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An Opposition-based Grey Wolf Optimization for Cluster Head Selection in Wireless Sensor Networks

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Abstract

Clustering is considered one of the practical approaches for boosting the lifespan of the Wireless Sensor Networks (WSNs). It involves in gathering the sensor nodes into groups and elects the cluster heads (CHs) in each group. CHs gather the data from cluster members and transfer the aggregate information to Base Station (BS). However, the most significant obligation in WSN is to elect the optimal CH to enhance the network's lifespan. This paper proposes an optimal cluster head election framework in WSN. A novel hybrid technique selects the optimal CHs: an oppositional grey wolf optimization (OGWO) algorithm that collaborates with generic GWO and opposition-based learning techniques. The hybrid OGWO algorithm dynamically balances between intensification and diversification search process in electing optimal CHs. In addition, the parameters like energy, distance, node degree, and node centrality aid in selecting the optimal CHs in the network. This CHs selection framework improves the efficacy of the network capability and enhances the network lifespan. Further, the superiority of the proposed OGWO technique is validated based on the various impacts like energy, alive nodes, BS location, and several packet delivery aspects. Accordingly, the proposed OGWO technique provides a better network lifetime of ~20%, ~30% and ~45% compared with GWO, ABC and LEACH techniques.

Keywords: Clustering; Wireless Sensor Networks; Oppositional based learning; Grey Wolf Optimization Algorithm; Network lifespan; Diversification.

1. Introduction

Wireless Sensor Networks (WSNs) consist of a collection of sensor nodes scattered in the deployed area to sense the physical activities of its surroundings. These sensors utilize an Analog Digital convertor (ADC) to gather the data [1]. The collected information will process to the controller or Base station (BS). The data received in the BS will process into decisions for several actions in different applications [2]. Several applications use WSNs for weather prediction, dense domain, medical field, and commercial and industrial purposes. Generally, sensor nodes cost expensive, and it holds the capacity for sensing, processing, and communicating information [3,4]. The sensors in WSN are compact and have a small-sized battery as their energy source. However, replacing or exchanging the energy source is quite complex due to the placement of sensors in complex or non-man movement environments. The WSN suffers from several issues like scalability, fault tolerance, energy constraints, path establishment, etc. Most of the sensors will drain their energy due to two cases a) based on data gathering (sensing) and b) communicating data to BS through hop nodes. Directly transmitting data to BS consume more energy than sensing its environment and processing data. Further, more sensor energy consumption will decrease the network's lifespan [5].

Moreover, an optimal energy handling model in WSN will increase the network's lifespan and improve its performance of WSN. Therefore, WSNs use clustering to reduce excess energy consumption and improve the network's steadiness. In clustering, each cluster group will elect a leader, known as Cluster Head (CH), with privileges to communicate with other CHs in the network. In addition, direct transmission of data to BS consumes high energy [6-8]. Hence, several researchers proposed an efficient routing protocol to identify the optimal path between the CHs and BS to decrease energy utilization. Several works are carried out in the literature to determine the optimal CHs in WSN. In WSN, the LEACH protocol is proposed to handle the CHs selection problem. In LEACH, the CHs are selected based on the best-fit method, and the rest of the sensors act as cluster members. Further, each sensor node in the network must be a member of any one of the CHs. The CHs gather the information collected by the cluster members and communicate the vital information to the BS via one-hop or many-hop modes [9].
Generally, the researchers classified the WSN clustering approaches into centralized, distributed, and hybridized. In addition, the researchers classified similar techniques such as LEACH, HEED [10], etc., and unequal techniques such as ULEACH [11], EDUC [12], EEUC [13], etc. Despite that, they categorized the WSN network into two networks: a Homogenous network consisting of equal energy for all sensor nodes. In contrast, a heterogeneous network has unequal power for all sensor nodes. Recently, several researchers utilized meta-heuristic algorithms to tackle the issue of cluster head selection in WSN. Some recent studies deliberate that using meta-heuristic algorithms provides better efficacy than traditional algorithms. Some of the famous algorithms such as Genetic algorithm [14], Artificial bee colony algorithm [15], grey wolf optimization algorithm [16], bat algorithm [17], firefly algorithm [18], particle swarm optimization algorithm [19], glow swarm optimization algorithm [20], Harris hawk optimizer [21], etc. are used in WSN to solve the clustering problem.
This study focuses on clustering protocols in WSNs based on optimization algorithms. Recent works on clustering techniques viz., Classical approaches, metaheuristic approaches, and hybrid approaches are extensively examined to reveal the methodology and properties of existing algorithms. Further, the author introduced an OGWO algorithm that merges oppositional-based learning with the generic GWO technique. This proposed methodology enriches the search capability and eradicates the existing algorithm's issue. It identifies the optimal CHs by considering various parameters in the objective functions. Concisely, in this work, different test phases are carried out to ensure the efficacy of the proposed model.

The main objectives of this work are given below:

- This paper has attempted to introduce an optimal energy-aware CH election methodology for energy-efficient routing in WSN by presenting a novel "hybrid" technique.
- For the optimal selection of CH, the author formulated the fitness function with parameters like energy consumption, minimal region among the nodes, the workload of elected CHs, and minimal delay during communication.
- Further, the proposed hybrid technique, OGWO, collaborates with the opposition-based learning technique and generic GWO algorithm, which dynamically trade-offs between intensification and diversification search modes during the CH electing process.

- Finally, the outcome of OGWO is compared with the state-of-art existing algorithm such as LEACH, ABC, and GWO under several test cases and validates the performance of the work.

The organization of this work is illustrated as follows: Section 2 describes the related work of existing clustering approaches in three different aspects. Section 3 discusses the energy-aware cluster head election framework and the objective function formulation in WSN. Section 4 provides insight into the proposed methodology for optimal cluster head election. Section 5 presents the experimental set-up, parameter assigning and introduced work result analysis with other state-of-art algorithms. Section 6 concludes the work with its outcomes toward the optimal CHs election.

2. Related Work

This section deliberates the various research studies on selecting cluster heads in WSN to extend the network lifespan. We have collected a diverse set of articles and divided them into three sectors: classical approaches, meta-heuristic approaches and hybrid meta-heuristic approaches for efficient cluster head selection in WSN.

2.1 Classical Approaches

Numerous classical approaches have been introduced to solve the clustering issues, reducing the high energy consumption in the network. LEACH [9] is considered one of the vital algorithms in solving clustering issues of WSN. The LEACH protocol enriches the network lifespan by minimizing the number of packet transmissions by forming the clusters. However, it has several limitations, like the arbitrary selection of CHs without looking at the distance to BS or residual energy of the node. In addition, another issue is transmitting packets to BS by CH using a single-hop mechanism, which leads the LEACH to suffer in large networks. In LEACH, a set of sensor nodes are grouped into clusters. Researchers have introduced several variations of LEACH approaches to tackle the above issues. Some variations of LEACH protocols in homogeneous networks include VH-LEACH, LEACH-F, LEACH-C, A-LEACH, O-LEACH, MH-LEACH, IMHT-LEACH, and DMHT-LEACH are used to elect the CH by considering the residual energy of the nodes.

In [22], the researchers introduced an improved clustering protocol, VH-LEACH. In VH-LEACH, the cluster and CHs have formed arbitrarily. Later, the vice-CHs are selected based on the maximum residual energy of elected CHs. However, the vice-CHs mechanism performs less when there are substantial cluster members. The author in [23] proposed the LEACH-C technique, which works according to the centralized algorithm. In this technique, the BS node makes the clusters and selects the CHs concerning nodes' position and the remaining energy of nodes. The F-LEACH [24] protocol is introduced to address the clustering issue by reducing the delay of the set-up stage and providing efficient CHs distribution. However, the clusters are fixed at the initial state and will be retained for the entire process and no possibility for re-clustering.

Advanced LEACH (A-LEACH) [25] is introduced to eradicate the issue of LEACH protocol that reduces energy consumption by electing adequate CHs in the network. A-LEACH intends to enhance the network's lifespan or increase the network's stability for longer epochs by minimizing the node death with the aid of heterogeneity attribute parameters. A-LEACH minimizes the data quantity (i.e., data to be transmitted to BS) using the data fusion technique.

In addition, the A-LEACH selects the nearest gateway node to minimize the data transmission distance. However, A-LEACH selects the CHs arbitrarily and utilizes the single hop for data transmission, leading the technique to provide poor performance in a certain number of iterations. In [26], the Orphan node-based LEACH protocol, namely O-LEACH, is proposed to enrich the better coverage in the network. However, the O-LEACH technique selects the CHs randomly and consumes high energy for grouping the data of neighboring CHs.

