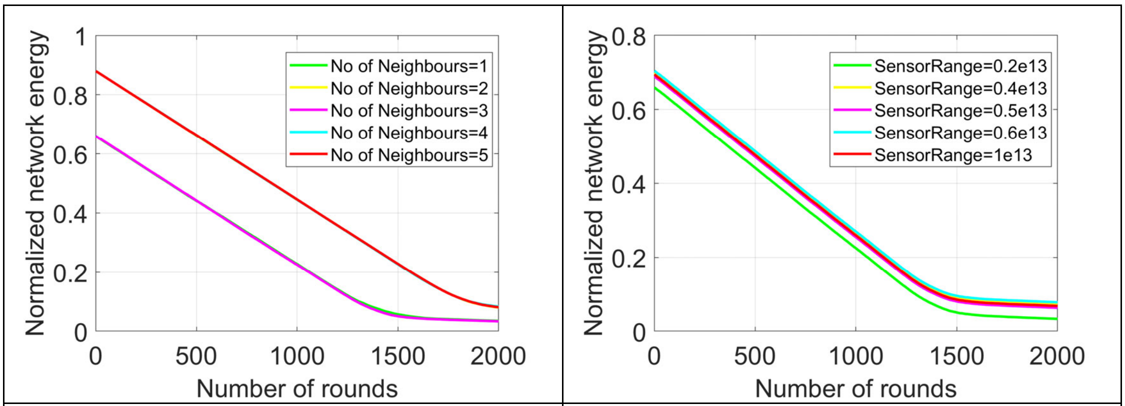


Fig. 3. Alive node analysis of proposed model by varying the (a) count of neighbours (b) sensor range

F. Normalized Energy Analysis

Fig 4 shows the analysis on normalized network energy by varying the count of neighbors and sensor ranges for 2000 rounds. From Fig. 4, it is evident that the network energy gradually minimizes with increase in the count of rounds. Especially, the proposed algorithm exhibits higher energy when sensor range is 0.6×10^{13}, which is 37.5%, 37.5%, 12.5% and 12.5% superior to the energy attained when the sensor range is at 0.2×10^{13}, 0.4×10^{13}, 0.5×10^{13} and 1×10^{13} respectively.



(a) (b)

Fig. 4. Analysis on Normalized Energy attained by proposed model by varying (a) count of neighbours (b) sensor range

6. Conclusion

This work has focused on CH selection model for increasing the EE and life span of network. For optimal selection of CH, this work has exploited FGF algorithm that was the hybridized version of FFOA and GSO models. At last, analysis was performed for authenticating the improvement of presented model by varying the count of neighbors and sensor ranges. Particularly, the implemented work has attained a minimal cost of 6 at iteration 10, when the count of neighbour was 5. That is, the cost of presented model at count of neighbour= 5 was 8.33%, 33.33%, 13.33% and 13.33% better than the cost values attained when the count of neighbours was 1, 2, 3 and 4 respectively. Thus, the superiority of the FGF model was confirmed effectively from the outcomes.

References

[1] Reeta BhardwajDinesh Kumar, "MOFPL: Multi-objective fractional particle lion algorithm for the energy aware routing in the WSN", Pervasive and Mobile Computing, vol. 58, Article 101029, August 2019.

[2] Bandi RambabuA. Venugopal ReddySengathir Janakiraman, "Hybrid Artificial Bee Colony and Monarchy Butterfly Optimization Algorithm (HABC-MBOA)-based cluster head selection for WSNs", Journal of King Saud University - Computer and Information SciencesIn press, corrected proofAvailable online 20 December 2019.

[3] Kale Navnath DattatrayaK. Raghava Rao, "Hybrid based cluster head selection for maximizing network lifetime and energy efficiency in WSN", Journal of King Saud University - Computer and Information SciencesIn press, corrected proofAvailable online 4 April 2019.

[4] Augustine, S., Ananth, J.P. "Taylor kernel fuzzy C-means clustering algorithm for trust and energy-aware cluster head selection in wireless sensor networks", Wireless Netw 26, pp. 5113–5132, 2020. https://doi.org/10.1007/s11276-020-02352-w.

[5] Pratik Goswami, Ziwei Yan, Amrit Mukherjee, Lixia Yang, Sidheswar Routray, and G. Palai, "An energy efficient clustering using firefly and HML for optical wireless sensor network", Optik, vol. 182, pp 181-185, 2019.

