

I-CSA based Cluster Head Selection Model in Wireless Sensor Network

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Abstract: In WSN, the clustering technique can be used to reduce the traffic in the network and it can be predominantly used to minimize the utilization of energy in the network, thus it leads to the multipath routing which increases the reliability of the network throughout the available paths. Since clustering is an effective and apt way on providing a better route that transmits data without any conflicts. However, in the concept of clustering, the selection of Cluster Head (CH) is considered as a complex process as it has to satisfy certain parameters for effectual performance. In this research work, a novel CH selection approach is developed based on a new optimization algorithm referred to as the Intensity-based Cuckoo Search Algorithm (I-CSA), which is an extended version of standard Cuckoo Search Algorithm (CSA). The optimized CH selection is done by I-CSA that considers the triplet objective function like delay, energy, and distance. Finally, the efficiency of the presented work is evaluated over other conventional works in terms of energy, alive nodes as well.

Keywords: WSN; Clustering; CH selection; Defined Triplet Objectives; Optimization

Nomenclature

Abbreviations	Descriptions
BS	Base Station
CH	Cluster Head
CSA	Crow Search Algorithm
FF	Firefly Algorithms
HSA	Harmony Search Algorithms
I-CSA	Intensity Based Cuckoo Search Algorithm
MOTCO	Multiobjective Taylor Crow Optimization
PSO	Particle Swarm Optimization
PSO-ECH	Energy-Efficient Cluster Head Selection Algorithm That Was Based On PSO

1. Introduction

In wireless communication, there is a tremendous development in the elements of sensor nodes and it empowers the transmission over short distances. These sensor nodes contain a few parts like “sensing, processing, and transmitting” information [1] [5] [18]. The generous information can be available, if the sensors are approved with the limit of conveying their observations among themselves, at that point the data can be gathered and handled at the base station. This data can be then recouped by the client to oversee environmental factors from the base station [18] [19]. WSN is considered as one of the most fundamental components of IoT [9] [10] [11]. The WSN is a selective system and it contains a few quantities of sensors at a gigantic degree. As such, it is an aggregate arrangement of distributed, homogenous little sensor nodes that might be in the transmission range or may not be in the transmission range. This system can detect information and the sensors generally speak with one another [5] [18] [7] [8] [19].

Clustering is an appreciated two-layered method in which the network is split into little convenient units. Clustering is done on the premise that the nodes arranged in the indistinguishable layer can be assembled into different groups. It is commonly used to advance the versatility of the system. In this assembled nodes to designate the obligations between the nodes, it ideally chooses the fitting node to work as a CH [2] [4] [6]. Because of the constraints and the energy usage of the system, the CH has been

chosen. The grouping methods use the correspondence between the information because the gigantic amount of information given by the sensors are practically identical and this outcome in a progressively capable energy usage [12] [16] [13] [14] [15]. Here the enduring energy is considered as the answer for every node to be chosen as a CH. Lower energy level nodes are assembled dependent on their separations to the close by CH and they straightforwardly dispatch their information to the subsequent CH. The CH goes to be chosen in far separations to the nodes and will end in higher energy usage of lower energy nodes. The CH is reliable for congregating the information from the typical nodes and afterward the information is figured and it is transmitted to the base station [6] [12] [17] [18] [19].

Optimal clustering is characterized as far as energy efficiency and it is utilized to take out all the overhead connected with the CH determination process and likewise with the node related to their comparing CHs. Further improvement in the unwavering quality of the WSN prompts the adjustments to the re-clustering component. The re-clustering system impressively follows the underlying CH choice. In WSN, the clustering technique can be used to reduce the traffic in the network and it can be predominantly used to minimize the "utilization of energy" in the network, thus it leads to the multipath routing which increases the reliability of the network throughout the available paths.

The main contribution of this paper is to propose a novel CH selection approach is developed based on a new optimization algorithm referred to as the I-CSA, which is an extended version of standard CSA.