In the MHT-LEACH technique [27], the cluster formation and head selection are similar to the LEACH initialization process. This technique will not transfer the data directly to the controller; instead, it splits the cluster groups into two divisions, external and internal groups, concerning the location among the sink and CHs. Internal and external groups CHs are selected based on the threshold distance d_0If the distance of CHs to sink is less than the d_0 then it belongs to internal groups; otherwise, the CHs belong to external groups. Further, DMHT-LEACH [28] and IMHT LEACH [29] are introduced to elect the CHs by considering their residual energy and an equal number of nodes in the cluster. However, the number of cluster heads will vary from one epoch to another, which may decrease the span of the network. In addition, the improved LEACH hierarchal protocols-based data communication mechanism is discussed in Table 1.

Table 1. General characteristics of LEACH protocols

Protocol	Year	Objectives	Network Type	Parameters	Complexity	Limitations
TB-LEACH [30]	2008	• To improve the network lifespan	Homogeneous	• Distance • Residual Energy	Yes	• It depends on the random timer • No. of the cluster is fixed for all epochs
A-LEACH [25]	2010	• Improve the network stability • Reduce the number of dead nodes	Homogeneous	• Residual energy	Yes	• Arbitrary selection of CHs • Supplementary treatment of CAG nodes
LEACH-F [24]	2013	• Utilize centralization for efficient CHs Distribution • Decrease the delay in the set-up process	Homogeneous	• Residual energy	Yes	• At the initial stage, clusters are fixed • No re-clustering processes • Removing the sensor from groups is impossible
MHT-LEACH [27]	2014	• Multi-hop technique • Division of CHs into two groups	Homogeneous	• Distance • Residual Energy	Yes	• Selects CHs without considering node energy • No. of the cluster are not equal
VH-LEACH [22]	2015	• To elect the CHs based on residual energy	Homogenous	• Residual Energy	Yes	• Utilizes a single hop to transmit the data from CHs to BS • Additional dealing for VH node
O-LEACH [26]	2016	• Better coverage of network • Orphan node election to transmit the data	Homogeneous	• Residual energy • Distance	Yes	• Arbitrary selection of CHs • Single Hop communication is utilized

IMHT-LEACH [29]	2016	• Multi-hop technique • Division of CHs into multi-groups	Homogeneous	• Distance • Residual Energy	Yes	• Random CHs election • The distance among CHs-to-CHs members is not considered
I-LEACH [31]	2016	• To elect the CHs based on energy and distance	Homogeneous	• Distance • Residual Energy	No	• Not considered node centrality
DMHT-LEACH [28]	2018	• Multi-hop technique • Division of CHs into multi-groups based on distance and energy	Homogeneous	• Distance • Residual Energy	Yes	• Arbitrary selection of CHs • No. of the cluster are not equal
BRE-LEACH [32]	2019	• To elect the CHs based on residual energy and distance among the node to BS	Homogeneous	• Residual Energy • Distance	Yes	• Node with maximum energy only considered for CH selection
EADCR-LEACH [33]	2020	• To improve the network lifetime • To elect the CHs based on distance and remaining energy	Homogeneous	• Residual energy • Distance	Yes	• Not considered node centrality

2.2 Metaheuristic approaches

In this sub-section, we discussed recent meta-heuristic algorithms utilized to solve the clustering issues in WSN. Generally, meta-heuristic algorithms are classified into two major divisions: evolutionary algorithms and swarm intelligence algorithms. The main aim of developing a meta-heuristic algorithm is to solve the NP-hard problems, which classical approaches may not translate in a stipulated period [34]. Though the algorithm suffers several challenges in obtaining optimal solutions, merging clustering approaches to meta-heuristic algorithms attains better performance in minimizing the energy consumption in WSNs. Based on the benefits of these techniques, a wide range of researchers has utilized several meta-heuristics algorithms to solve the clustering issues in WSN [35].

In [36], the author utilized an evolutionary-based algorithm, namely a genetic algorithm (GA), for solving clustering and routing issues in WSNs. The GA enhances the CHs lifetime to prolong the network lifespan. However, generic GA suffers from local optimal struck that might lead to poor performance during iterations. To eradicate the issue, the author in [37] proposed a GA-based threshold-sensitive energy-efficient cluster selection mechanism that uses cohesion and cluster division processes. The author utilized the inter-cluster data communication technique to prolong the network lifetime by considering the load balance between the nodes and the residual energy of the nodes. The author introduced the multi-path routing protocol [38] by hybridizing the dynamic clustering and Ant colony optimization (ACO) algorithm. The algorithm uses three phases to elect the CHs and route among the cluster members from CHs to BS. This three-phase process aids the network in prolonging the lifetime by selecting optimal CHs. However, the stability of the network path is inefficient in the course of iterations.

The author [39] introduced an energy-efficient clustering algorithm with the aid of a swarm intelligence-based artificial bee colony (ABC-SD). This technique reduces energy consumption by intensifying the ABC's search process. Further, the centralized control technique simulates the LP formulation that handles the multi-objective function within the sink node. The author in [40] proposes Fractional Lion (FLION) clustering technique. This clustering technique includes the residual energy of the sensor node and the distance between the CHs to BS to elect the CHs. The cluster formation is processed based on objectives such as inter and intra-cluster space, residual energy, and delay. The algorithm's performance is compared with other methods such as PSO, LEACH, ABC, and Fractional ABC technique shoed that the protocol enriches the packet delivery ratio, network coverage and lifetime.

The author introduced two-tier particle swarm optimization (PSO) for handling the clustering and routing process (TPSO-CR) in ref. [41]. TPSO-CR protocol is used to mitigate the clustering issues by electing the optimal CH by considering the residual energy and distance among the nodes. The development of TPSO-CR is to improve the network coverage and transmission reliability. TSO-CR works as a centralized infrastructure, and data dissipated among the CHs to BS is similar to the PSO-HC technique. The technique's performance is evaluated in two scenarios: homogenous and heterogeneous nodes. The outcome of the technique compared with other methods showed less power consumption and better stability between the nodes. However, TPSO-CR leads to a huge overload in the set-up phase due to the high volume of message transmission between the sensors. In addition, we have discussed some sets of other meta-heuristics-based clustering approaches in Table 2.

Table 2. Review of Metaheuristics based clustering approaches

Algorithm	Year	Objectives	Mechanism	Metrics	Complexity	Simulation
HACH [42]	2017	Network Lifetime	• GA-based method to move actively to inactive nodes	• Average energy • Stability • Network lifetime	Low	MATLAB
ICWAQ [43]	2012	Reduce energy consumption	• ICWAQ intensify the better and more efficient ABC technique to optimize senor clustering	• Residual energy • Throughput	Yes	MATLAB
EC-PSO [44]	2019	Energy hole	• Geometric-based CH election • Nodes close to the energy centre are elected using improved PSO	• Average energy consumption • The average number of hops • Alive node	Yes	MATLAB
I-FBECS [45]	2021	Network Lifetime	• Novel fitness function is formulated • The rank-based technique is used for non-cluster nodes	• Alive nodes per round • First node death • Half node death • Average energy consumption • Throughput	Yes	MATLAB
LB-CR-ACO [46]	2018	Network Lifetime	• Priority weights are assigned to elect the CHs • Dynamic selection of CHs in every epoch	• Average energy • Throughput • Packet delivery ratio	Yes	MATLAB
MHACO-UC [47]	2019	Reduce Energy consumption	• Electing relay nodes to decrease the maximal	• Packet delivery ratio	Yes	MATLAB

			distance of data transmission • Link maintenance and neighbour finding using MHACO-UC	• Energy consumption • Residual energy • Node death rate		
GWO-CH [48]	2020	Network Lifetime	• GWO algorithm used to select the optimal CHs • Mitigate the energy holes	• Energy consumption • Residual energy • Node death rate	Low	MATLAB
SMO-CH [49]	2018	Load balancing Network Lifetime	• Threshold sensitive energy efficient protocol to elect the CHs	• Energy consumption • Network Lifetime	Yes	MATLAB

2.3 Hybrid Metaheuristic approaches

The author [50] addressed cluster head selection and sink mobility-based data communication by introducing a hybrid GAPSO algorithm. In this algorithm, genetic algorithm and particle swarm optimization are merged to improve the network's lifespan. Magesh et al. [51] proposed a hybrid algorithm named dolphin echolocation-based crow search technique to address the clustering problem. In this algorithm, CHS is elected based on the multiple constraints and improves the convergence rate. Further, the energy-aware routing is processed in data for efficient data transmission. The algorithm's performance is validated using different node scenarios, achieving a better network lifetime. Sengathir et al. [52] proposed a hybrid modified algorithm, namely artificial bee colony and firefly algorithm (HMABCFA), to elect the optimal cluster head. The author improved the exploration and exploitation process in the standard ABC and FA algorithm and achieved a trade-off between search processes. The performance of the HMABCFA improved the network's lifetime and energy stability and decreased the network latency compared to other approaches.