[6] AmanjotSinghToor, A.K.Jain," Energy Aware Cluster Based Multi-hop Energy Efficient Routing Protocol using Multiple Mobile Nodes (MEACBM) in Wireless Sensor Networks", AEU - International Journal of Electronics and Communications, vol.102, pp.41-53, April 2019

[7] SupreetKaur, RajivMahajan," Hybrid meta-heuristic optimization based energy efficient protocol for wireless sensor networks", Egyptian Informatics Journal, vol.19, no.3, pp.145-150, November 2018

[8] WangTianshu, Zhang Gongxuan, YangXichen, VajdiAhmadreza," Genetic algorithm for energy-efficient clustering and routing in wireless sensor networks", Journal of Systems and Software, vol.146, pp.196-214, December 2018.

[9] Alagumuthukrishnan S, Dr. Geetha K, "A Locality Based Clustering and M-Ant Routing protocol for QoS in

Wireless Semsor Networks", Department of science and engineering, vol. 6, no. 10, 14 october 2016.

[10] M. Yuvaraja, Sabrigiriraj M, "Lifetime Enhancement of WSN using Energy-Balanced Distributed Clustering Algorithm with Honey Bee Optimization",Asian Journal of research in social sciences and humanities, vol. 6, no. 11, 2016.

[11] Q. Ni, Q. Pan, H. Du, C. Cao and Y. Zhai, "A Novel Cluster Head Selection Algorithm Based on Fuzzy Clustering and Particle Swarm Optimization," IEEE/ACM Transactions on Computational Biology and Bioinformatics, vol. 14, no. 1, pp. 76-84, 1 Jan.-Feb. 2017.

[12] S. H. Kang and T. Nguyen, "Distance Based Thresholds for Cluster Head Selection in Wireless Sensor Networks," IEEE Communications Letters, vol. 16, no. 9, pp. 1396-1399, September 2012.

[13] J. Leu, T. Chiang, M. Yu and K. Su, "Energy Efficient Clustering Scheme for Prolonging the Lifetime of Wireless Sensor Network With Isolated Nodes," IEEE Communications Letters, vol. 19, no. 2, pp. 259-262, Feb. 2015.

[14] Jin Wang, Yiquan Cao, Bin Li, Hye-jin Kim, and Sungyoung Lee, "Particle swarm optimization based clustering algorithm with mobile sink for WSNs, Future Generation Computer Systems, vol. 76, pp 452-457, 2017.

[15] Shishupal Kumar, Nidhi Lal, Vijay Kumar Chaurasiya, "A forwarding strategy based on ANFIS in internet-of-things-oriented wireless sensor network (WSN) using a novel fuzzy-based cluster head protocol", Annals of Telecommunications, vol. 73, no. 9-10, pp 627–638 , 2018.

[16] D. Jia, H. Zhu, S. Zou and P. Hu, "Dynamic Cluster Head Selection Method for Wireless Sensor Network," IEEE Sensors Journal, vol. 16, no. 8, pp. 2746-2754, April15, 2016.

[17] Yongquan Zhou, Guo Zhou, Yingju Wang and Guangwei Zhao, " A Glowworm Swarm Optimization Algorithm Based Tribes", Applied Mathematics & Information Sciences, vol. 7, no.. 2L, pp. 537-541, 2013.

[18] Wen-TsaoPan, " A new Fruit Fly Optimization Algorithm: Taking the financial distress model as an example", Knowledge-Based Systems, vol. 26, pp. 69-74, February 2012.

[19] Yogesh R kulkarni,Senthil Murugan T, "Hybrid Weed-Particle Swarm Optimization Algorithm and C-Mixture for Data Publishing", Multimedia Research, Vol.2,No.3, pp.33-42,2019.

[20] Amit Kelotra and Prateek Pandey, "Energy-aware Cluster Head Selection in WSN using HPSOCS Algorithm", Journal of Networking and Communication Systems, Vol.2,No.1, pp.24-33,2019.

[21] Remmiya R and W.Brajula, "Available Transfer Capability Enhancement using Fruitfly Optimization", Journal of Computational Mechanics, Power System and Control, Vol.2,No.1, pp.1-8,2019.

Kale Navnath Datttatraya is a Research Scholar in Department of Computer Science and Engineering, K. L. University, Vijayawada Campus, Koneru Lakshmaiah Educational Foundation. He received his M.Tech (CSE) degree from Visvesvaraya Technological University, Belgaum, India, in 2008. He pursued his Bachelor in Computer Science and Engineering from Bundelkhand University, Jhansi. His research interests include Wireless Sensor Networks, Computer Networks and Information Security. He is a Professional member of ACM.

S. Ananthakumaran is working as an Associate Professor in the Dept. of Computer Science and Engineering, Koneru Lakshmaiah Educational Foundation, Vaddeswaram, Guntur, Andhra Pradesh, India. He has received his Ph.D., degree in Computer Science and Engineering from Manonmaniam Sundaranar University, Tamilnadu, India in 2016. He has more than 16 years of academic and 9 years of research experience. His recent research interest includes Secure Data Communication, Blockchain Technology, IoT and Deep Learning.