The rest of the paper is organized as: The most interesting works done in CH selection in WSN is discussed in Section 2. Section 3 tells about the proposed CH selection model in WSN: network model. Then, the defined triplet- objectives and proposed I-CSA optimization algorithm is depicted in Section 4. The resultants acquired with the presented work are discussed in Section 5. Finally, a strong conclusion is given to the current research work in Section 6.

2. Literature Review

2.1 Related Works

In 2018, Vijayalakshmi and Anandan [1] have developed a new approach for exploring the optimized CH with the aid of the PSO and Tabu search algorithms. In WSNs, the data packets' optimal path is selected by the proposed Tabu PSO. The proposed model was found to improve the "network lifespan, as well as the network's energy efficiency".

In 2018, Mahesh and Vijayachitra [2] have developed a dolphin echolocation-based crow search algorithm in SN for energy-aware routing by selecting the CH. The multi-constraints like were considered for efficient CHs selection that enhanced the convergence rate. The resultant had exhibited a higher network lifetime as well as a higher count of alive nodes.

In 2016, Srinivasa Rao et al. [4] developed PSO-ECHS for CH selection in WSN. The authors have selected the optimal CH in WSN based on various parameters like the "intra-cluster distance, sink distance, and residual energy of sensor nodes". The superiority of the PSO-ECHS was demonstrated by the simulation procedures.

In 2019, John and Rodrigues [4] have introduced the MOTCO algorithm in WSN for optimal selection of CH. The proposed model was a hybridized form of "Taylor series and the CSA". Further, the target behind this work was to lessen the node distance, energy, and delay in data packet transmission. The proposed MOTCO was said to outperform the existing models in terms of "throughput and network energy".

In 2019, Bongale et al. [5] have developed a hybrid selection model for CH in WSN based on the "FF and HSA". In the initial contribution, the CH nodes were selected based on the "energy" using the harmony search algorithm. Then, based on the parameters like the "node density, cluster compactness, and energy", the CH nodes were refined. Thus, the energy consumption of the presented work was reduced.

3. Proposed CH Selection Model in WSN: Network Model

3.1 Network Model

WSN comprises various sensor nodes and they are together referred to as N_p . These sensors are fixed in terms of location and have their equivalent capabilities. A node can act in the form of a CH as well as a functioning sensor. Fig. 1 manifests the proposed CH selection model in WSN by considering various sensors nodes and concentrated BS. In general, clustering is nothing but the grouping of the nodes. It is an eminent strategy to broaden the future of WSN. The CH selection is the most challenging among the

clustering approach. “Clustering helps to group the nodes that are found to be nearer, to form the clusters, and it chooses the CH (N_{CH}) for every cluster (N_C)”. In the current research work, the sensor nodes assign its CH based on a triplet- objective function that encloses the distance, delay, and energy. At first, the whole picked CHs inside the system to move the commercial message to pronounce that they go about as the CH. Under such conditions, every sensor node of the system quantifies the specific good ways from the CH. Once, the CH is selected, the nodes that are closest to CH join together to form a cluster.