Dattatraya et al. [53] proposed a novel fitness function along with a hybrid Glowworm swarm with Fruitfly Algorithm (FGF) to elect the best CHs. The optimal CHs improved the network's lifetime by considering parameters such as delay, distance and residual energy in the CH election. Shankar et al. [54] proposed a hybrid algorithm, namely the Harmony search algorithm and PSO (HSAPSO), in which exploration and exploitation are improved to select the optimal CHs. However, the author did not consider the significant parameters such as node centrality and node degree to elect the cluster head, which might decrease the network's performance. Later, a hybrid technique, namely the firefly algorithm with particle swarm optimization (HFAPSO) [55], is introduced to determine the optimal CHs in the LEACH-C approach. The performance of the HFAPSO technique is evaluated based on the number of alive nodes, residual energy and throughput. The resulting outcome was that the proposed method improved the network's lifetime. In addition, hybrid grey wolf and crow search optimization (GWCSO) is introduced to select the cluster head by considering minimal delay, minimum distance, and energy stabilization. It concentrates on enhancing the network's lifetime by preventing the possibility of an initial death of cluster heads in the network [56].

2.4 Exact from the literature

The main drawbacks of the existing works in the literature are

i) The capability of maintaining the trade-off between the intensification and diversification during the search process is not sustained and fails to obtain the optimal solution within a minimal time.

ii) The energy balance ensured by the existing meta-heuristic techniques is inadequate in improving or sustaining the network lifespan.

The actual literature work motivates to propose a novel hybrid optimization algorithm, namely the grey wolf optimization algorithm with oppositional-based learning to determine the optimal cluster head. It also ensures the trade-off between intensification and diversification in the search process.

3 Energy-Aware cluster head selection framework

This section elaborates on the concept of the network, energy, distance, and objective models used for experimental purposes in detail. Further, we also discussed the network's lifespan and parameters used in this work.

3.1 Network Model

In this work, WSN consists of n several collective sensor nodes and a BS. Further, the wireless network model is adopted from the reference papers such as [57], [58] and [59], and the set-up of the WSN holds the following possessions.

a) All sensor nodes in WSN are arbitrarily scattered among the 2-D plane of the sensing environment that includes unique latitude and longitude location points.
b) Sensor nodes are energy constrained; once the sensors are deployed in the sensing environment, they are left unattended since recharging them is impractical.
c) All the sensors are consistent and hold typical processing and transmission capabilities; thus, they consume the same energy level for the transmission and processing of data bits.
d) Once the sensors are deployed in the sensing field, they are static concerning BS; all sensors in the network have equal opportunities to act as a regular node or CH.
e) All sensor nodes have to sense information about their environment to be transmitted to CH. Further, the number of sensor nodes must be greater than the number of CHs in the network.
f) The position of the BS is changeable according to the analysis of performance within the sensing region.
g) The transmission route between the sensor nodes and CHs is wireless, and its path is determined within the transmission region.
h) Finally, the sensor nodes can avail different communication power hierarchies concerning data transmission distance.

3.2 Energy Utilization Model

We adopted the energy utilisation model based on the author's reference in [58,59]. In this model, we computed the overall network energy consumption (E) based on the energy dissipated by the transmitter (E_{TX}) and receiver (E_{RX}) and we mathematically formulated as:

$$E_{Total}(n,\theta) = E_{TX}(n,\theta) + E_{RX}(n) \tag{1}$$

Where $E_{Total}(n, \theta)$ represented as overall network energy consumption, $E_{TX}(n, \theta)$ denoted as the energy utilised to operate the radio amplifier and power electronics. The mathematical formulation of energy consumption by the transmitter for transmitting n bits of data is given by:

$$E_{TX}(n, \theta) = \begin{cases} n \times E_{elec} + n \times \varepsilon_{fs} \times \theta^2 & if\ \theta < \varphi \\ n \times E_{elec} + n \times \varepsilon_{mp} \times \theta^4 & if\ \theta \geq \varphi \end{cases} \tag{2}$$

where, E_{elec} denoted as energy consumed per bit to run the transmitter. ε_{fs} and ε_{mp} represent the amplification energy for the free space model and multi-path model, whereas φ represents the threshold communicating distance, and its value is measured by $\varphi = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}}$. θ denotes the distance parameter for computing transmitter energy utilisation concerning the amount of data transmission. If the data transmission is within the φ then the transmittance energy is equal to θ^2; otherwise θ^4. Therefore, the distance and workload are considered significant parameters to improve the network lifetime.

Further, energy utilisation by the receiver for receiving n-bit of data ($E_{RX}(n)$) is given by:

$$E_{RX}(n) = n \times E_{elec} \tag{3}$$

The overall lifetime of the network (NL) is computed based on the residual energy level termed as ($E_{residual}$) and the total energy of the node termed as (E_{total}) after transmitting and receiving, the n-bit data is expressed as follows:

$$NL(S_i, CH_j) = \frac{E^i_{residual}}{E^i_{total}(n,\theta)} \tag{4}$$

where $NL(S_i, CH_j)$ denoted as network lifetime concerning i number of sensor nodes (i.e., $S_i \in SN$) and j number cluster heads elected; $E_{residual}$ represents residual energy of the sensor node, and E_{total} represented as the total energy consumed by the sensor nodes in the network. We computed the network lifetime concerning the first node dead (FND).

3.3 Distance Model

Generally, any communication among the sensor nodes to CH or CH to BS may require some amount of energy according to the role or position acted by the node in the network. Transmission of data between the sensor with the maximum distance might consume high energy, whereas the information of data with less space consumes less power. We computed the distance among the sensor nodes to BS as:

$$\theta_i = \sqrt{(x_{BS} - x_i)^2 - (y_{BS} - y_i)^2}\ ; \quad (i = 1,2, \ldots, SN) \tag{5}$$

Where, θ_i denotes the distance of the i^{th} sensor node to BS position; (x_{BS}, y_{BS}) represents the x-coordinate and y-coordinate of the BS; (x_i, y_i) specifies the position of the i^{th} sensor node; SN denotes the number of sensor nodes deployed in the network.

Further, the Euclidean distance between the sensor and CH is computed as follows:

$$\theta(SN_i, N_{CH\,j}) = \sqrt{\left(x_j - x_i\right)^2 - \left(y_j - y_i\right)^2}\ ; \quad (i = 1,2, \ldots, SN; j = 1,2, \ldots, N_{CH}) \tag{6}$$

Where, N_{CH} denotes the number of cluster heads elected in the network.

3.4 Objective Model

This subsection formulated the fitness function for electing the optimal CH from the set of sensor nodes in the network. The formulation of the fitness function utilizes the five different parameters such as residual energy of sensors, distance model (i.e., the distance between the sensor nodes and distance between the CHs and BS), node degree and node centrality.

a) The residual energy of the CH

Initially, we use the residual energy of the sensor node to eradicate the non-alive nodes as a CH in the clustering process. CH performs various assignments like collecting information from other sensors (i.e., cluster members), aggregating the data, and transmitting the data to BS. Thus, the CH requires more energy to perform the above the said assignments, so we prioritised the sensor with maximum residual liveliness to act as CH. The residual energy (f_1) is illustrated as follows:

$$f_1 = \sum_{j=1}^{N_{CH}} \frac{1}{E_{CH_i}} \tag{7}$$

Where, E_{CH_i} denotes the residual energy of the i^{th} sensor node.

b) The distance among the sensor nodes

Secondly, we compute the distance among the cluster members and their CH. The senor node energy overindulgence is due to the length of the transmission path, as stated in section 3.2. The energy utilization is high when the transmission distance is more and vice versa. We mathematically formulated the distance between the sensor node and CH (f_2) as:

$$f_2 = \sum_{i=1}^{SN} \left(\sum_{j=1}^{N_{CH}} \theta(SN_i, N_{CH\,j}) / N_{CH} \right) \tag{8}$$

Where the distance between sensor i and $N_{CH\,j}$ is represented as $\theta(SN_i, N_{CH\,j})$.

c) Distance between CH and BS

It specifies the distance between the cluster head and BS. The sensor energy mainly relies on the length of the communication track. For instance, let us consider that BS is far away from the CH, then it requires high energy for information exchange. Hence, the abrupt changes in CH energy levels are due to excess energy utilization. Therefore, the node with minimal distance to BS is given higher priority for information exchange. We mathematically formulated the fitness function (f_3) of the distance between the CH and BS as:

$$f_3 = \sum_{j=1}^{N_{CH}} \theta(N_{CH\,j}, BS) \tag{9}$$

where the distance among the $N_{CH\,j}$ and Bs is represented as $\theta(N_{CH\,j}, BS)$.

d) Node degree

It represents the collection of sensors grouped to the corresponding CH. Due to energy constraints, we elected the CH with a limited number of sensors. The CH with high cluster members requires high energy for data collection and aggregation; therefore, it will reduce the lifespan of CH over time. We formulated the node degree (f_4) as:

$$f_4 = \sum_{j=1}^{N_{CH}} N_{CH\,j} \tag{10}$$

Where, $N_{CH\,j}$ denoted as the number of j cluster heads.

e) Node centrality

It represents the number of neighbor nodes surrounded by a sensor node or the node which centrally positioned from the adjacent nodes, and we mathematically expressed it as:

$$f_5 = \sum_{j=1}^{N_{CH}} \frac{\sqrt{\sum_{i \in m} \theta^2(j,i)/m(i)}}{Network\ area} \tag{11}$$

Where $m(i)$ is denoted as the number of adjacent nodes of $N_{CH\,j}$

We converted the multi-objective function into a single-objective process using weight factors for each fitness function. The weight factors such as ϑ_1, ϑ_2, ϑ_3, ϑ_4, and ϑ_5. We formulated the overall objective function as given below:

$$f = \vartheta_1 f_1 + \vartheta_2 f_2 + \vartheta_3 f_3 + \vartheta_4 f_4 + \vartheta_5 f_5 \tag{12}$$

Where the factors of ϑ_1, ϑ_2, ϑ_3, ϑ_4, and ϑ_5 are assigned with the value of 0.3, 0.25, 0.2, 0.15 and 0.1 respectively. Firstly, the weight factor ϑ_1 is considered a high priority because of residual energy of CH, which may eradicate electing node with less energy as a CH. Then, the second and third superiority weight factors are ϑ_2 and ϑ_3 are used to determine the distance from the sensor to CH and CH to BS. Later, the weight factor ϑ_4 is considered the fourth superiority for electing CH with a minor node degree. Finally, the weight factor ϑ_5 is assigned as the fifth priority that aids in improving the closeness among the CH and corresponding cluster members.

4 Proposed Methodology

4.1 Solution Representation

This work has introduced a hybrid optimization algorithm, namely OGWO, which merges the conventional GWO and Oppositional based learning algorithm to elect the energy-aware optimal CH within the network. We formulated the solution representation for the proposed algorithm as shown in figure 1, in which $\left(CH_1, CH_2, \ldots, CH_{N_{CH\,j}}\right)$ is the CHs and $N_{CH\,j}$ represents the total number of cluster heads.

CH_1	CH_2	...	$CH_{N_{CH\,j}}$

Figure 1. Solution Representation

4.2 Conventional GWO

Seyedali Mirjalili recently introduced grey wolf optimization (GWO) in 2014 [60], in which the intellectual behaviors, namely good leadership and hunting strategy of grey wolves, are represented. Generally, grey wolves hunt the prey based on the group-based hunting mechanism that includes a pack of 5-12 wolves gathering together to attack the target. The collection of wolves works in a four-level leadership hierarchy; namely, the first leader termed alpha (α), the second leader denoted as beta (β), the third leader termed delta (δ) and the rest as members termed omega (ω). The $\alpha, \beta,$ and δ are dominant wolves which control the (ω) to sustain the safety and integrity of the pack. The author mathematically formulated the working process of grey wolves in three methods: encircling, hunting, and searching.

a) Encircling

Initially, grey wolves process the encircling to trap the prey before initiating the hunting process. The encircling method is expressed mathematically as below:

$$\vec{D} = \left|\vec{C}.\overrightarrow{X_p}(mx) - \vec{X}(mx)\right| \tag{13}$$

$$\vec{X}(mx+1) = \left|\overrightarrow{X_p}(mx) - \vec{A}.\vec{D}\right| \tag{14}$$

where, $\vec{D}$ denotes interspace between the wolf and the prey, $\vec{X}$ specifies the present location of the wolf in mx generations and $\overrightarrow{X_p}$ determines the prey location. The coefficient parameters, namely $\vec{A}$ and $\vec{C}$ are computed as below:

$$\vec{A} = 2\vec{a}.\overrightarrow{\Upsilon_1} - \vec{a} \tag{15}$$

$$\vec{C} = 2.\overrightarrow{\Upsilon_2} \tag{16}$$

Where, $\overrightarrow{\Upsilon_1}$ and $\overrightarrow{\Upsilon_2}$ specifies the random values computed within the boundary of [0,1]. These values help to change the circumference of wolves randomly towards the prey. The parameter $\vec{a}$ used to limit the crusade of the technique, which slowly converges within the range of [2,0].

b) Hunting

Secondly, the hunting process is initiated slowly by adjusting the location of all the ω wolves with the aid of dominant wolves α, β, and δ. The author mathematically formulated the location adjustment of dominant wolves as:

$$\overrightarrow{D_\alpha} = \left|\overrightarrow{C_1}.\overrightarrow{X_\alpha} - \vec{X}\right|, \overrightarrow{D_\beta} = \left|\overrightarrow{C_2}.\overrightarrow{X_\beta} - \vec{X}\right|, \overrightarrow{D_\delta} = \left|\overrightarrow{C_3}.\overrightarrow{X_\delta} - \vec{X}\right| \tag{17}$$

$$\overrightarrow{X_1} = \left|\overrightarrow{X_\alpha} - \overrightarrow{A_1}.\overrightarrow{D_\alpha}\right|, \overrightarrow{X_2} = \left|\overrightarrow{X_\beta} - \overrightarrow{A_2}.\overrightarrow{D_\beta}\right|, \overrightarrow{X_3} = \left|\overrightarrow{X_\beta} - \overrightarrow{A_3}.\overrightarrow{D_\beta}\right| \tag{18}$$

The author formulated the overall position update of all wolves using (17) and (18) as:

$$\vec{X}(k+1) = 0.33 * \sum_{i=1}^{3} \overrightarrow{X_\iota} \tag{19}$$

Where, $\overrightarrow{X_\iota}$ denotes the arbitrary position of wolves concerning the distance between the α, β, and δ wolves.

c) Attack and search the prey

Finally, the attack and search prey defines the prey attack by the wolf and searching for a new target within the search boundary. The coefficient parameter $\vec{A}$ generates the random value to intensify and diversify the search location of the grey wolves. Grey wolves strengthen the spot toward the prey if $\left|\vec{A}\right| < 1$ or else it searches for a new target or prey (i.e., $\left|\vec{A}\right| > 1$). The parameter $\vec{C}$ linearly adjust its values within the limit of [0,2], which prevents the algorithm from local optima struck.

The author formulated the working principle of generic grey wolf optimisation as given in algorithm 1.

Algorithm 1 Generic Grey Wolf Optimization

1: Initialise the parameters such as population size, A and C.
2: Generate the random position of wolves X_i within the search region
3: Compute the fitness of wolves f_i
4: Determine the α, β, and δ dominant wolves
5: **while** $(mx \leq \max\_Iter)$ // Initially, $mx = 1$
6: **for** $i = 1{:}N_p$
7: Update the position of the wolf using Eq. (19)
8: Compute the fitness of wolves f_i
9: **end for**
10: Update the α, β, and δ dominant wolves
11: Increase mx value to 1 for every iteration (i.e., $mx{+}{=}\ 1$)
12: **end while**

4.3 Opposition based Learning Technique

Opposition based learning technique (OBL) was introduced by Tizhoosh [61] to enhance the convergence speed of the traditional metaheuristic algorithms. This method utilises the valuation of the contemporary population than the opposite population to determine a better solution for a specific problem. OBL method has been used in different metaheuristic algorithms to boost the convergence speed [62,63]. The mathematical formulation of the OBL is defined as follows:

Let $\mu(\mu \in [p, q])$ be an actual integer. The contradictory integer μ^0 is formulated as

$$\mu^0 = p + q - \mu^0 \tag{15}$$

For d – dimensional search space, the contradictory integer μ^0 is defined as

$$\mu_j^0 = p_j + q_j - \mu_j \tag{16}$$

where $\mu_1, \mu_2, \dots, \mu_D$ be a point in d-dimensional search space and $\mu_i \in [p_j, q_j]$; $j = \{1,2,3, \dots, d\}$.

This oppositional based technique is utilised at the time of initialisation procedure and also in every generation with the aid of iteration jumping rate J_r. The author represented the process of OBL as given in algorithm 2.