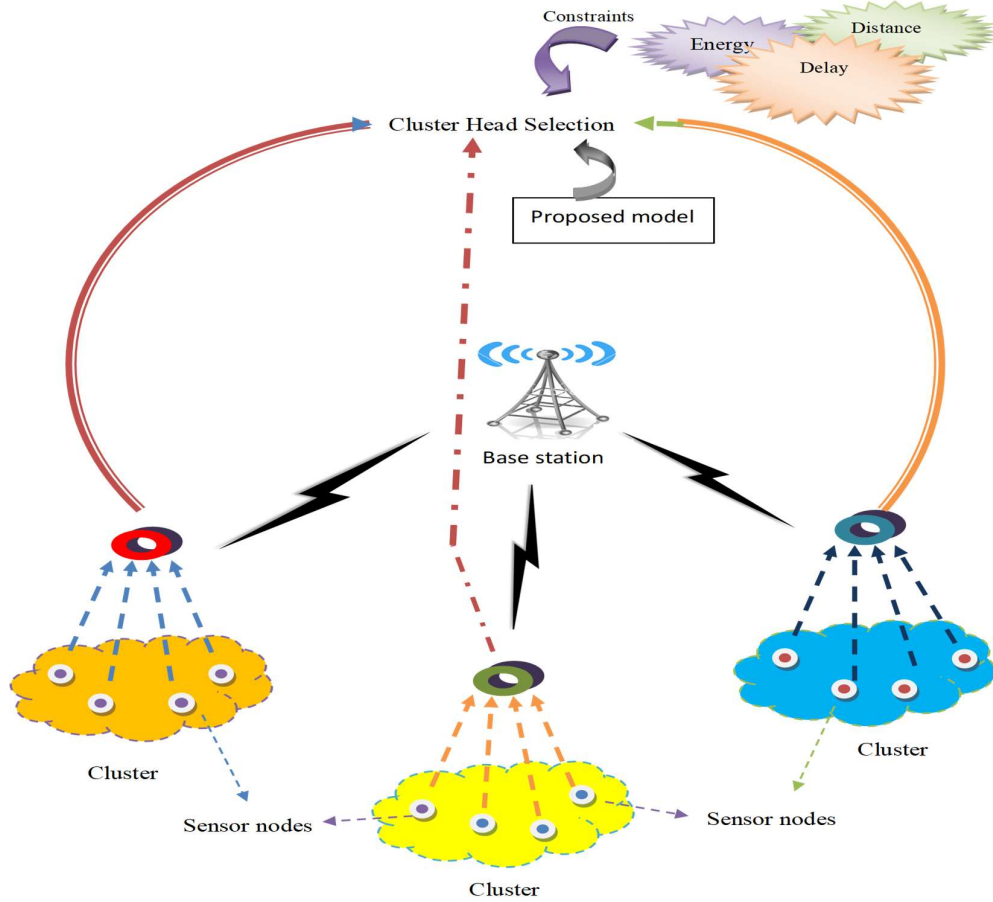


Fig. 1. Diagrammatic representation for CHS in WSN

4. Defined Triplet- Objectives and i-CSA Optimization Algorithm

In this research work, the selection of the optimal CH was based on three major key factors: “energy, distance, and delay”. The objective model of the CH selection in this research work is shown in Eq. (1). In which, the value of β is $0 < \beta < 1$.

$$F_n = \beta f_b + (1 - \beta) \text{fit}_a \quad (1)$$

The functions f_a and f_b are determined using Eq. (2) and Eq. (3), respectively.

$$\text{fit}_a = \sigma_1 * \text{fit}_i^{\text{dis}} + \sigma_2 * \text{fit}_i^{\text{ene}} + \sigma_3 * \text{fit}_i^{\text{del}} \quad (2)$$

The constant parameters σ_1 , σ_2 and σ_3 are “distance, energy and delay”, respectively.

$$\text{fit}_b = \frac{1}{n} \sum_{x=1}^n \|N^x - B_s\| \quad (3)$$

The distance, energy, and the delay function are discussed in the subsequent section.

4.1 Distance Model

The data transmission between the clusters takes place via the selected CHs. Unexpectedly, the sensor hub moves the message straightforwardly to BS, if the distance of the separation between the node as

well as the BS is found to be higher. This is the arrangement of framing a group dependent on the calculation of close by separation. Consequently, the node can be re-clustered in the system with the chose CH utilizing a separation network. The distance matrix (DM(m*n)) in the network aids in reclustering and this event occurs with the aid of the selected CH. Then, DM(m*n) is shown in Eq. (4), in which the “Euclidean distance between the CH and node” is denoted as d_{N_c} and sensor nodes are denoted as x_1, x_2, \dots, x_n .

$$DM(m*n) = \begin{bmatrix} d_{N_{c1},x_1} & d_{N_{c1},x_2} & \dots & d_{N_{c1},x_n} \\ d_{N_{c2},x_1} & d_{N_{c2},x_2} & \dots & d_{N_{c2},x_n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{N_{cm},x_1} & d_{N_{cm},x_2} & \dots & d_{N_{cm},x_n} \end{bmatrix} \quad (4)$$