Algorithm 2: Oppositional Based Learning Algorithm

1: Foremost, the algorithm first initialises the random solutions with the upper and lower boundary regions.
2: Determine the opposite solutions:
2.1: $for\ i = 1{:}N_p$
2.2: $for\ j = 1{:}d$
2.3: $\mu_{i,j}^0 = p_j + q_j - \mu_{i,j}$
2.4: $end\ for$
2.5: $end\ for$
3: Sort the current and opposite solutions into minimum to maximum values.
4: Choose N_p number of best candidate solutions from the recent and contrary solutions.
5: Update the control parameters for the quantified problem utilising the OBL technique.
6: Generate the opposite solutions from current solutions using the jumping rate J_r:
6.1: $for\ j = 1{:}N_p$

6.2: $for\ i = 1: d$
6.3: $if\ J_r > rand$
6.4: $opp(j,i) = min(i) + max(i) - P(j,i);$
6.5: $else$
6.6: $opp(j,i) = P(j,i);$
6.7: end
6.8: $end\ for$
6.9: $end\ for$

7: Sort the solutions (P) and opposite solutions (opp) from minimum to maximum and choose N_p number of best candidate solutions from the current and opposite solutions.

8: Repeat step 5 until the termination criterion is met.

4.3 Proposed OBL-GWO algorithm

OBL is the recent concept in machine learning that mimics the process of opposite relationships between entities. Researchers have widely used this algorithm to enhance the convergence speed and boost the searching process in meta-heuristic algorithms. GWO is a variant of the swarm intelligence family that mimics the working principle of the grey wolf that intakes the leadership and hunting strategy. This algorithm has inspired several researchers with its simplicity and ease of use in solving several complex optimization problems. However, the conventional algorithm suffers from common issues such as local optimal struck and premature convergence. It may lead to lousy accuracy in determining optimal solutions in multi-model optimization problems. We hybridized the OGWO algorithm to overcome the issues mentioned above. This hybridized algorithm merges the OBL and the GWO algorithm to improve the search capabilities of GWO and speed up the convergence in electing the optimal CHs within the network. The working architecture of cluster head selection using OGWO is given in Figure 1.

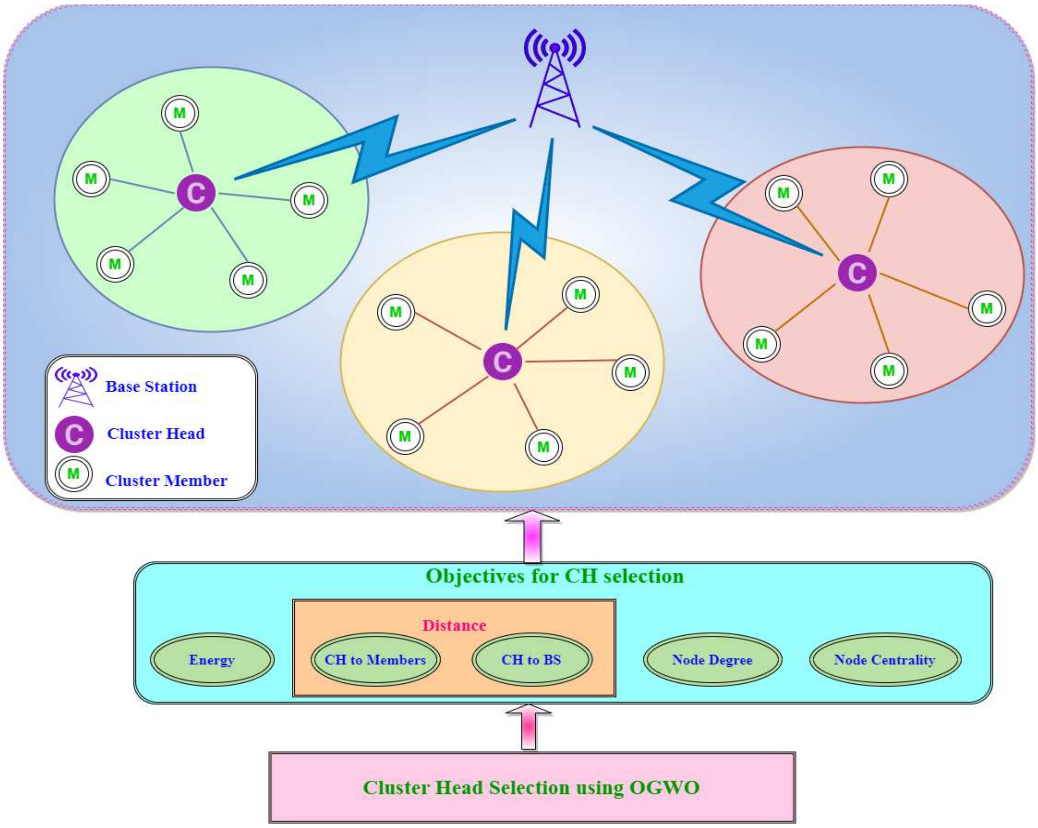

Fig. 1. Cluster Head Selection using OGWO

The working process of OGWO as follows: Firstly, we initialized the population by the OBL method within the search limits in the proposed method. Later, the position of wolves is updated using conventional GWO, and OBL determines the opposite part of wolves. Moreover, the proposed algorithm updates wolves' location by merging the best OBL and GWO algorithms. The algorithm maintains the trade-off between the intensification and diversification in searching for the optimal CHs within the network. We formulated the working algorithm of OGWO as given in algorithm 3.

Algorithm 3 Cluster head Selection using DOL-GWO

Generate arbitrary initial Population Φ;
For $i = 1{:}N$
  $r_{1,i} = rand(0,1), r_{2,i} = rand(0,1)$;
  For $j = 1{:}D$
      $\Phi_{ij}^{do} = \Phi_{ij} + r_{1,i}.(r_{2,i}.(\lambda_j + \alpha_j - \Phi_{ij}) - \Phi_{ij})$;
      Ensure the search boundary;
  End For
End For
Compute the fitness of all search agent
Pick the top best *N* solutions from $\Phi^{do} \cup \Phi$ to Φ^{S}
Determine the first three best search agents of α, β and δ from Φ^{S}
While $t <= max\_Iter$
For $i = 1{:}N$
      Update the Position of the search agents Φ^{S} using Eq. (2)
      Ensure the boundary limits of all search agents;
End For
      For $i = 1{:}N$
            If $rand < \delta$
                  $r_{3,i} = rand(0,1), r_{3,i} = rand(0,1)$;
            For $j = 1{:}D$
                  $\Phi_{ij}^{do} = \Phi_{ij}^{S} + r_{1,i}.(r_{2,i}.(\lambda_j + \alpha_j - \Phi_{ij}) - \Phi_{ij}^{S})$;
                  Ensure the boundary limits;
            End For
      End if
End for
      Compute the fitness of all search agent
      Pick the top best *N* solutions from $\Phi^{do} \cup \Phi$ to Φ^{S}
      Update the three best search agents of α, β and δ from Φ^{S}
Update the power exponent value
End While
Output: CHs from the network (Optimal Solution)

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5 *Result and Discussion*

5.1 Experimental Set-up

In this section, we set up a simulation environment in MATLAB version 2018a, which is functioned in the Windows 10 operating system with a hardware platform of Intel Xenon, i5-3570 CPU with a speed of 3.6GHz and 16 GB RAM, 10MB cache, respectively. Selecting the MATLAB tool is due to ease of mathematical operations and adequate data examination. In our work, We randomly scattered 400 sensor nodes in the WSN network within the deployment area of $200\ x\ 200\ m^2$. We presented the experimentation parameters in Table 1. The main goal of this work is to identify the optimal cluster head to improve the network's lifespan. The author of this work used the input parameters such as residual energy, length of transmission between sensors to CH to BS, node degree, and node centrality to select the optimal CHs in the network. Furthermore, we presented the OGWO parameters in Table 2, and the parameters of ABC and GWO were adopted from the authors' reference [15, 16]. We compared the proposed OGWO algorithm with a few state-of-art conventional algorithms such as GWO, ABC, and LEACH. The authors of the traditional algorithm proved their efficacy in improving energy efficiency in WSN.

Table 1 Various Parameters used in Simulation

Parameter	Value
Deployment Area	$200\ x\ 200\ m^2$
BS Location	(0,0) (50,50), (100,100), (150,150)
Number of Senor Nodes	100 to 400 Nodes
Initial Node energy	$2.0\ J$
Number of CHs (%)	$10\%\ to\ 25\%$
E_{elec}	$50\ nJ/bit$
E_{fs}	$10pJ/bit/m^2$
E_{mp}	$0.0013pJ/bit/m^4$
D_{max}	100m
D_o	30m

Table 2 Parameters of OGWO

Parameter	Value
Number of wolves	100
Maximum number of Iterations	10e3
Jumping rate (δ)	0.4
Coefficient parameter (c)	[2,0]

5.2 Performance Evaluation Metrics

In this section, we discussed the evaluation performance metrics as follows:

First Node Dead (FND): It defines the number of iterations when the initial node of the network dies. we used this metric to determine the maximum duration the network can withstand in active mode.

The number of Alive Nodes (NoAN) specifies the number of active nodes in the network. The network lifespan extends when the number of active nodes is high.

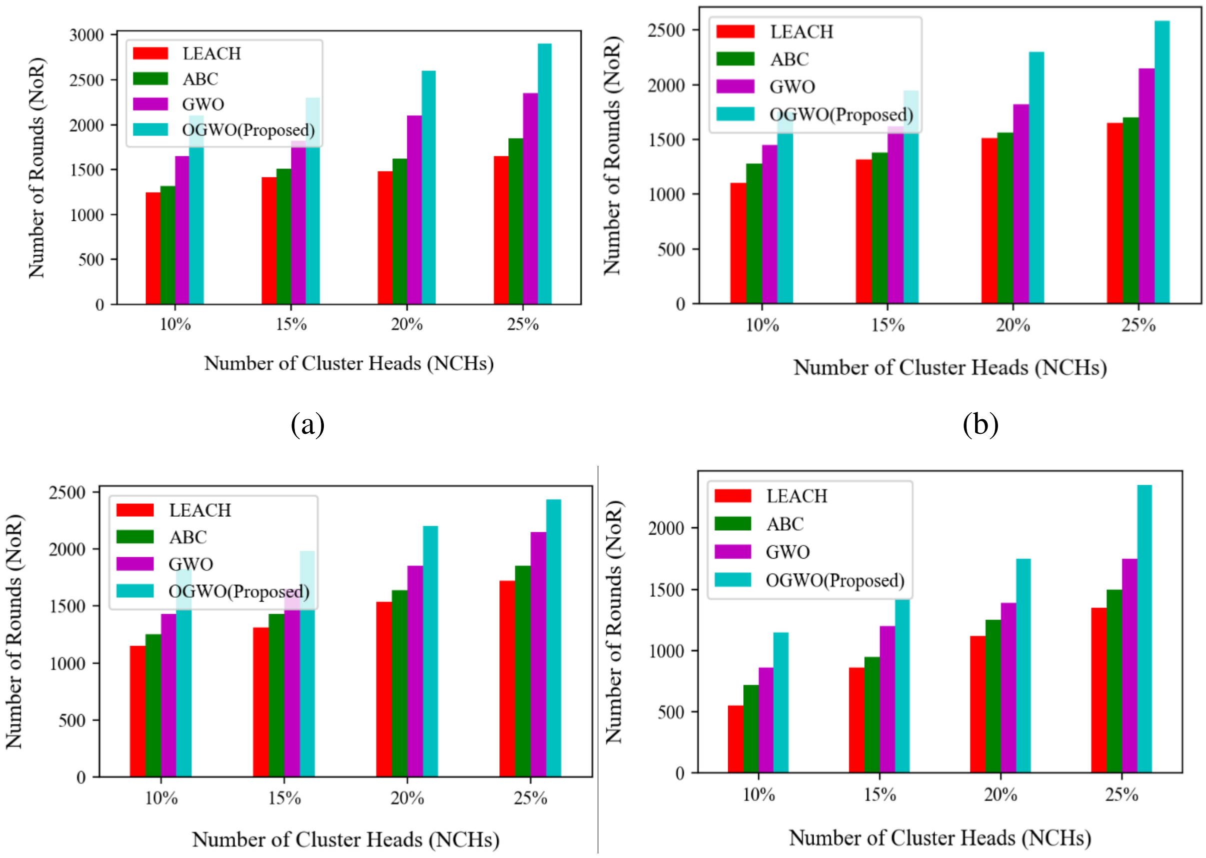
Number of Packets Received (NoPR) by BS: The total number of packets received at BS is directly relative to the alive nodes and the remaining energy of the sensors. If the active nodes are high, the number of packets received by BS is high.

Average energy utilization specifies the collective amount of power each sensor uses per generation.

5.3 Result analysis and Discussion

In this work, we used diverse test cases for our experimentation to analyses various outcomes. We used a different number of sensor nodes (NSNs) in our investigation, and we observed the corresponding results. Furthermore, the effects are marked based on the impact of BS and CHs. We considered four different test cases to validate the performance of the proposed algorithm. We discussed the detailed set-up of each test case and its outcomes as follows:

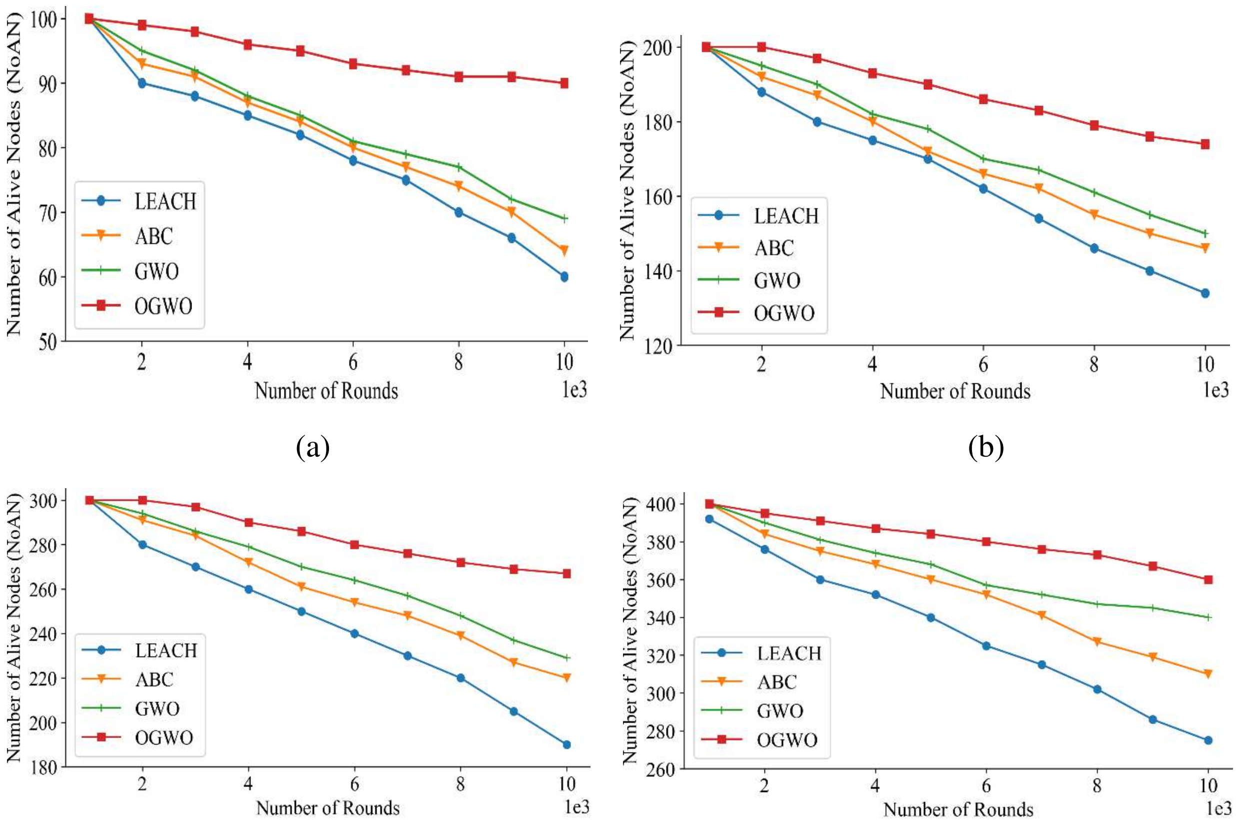
a) *Test Case 1 (NoR):* In this test case, we used the deployment area as $200\ x\ 200\ m^2$, NSNs = 100 to 400, Initial energy = 2.0J, BS = (100,100), and NCHs = (10%, 15%, 20%, 25%) the outcome of the proposed methodology is measured based on the NoR after first node death in the network. This test case deliberates the results of the network lifetime. This performance measure is significant to analyzing the algorithm's efficacy in selecting optimal CHs in the network []. The performance of the proposed methodology over existing methods is noted and illustrated in figure 2. We used a different set of sensor nodes such as 100, 200, 300, and 400 in this experimentation, and we graphically illustrated this in fig. 2(a), fig 2(b), fig 2(c), and fig. 2(d) respectively. We compared the proposed work with other traditional clustering algorithms like LEACH, ABC, and GWO. OGWO algorithm attains a better enhancement of ~50%, ~30%, and ~20% over LEACH, ABC and GWO, respectively, based on NoR after FND.
The reason behind the achievement of LT in OWGO over LEACH is due to certain limitations of LEACH. Generally, the LEACH algorithm utilizes the probabilistic method and arbitrarily selects CHs, resulting in high energy consumption and reducing the network lifetime. Furthermore, LEACH selects the minimal residual energy sensor as CH. Similarly, the ABC algorithm performs well in the population-based clustering approach, but it fails to consider the workload of the sensor. On the other hand, the conventional GWO algorithm provides a better solution for several complex optimization problems. However, it fails to explore the search space and suffers in maintaining the trade-off between the intensity and diversity. Compared to conventional GWO, ABC and LEACH techniques, our proposed OGWO algorithm attains more rounds after FND. Furthermore, the OGWO algorithm also outperforms better in exploring search space during cluster formation. Our proposed algorithm achieves a higher network lifespan than LEACH, ABC and GWO algorithms concerning NoR after FND.