Each element of the matrix denotes the distance that existing among the q^{th} node and p^{th} CH. The Euclidean distance corresponding to the measurement of $d_{p,q}$ is shown in Eq. (5).

$$d_{p,q} = \sqrt{(p_y - q_y)^2 + (p_z - q_z)^2} \quad (5)$$

Let p (CH) and q (normal node) be taken into consideration and their corresponding positions be denoted as y and z , respectively. The two channels like the "multi-path fading and free space channels" are utilized, in view of the separation of the recipient from the transmitter. At the point when the specific limit esteem does out a higher incentive than the separation, the “free space channel” is abused. The threshold distance is defined mathematically in Eq. (6).

$$d_0 = \sqrt{\frac{E_{fs}}{E_{pw}}} \quad (6)$$

Where the essential free space energy level is denoted as E_{fs} and the power amplifier energy is indicated as E_{mp} .

The fitness function of distance fit_i^{dis} is expressed in Eq. (7).

$$fit_i^{dis} = \frac{fit_{(a)}^{dis}}{fit_{(b)}^{dis}} \quad (7)$$

$$fit_{(b)}^{dis} = \sum_{x=1}^{N_c} \sum_{y=1}^{N_y} \|C_x - X_y\| \quad (8)$$

$$fit_{(a)}^{dis} = \sum_{x=1}^{N_s} \left[\|C_x - B_s\| + \sum_{y=1}^{N_s} \|C_x - X_x\| \right] \quad (9)$$

Here, “ $C_x - B_s$ ” specifies the distance among the CH and BS, $C_x - X_x$ denotes the distance among the CH and normal node and $X_x - X_y$ specifies the distance between two normal nodes N_x and N_y .

4.1.1 Energy Model

The utilization of energy is said to be a significant issue in WSN and it should be lower for more efficient data transmission as well as optimal path selection. Actually, in WSN, the battery utilized can't be revived, i.e., no condition exists of any force flexibly, when the battery is exhausted. Further, the energy required for “transmitting the data from the sensor node to CH” and vice versa is larger. As a rule, the system expends more Energy as it performs various activities like “transmission, gathering, detecting, and aggregation”. During the data transmission, the whole energy required is denoted as $E_{TX}(N:d)$, and it is expressed in Eq. (10). In other words, it can be said as the transmission of N bytes at a distance d .

$$E_{TX}(N:d) = \begin{cases} E_{el} * N + E_{fs} * N * d^2, & \text{if } d < d_0 \\ E_{el} * N + E_{pw} * N * d^2, & \text{if } d \geq d_0 \end{cases} \quad (10)$$

The overall energy required is defined as per Eq. (11)

$$E_{total} = E_{TX} + E_{RX} + E_I + E_S \quad (11)$$

Here, idle state energy is E_I and during sensing the energy cost is E_S . The electronic energy E_{el} is the sum of the transmission energy E_{TX} and data aggregation energy E_{ac} .

$$E_{el} = E_{TX} + E_{ac} \quad (12)$$

The total consumed energy during the reception mechanism is expressed in Eq. (13) and the amplification energy is expressed as per Eq. (14).

$$E_{RX}(N:d) = E_{cl}N \quad (13)$$

$$E_{am} = E_{fs}d^2 \quad (14)$$

The fitness function of energy fit_i^{enc} is depicted below:

$$fit_i^{enc} = \frac{fit_{(a)}^{enc}}{fit_{(b)}^{enc}} \quad (15)$$

4.1.2 Delay

In addition to the delay in data transmission is also considered as a key for achieving the optimal CH. Lower is the delay, higher is the system efficiency.

The fitness function of delay fit_i^{del} is depicted below:

$$fit_i^{del} = \frac{\max \left(\left\| C_x - X_x \right\| \right)_{x=1}^{N_c}}{N_c} \quad (16)$$

The value of fit_i^{del} in Eq. (16) must be within the range [0, 1].

These entire objectives are optimized with the aid of the proposed optimization concept.

4.2 I-CSA Algorithm

CS [21] is a technique, which is introduced based on the motivation of the reproduction of cuckoos. Generally, cuckoos put down their eggs in the nests of other cuckoos and it expects its babies to be fully-grown up by other parents. After a specific interval, the cuckoo that owns the nest identifies the other eggs and it pushes out the unfamiliar eggs from the nests. The existing Cuckoo Search (CS) approach is a simple and proficient scheme for resolving the global issues; but, it cannot be directly exploited for resolving the multimodal optimization issues. Therefore, the conventional CS model is upgraded and it is referred to as the Intensity-based CS Algorithm (I- CSA). The optimization algorithms have undergone various improvements in terms of many factors. One of them is by introducing adaptive operators or adaptive functions [23] [24][25] [26].

The steps followed in the proposed model is depicted below [27]:

Step 1 (Initialization): The search agents (cuckoos) are initialized. The current iteration is denoted as t

Step 2: While ($t < \text{Max}(t)$), then Compute the cuckoo by assuming i randomly by Levy distribution.

Step 3: Then, Compute the fitness of the search agents F_i . Subsequently, select a nest amongst n by assuming j in a random manner.

Step 4: Compute F_j and If ($F_i > F_j$), then update the solutions using Eq. (17).

$$X_i^{t+1} = X_i^t + \beta N(s, \tau) \quad (17)$$

Here, X_i^t and X_k^t refers to the current positions elected by random permutation, β points out the “positive step size scaling factor”, X_i^{t+1} is the “subsequent positions”, s indicates the “step size”.

Step 5: If ($F_i < F_j$), then Compute opposition intensity γ as per Eq. (18)

$$X_i^{t+1} = X_i^t + \beta N(s, \tau) - \gamma [X_i^{(w)} - X_i^t] \quad (18)$$

Here, $X_i^{(w)}$ denotes the worst solution, X_i^t specifies the present solution, and γ gets varied from 0 to 1.

Step 6: The construction of the novel nests occurs at new locations and the best solutions are preserved. Then, the best solution is determined and ranked.

Step 7: Terminate.

5. Results and Discussion

5.1 Simulation Procedure

The WSN based clustering of nodes with the proposed I-CS mechanism was implemented in MATLAB and the resultant thus acquired was noted. This evaluation was done to verify the potential of the presented work (I-CSA) over the existing works CS [21] and FF [22]. The assessment is done in terms of the “alive nodes and normalized energy”

5.2 Evaluation of the Count of Alive Nodes

The count of alive nodes decides the life span of the network. In general, as the count of rounds gets increased, the count of alive nodes gets reduced. This evaluation is done by varying the “count of rounds” from 0, 400, 800, 1200, 1600, and 2000. The resultant acquired is shown graphically in Fig. 2. At the 0th round, the count of alive nodes in the existing CS is 75 and FF is 85 and the presented work is 100. “As the count of rounds increases, the count of alive nodes tends to decrease”. Then, in each of the rounds, the presented work is said to have the highest count of alive nodes and this is verified from the Fig. 2.

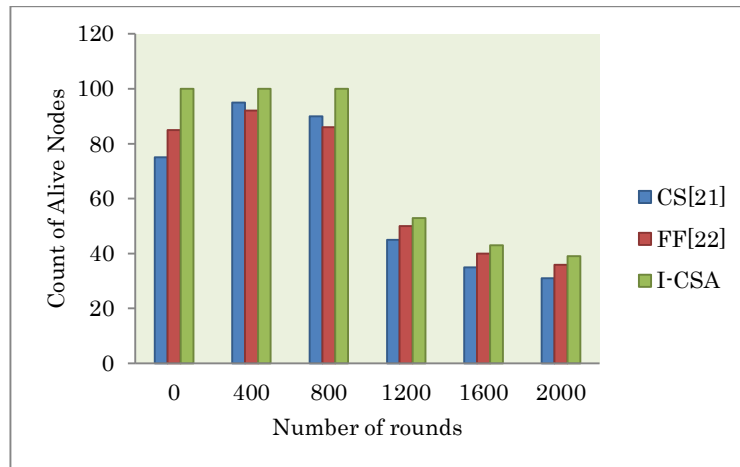


Fig. 2. Evaluation on the count of alive nodes for presented as well as existing models: by varying the rounds