(c) (d)

Fig. 2 Results of Number of Rounds (NoR) after First Node Dead (FND) with respect to different Number of cluster heads (NCHs) in various Number of Sensor Nodes (NSNs) (a) NSNs = 100, (b) NSNs = 200, (c) NSNs = 300, (d) NSNs = 400.

b) *Test case 2 (NoANs):* In this test case 2, we considered the sensing region as $200 \times 200\ m^2$, NSNs = 100 to 400, Initial energy = 2.0J, BS = (50,50), and NCHs = 25%. We analyse the performance of the OGWO in terms of the number of alive nodes. This test case determines the NoANs after a certain number of iterations of NoR. We presented the observed results of the proposed OWGO with LEACH, ABC and GWO in fig 3. The x and y coordinates of figure 3 represent NoR and NoANs, respectively. Fig. 3(a), (b), (c) and (d) presents the NoANs comparison for NSNs = (100,200,300,400), sequentially. The proposed OGWO algorithm provides a better outcome than compared algorithms of LEACH, ABC and GWO. OGWO achieves an overall efficacy of ~45%, ~30% and ~20% than LEACH, ABC and GWO. In contrast to LEACH, OGWO renovates the bunching when a CH's death occurs and links the sensor nodes to other CHs in the network. The main limitation of LEACH is that when CH's death occurs, the corresponding cluster becomes futile, and the collected information fails to transfer to the sink, i.e., BS. Moreover, LEACH picks the CH at the boundary of the network, which may lead to improper bunching and, thereby, degrades the network's performance. In our work, OGWO also achieves the consistent dispersal of CHs. In addition, the optimal selection of CHs plays a vital role in improving the network's lifespan. Our algorithm with a novel objective function performs well in determining the optimal CHs. Hence, the proposed OGWO algorithm achieves a better outcome than the LEACH technique. Furthermore, the existing meta-heuristic algorithm of ABC and GWO fails to provide a better outcome because of an imbalance of intensification and diversification. Concisely, OGWO is an effective technique for identifying optimal CHs and improving the lifespan of the overall network.



(a) (b)

(c) (d)

Fig. 3 Results of Number of Alive Nodes (NoAN) with respect to number of NCHs = 25% and different NSNs at BS= (50,50). (a) NoAN at Sensors = 100 (b) NoAN at Sensors = 200, (c) NoAN at Sensors = 300 (d) NoAN at Sensors = 400.

c) *Test case 3 (NoPR):* In this test case 3, we used the deployment area as $200 \times 200\, m^2$, BS location as ((0,0), (50,50), (100,100),(150,150), initial energy considered as 2.0J, NSNs = 100 to 400 nodes, and NCHs = 10%. We used this test case to analyze the performance of the proposed algorithms in terms of the number of packets delivered at the BS. We graphically illustrated the observed results of the proposed algorithm and other state-of-art algorithms in figure 4. Furthermore, we used a varying number of sensor nodes from 100 to 400 concerning BS variations, respectively. From figure 4, the outputs are measured based on the various number of sensor nodes such as fig. 4(a) represents the output for NSNs=100, fig 4(b) for NSNs=200, fig 4(c) for NSNs=300 and 4(cd NSNs=400. Similarly, the x-axis and y-axis represent the BS location and Number of packets received (NoPR). The proposed OGWO algorithm achieves a better outcome than the LEACH, ABC and GWO techniques. The achievement of OGWO is due to the efficient selection of CHs by processing unified diversity among the search agents than other algorithms. In addition, we observed that the network's lifespan is improved and consumes minimal energy to transmit the data packets to BS by electing the CHs within a minimal distance. Thereby, it increases the NoPR at the BS though the position of BS is changeable. Our work provides higher NoPR when BS locates at (100,100), whereas positioning BS in other locations provides less NoPR than the BS position in the centre region of the deployment area.

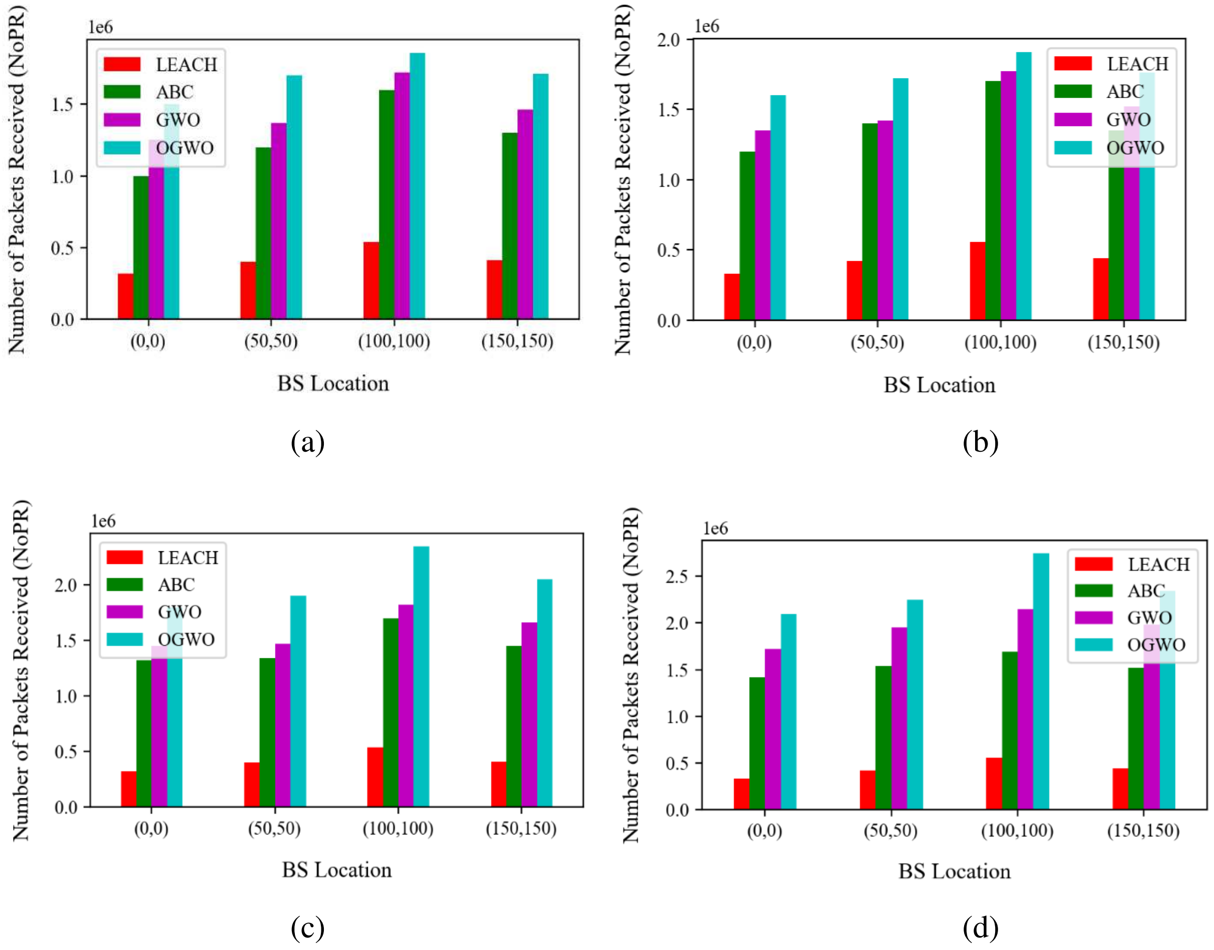


Fig. 4 Results of Number of Packets Received (NoPR) by BS concerning NCHs = 10% at the various number of sensor nodes and base station positions. (a) NoPR at sensors = 100, (b) NoPR at sensors = 200, (c) NoPR at sensors = 300, (d) NoPR at sensors = 400

d) Test case 4: Our work considers this test case for analyzing the performance of the proposed OGWO algorithm by the impact of BS and NCHs. The parameters used in this work are a deployment area of $200 \times 200\, m^2$ with the varying number of sensor nodes from 100 to 400 and initial energy as 2.0J. Initially, we used the number of sensor nodes as 100 to 400, the number of BS locations as (0,0), (50,50), (100,100), (150,150) and NCHs as 25% for analyzing the performance impact of base station location concerning the number of rounds after fist node death. The x-axis and y-axis represent the number of sensor nodes and iterations. The BS locations (100,100) significantly increase the performance of the number of rounds in all the different sensor nodes, as shown in Fig. 5(a). Concisely, the BS locations (0,0), (50,50) and (150,150) decreases the performance of the network than BS location (100,100). This lack of performance occurs due to the BS location located far from the selected CHs. Therefore, the transmission of data packets from CHs might travel a maximum length to reach the BS at a distant location, leading to minimal LT of the network. The BS at the centre of the deployment area maximizes the LT and reduces the length of data travel between the CHs and BS. In addition, the BS location at (100,100) improves the LT by ~50% more than the other BS locations.