5.3 Evaluation on Normalized Energy

The assessment on the resultant of the “normalized network energy” is specified in Fig. 3. The “normalized network energy” gets minimized with an increase in the number of rounds. However, the presented model reveals with high network energy when evaluated over the other conventional schemes. Here, a statistical evaluation is done in terms of best-normalized energy, worst normalized energy, mean normalized energy, median normalized energy, and standard deviation (Std-dev) based normalized energy. The best-normalized energy of the presented work is 0.55857, which is higher than the existing models CS= 0.49957 and FF= 0.50957. Then, the mean normalized energy of the presented work is the highest 0.23572 and it is 12%, 8.2% is much superior to extant models like CS and FF, respectively. Thus, the superiority of the presented model has been proved over other conventional models with high normalized energy.

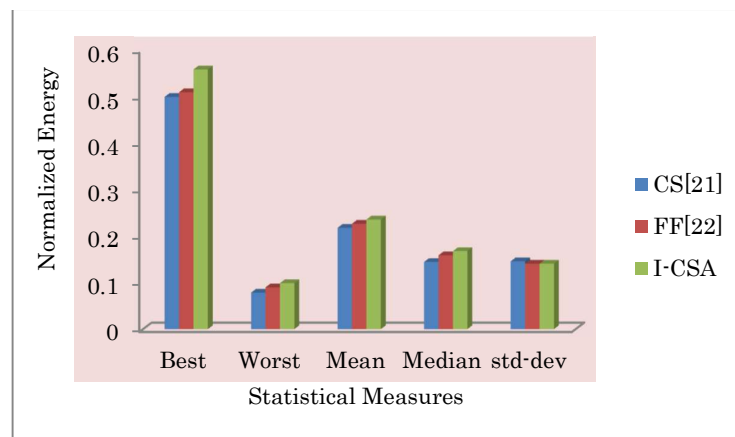


Fig. 3. Statistical evaluation on normalized energy for presented as well as existing models

5.4 Evaluation of Overall Fitness

The overall objective of the presented work is contrasted over extant approaches and the resultant in terms of statistical measures is shown in Fig. 4. The best fitness recorded by the presented work is 532.38, while the CS and FF had recorded their best fitness as 442.95 and 509.38, respectively. Then, the

highest mean fitness is obtained by the presented work as 374.01 and it is 14.61% and 6.75 better than extant models like CS and FF, respectively. Thus, from the evaluation, it is vivid that the presented work has achieved the objective of delay minimization, lower energy consumption, and lower distance for optimal CH selection.

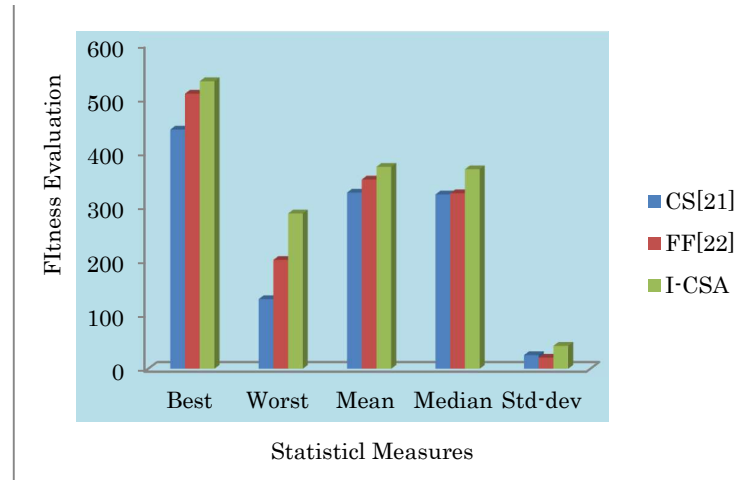


Fig. 4. Statistical evaluation on Overall fitness of presented as well as existing models

6. Conclusion

In this research work, a novel optimized CH selection model was developed for energy-efficient routing protocol in WSN. A new optimization algorithm referred to as I-CSA was developed that was based on the defined triplet based objective function. The CH node was chosen by I-CSA that considers the parameters namely, distance, delay, and energy. At last, the performance of the proposed work was efficiently determined by the adopted model. Then, the highest mean fitness is obtained by the presented work as 374.01 and it is 14.61% and 6.75 better than extant approaches like CS and FF, respectively.

References

- [1] K. Vijayalakshmi and P. Anandan, "A multi objective Tabu particle swarm optimization for effective cluster head selection in WSN", *Cluster Computing*, vol.22, pp.12275–12282, 2019
- [2] N. Mahesh and S. Vijayachitra, "DECSA: hybrid dolphin echolocation and crow search optimization for cluster-based energy-aware routing in WSN", *Neural Computing and Applications*, vol.31, pp.47–62, 2019
- [3] P. C. Srinivasa Rao, Prasanta K. Jana & Haider Banka, "A particle swarm optimization based energy efficient cluster head selection algorithm for wireless sensor networks", *Wireless Networks*, vol.23, pp.2005–2020, 2017
- [4] Jacob John and Paul Rodrigues, "MOTCO: Multi-objective Taylor Crow Optimization Algorithm for Cluster Head Selection in Energy Aware Wireless Sensor Network", *Mobile Networks and Applications*, vol.24, pp. pages1509–1525, 2019.
- [5] Anupkumar M. Bongale, C. R. Nirmala & Arunkumar M. Bongale, "Hybrid Cluster Head Election for WSN Based on Firefly and Harmony Search Algorithms", *Wireless Personal Communications*, vol.106, pp.275–306, 2019
- [6] H. Fotouhi, M. Alves, and M.Z. Zamalloa, "Reliable and Fast Hand-Offs in Low-Power Wireless Networks," *IEEE transactions on mobile computing*, vol. 13, no. 11, pp. 2621-2633, 2014.
- [7] Fan and C. Shuo, "Rich:Region-based Intelligent Cluster-Head Selection and Node Deployment Strategy in Concentric-based WSNs," *Advances In Electrical And Computer Engineering*, vol. 13, no. 4, pp. 3-8, 2013
- [8] S. Tyagi and N. Kumar, "A systematic review on clustering and routing techniques based upon LEACH protocol for wireless sensor networks," *Journal Of Network And Computer Applications*, vol. 36, no. 2, pp. 623-645, 2013.
- [9] Y. Zou and K. Chakrabarty, "Sensor Deployment and Target Localizations Based on Virtual Forces," *Proc. IEEE INFOCOM'03*, 2003.
- [10] S. Poduri and G.S. Sukhatme, "Constrained Coverage for Mobile Sensor Networks," *Proc. IEEE Int'l Conf. Robotics and Automation (ICRA'04)*, pp. 165-172, May 2004.
- [11] N. Javaid, M. Waseem M, Z.A. Khan, "ACH: Away Cluster Heads Scheme for Energy Efficient Clustering Protocols in WSNs," *Saudi International Electronics, Communications and Photonics Conference*, Piscataway: IEEE, pp. 364-367, 2013.
- [12] Dongyao Jia, Huaihua Zhu, Shengxiong Zou and Po Hu, "Dynamic cluster head selection method for wireless sensor network", *IEEE Sensors Journal*, vol.16, no.8, pp.2746 - 2754, December 2015

- [13] Rajeev Kumar and Dilip Kumar, "Multi-objective fractional artificial bee colony algorithm to energy aware routing protocol in wireless sensor network", *Wireless Networks*, vol.22, no.5, pp 1461-1474, July 2016
- [14] Ping He1, Hui Tian and Hong Shen, "Energy-efficient Cooperative MIMO Routing in Wireless Sensor Networks", *IEEE Int. Conference on Networks*, pp.74-79, Dec 2012.
- [15] Haiying Shen and Ze Li, "A P2P-Based Market-Guided Distributed Routing Mechanism for High-Throughput Hybrid Wireless Networks", *IEEE Tans. On Mobile Computing*, vol.14, February 2015
- [16] Alberto Puggelli and Alberto Puggelli, "Routing-Aware Design of Indoor Wireless Sensor Networks Using an Interactive Tool", *IEEE Systems Journal*, vol.9, no.3, September 2016
- [17] Buddha Singh and Daya Krishan Lobiyal, "A novel energy-aware cluster head selection based on particle swarm optimization for wireless sensor networks", *Human-Centric Computing and Information Sciences*, pp 1-18, 2012
- [18] Di Tang, Tongtong Li, Jian Ren and Jie Wu, "Cost-Aware SEcure Routing (CASER) Protocol Design for Wireless Sensor Networks", *IEEE Trans. On Parallel and Distributed systems*, vol.26, no.4, pp.960-973, 2015
- [19] Zhao Han, Jie Wu, Jie Zhang, Liefeng Liu, and Kaiyun Tian, "A General Self-Organized Tree-Based Energy-Balance Routing Protocol for Wireless Sensor Network", *IEEE Transactions on Nuclear Science*, vol.61, no.2, pp.732-740, 2014
- [20] L. Cheng, J. Niu, J. Cao, S.K. Das and Y. Gu, "QoS Aware Geographic Opportunistic Routing in Wireless Sensor Networks," *IEEE transactions on parallel and distributed systems*, vol.25, no. 7, pp. 1864-1875, July 2014.
- [21] M. Mareli, B. Twala, "An adaptive Cuckoo search algorithm for optimisation", *Applied Computing and Informatics*, vol.14, no.2, pp.107-115, July 2018
- [22] Iztok Fister, Iztok Fister Jr, Xin-She Yang and Janez Brest, "A comprehensive review of firefly algorithms", *Swarm and Evolutionary Computation*, vol. 13, pp. 34-46, 2013.
- [23] B. R. Rajakumar, "Impact of Static and Adaptive Mutation Techniques on Genetic Algorithm", *International Journal of Hybrid Intelligent Systems*, Vol. 10, No. 1, pages: 11-22, 2013, DOI: 10.3233/HIS-120161
- [24] S. M. Swamy, B. R. Rajakumar and I. R. Valarmathi, "Design of Hybrid Wind and Photovoltaic Power System using Opposition-based Genetic Algorithm with Cauchy Mutation", *IET Chennai Fourth International Conference on Sustainable Energy and Intelligent Systems (SEISCON 2013)*, Chennai, India, Dec. 2013, DOI: 10.1049/ic.2013.0361
- [25] Aloysius George and B. R. Rajakumar, "APOGA: An Adaptive Population Pool Size based Genetic Algorithm", *AASRI Procedia - 2013 AASRI Conference on Intelligent Systems and Control (ISC 2013)*, Vol. 4, pages: 288-296, 2013, DOI: <https://doi.org/10.1016/j.aasri.2013.10.043>
- [26] B. R. Rajakumar and Aloysius George, "A New Adaptive Mutation Technique for Genetic Algorithm", In *proceedings of IEEE International Conference on Computational Intelligence and Computing Research (ICCIC)*, pages: 1-7, December 18-20, Coimbatore, India, 2012, DOI: 10.1109/ICCIC.2012.6510293
- [27] G.K. Shailaja and Dr C.V. Guru Rao, "Impact of Opposition Intensity on Improved Cuckoo Search Algorithm for Privacy Preservation of Data", *Journal of Networking and Communication Systems*, September 2019