Later, we set up a scenario with CHs of 10% to 25%, NSNs as 100 to 400 and BS location at (100,100) to measure the performance of the impact of CHs as given in Fig. 5(b). The x-coordinate and y-coordinate represent the number of sensors and rounds after the first node death. From the fig. 5(b), we noticed that the number of iterations increases when the CHs have opted as 15% than CHs as 25%. Though the CHs with 25% provide better outcomes in 100 and 200 sensor nodes environment, it degrades slowly when the number of the sensor increases to 300 and 400 nodes. Generally, CHs consume more energy than the normal nodes because the CHs collect the data from the non-CHs, aggregate the data, and transmit the data to BS. Therefore, the optimal CHs for the appropriate number of sensor nodes in the network is challenging. However, the low selection of CHs will lead to high energy consumption and reduce the network's LT. Based on the result analysis, we noticed that CHs with 15% provide adequate results than the CHs with 10%, 20% and 25%. In addition, the CHs with 15% increase the network's lifetime by holding the maximum number of rounds after the first node death.

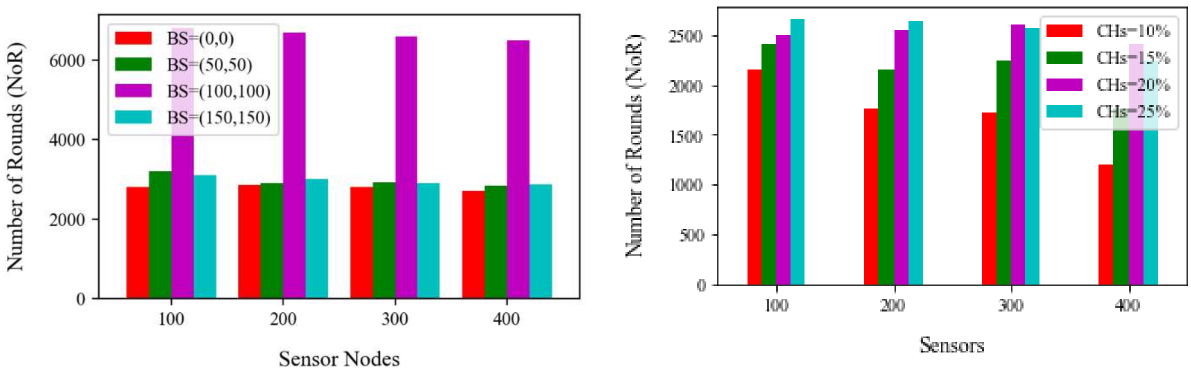


Fig. 5 Impact of the base station and cluster heads on a lifetime of the network (a) Impact of Base Station (BS) (b) Impact of NCHs

We obtained the overall network lifespan enhancement of ~20%, ~30% and ~45% compared with GWO, ABC and LEACH techniques. In addition, we noticed that for obtaining the improved network lifespan, the BS location and CHs percentage play a vital role in the deployment area.

6 Conclusion

This research work has aimed to introduce an optimal cluster head election framework by developing novel hybrid optimization techniques. We used different objective constraints for electing the optimal CHs, such as residual energy and various distance metrics, node degree and node centrality. The formulated non-linear objective function has achieved the network's lifespan improvement. A novel hybrid technique, namely oppositional grey wolf optimization (OGWO), has been proposed by incorporating generic GWO and opposition-based learning techniques. This approach enriches the limitations of the existing algorithm by balancing the intensification and diversification of search agents in electing the optimal CHs. We implemented our proposed work in MATLAB 2018a with an adequate simulation environment. The experimental results suggest that our proposed algorithm provides a better outcome in improved network lifespan. The proposed OGWO algorithm attains the overall network lifespan of 45%, 30% and 20% over LEACH, ABC and generic GWO techniques. In addition, we also analyzed

the impact of varied BS locations and CHs percentage concerning the different number of sensor nodes. We noticed that the improvement of networks lifespan depends on the position of BS and the portion of CHs in the network.
In future, we plan to use various GWO variants to solve the cluster head selection problem in heterogeneous WSN. In addition, we compare and analyze the performance of different GWO variants to such issues; we also try different approaches to reduce the computation time and prolong the network lifespan.

Declaration of Competing Interest

The All authors are declared that they have no conflict of Interest. The authors are certified that they have NO affiliations with or involvement in any organization or entity with any financial interest in the subject matter or materials discussed in this manuscript.

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Author Contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by R Rajakumar, M Reddy Prakash, G Thanuja, and Kadiyala Kundan Koushal. The first draft of the manuscript was written by R Rajakumar, K Dinesh, M Sreedevi and Abdul Jaleel and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Data Availability

The datasets generated during and/or analysed during the current study are not publicly available but are available from the corresponding author on reasonable request.

References

1. Vajdi, G. Zhang, Y. Wang, T. Wang, A new self-management model for largescale event-driven wireless sensor networks, IEEE Sens. J. 16 (20) (2016) 7537–7544.
2. Kaushik, S. Indu, D. Gupta, A Grey Wolf Optimization Approach for Improving the Performance of Wireless Sensor Networks, Wireless Personal Communications 106 (3) (2019) 1429–1449.
3. P. Kevin, U.T. Samarakoon, Performance analysis of wireless sensor network localization algorithms, International Journal of Computer Networks and Applications (IJCNA) 6 (6) (2019) 92–99
4. Sekaran, Kaushik, R. Rajakumar, K. Dinesh, Y. Rajkumar, T. P. Latchoumi, Seifedine Kadry, and Sangsoon Lim. "An energy-efficient cluster head selection in wireless sensor network using grey wolf optimization algorithm." *TELKOMNIKA (Telecommunication Computing Electronics and Control)* 18, no. 6 (2020): 2822-2833.
5. Gherbi, C.; Aliouat, Z.; Benmohammed, M. An adaptive clustering approach to dynamic load balancing and energy efficiency in wireless sensor networks. Energy 2016, 114, 647–662.
6. A.J. Yuste-Delgado, J.C. Cuevas-Martinez, A. Trivino-Cabrera, ˜ EUDFC-Enhanced Unequal Distributed Type-2 Fuzzy Clustering Algorithm, IEEE Sens. J. 19 (12) (2019) 4705–4716.
7. J. Sathiamoorthy, B. Ramakrishnan, M. Usha, “A Three-Layered Peer-to-Peer Energy Efficient Protocol for Reliable and Secure Data Transmission in EAACK MANETs, Springer Journal of Wireless Personal Communication 102 (1) (September 2018) 201–227.
8. J. Sathiamoorthy, B. Ramakrishnan, M. Usha, A Trusted Waterfall Framework Based Peer to Peer Protocol for Reliable and Energy Efficient Data Transmission in MANETs, Springer Journal of Wireless Personal Communication 102 (1) (September 2018) 95–124.

9. 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*, 2000, pp. 10 pp. vol.2-, doi: 10.1109/HICSS.2000.926982.
10. Younis, Ossama, and Sonia Fahmy. "HEED: a hybrid, energy-efficient, distributed clustering approach for ad hoc sensor networks." *IEEE Transactions on mobile computing* 3, no. 4 (2004): 366-379.
11. Kumar, Naveen, Pawan Bhutani, and Prity Mishra. "U-LEACH: A novel routing protocol for heterogeneous Wireless Sensor Networks." In *2012 International Conference on Communication, Information & Computing Technology (ICCICT)*, pp. 1-4. IEEE, 2012.
12. Yu, Jiguo, Yingying Qi, and Guanghui Wang. "An energy-driven unequal clustering protocol for heterogeneous wireless sensor networks." *Journal of Control Theory and Applications* 9, no. 1 (2011): 133-139.
13. Bagci, Hakan, and Adnan Yazici. "An energy aware fuzzy approach to unequal clustering in wireless sensor networks." *Applied Soft Computing* 13, no. 4 (2013): 1741-1749.
14. Mazumdar, Nabajyoti, and Hari Om. "An energy efficient GA-based algorithm for clustering in wireless sensor networks." In *2016 International Conference on Emerging Trends in Engineering, Technology and Science (ICETETS)*, pp. 1-7. IEEE, 2016.
15. Karaboga, Dervis, Selcuk Okdem, and Celal Ozturk. "Cluster based wireless sensor network routing using artificial bee colony algorithm." *Wireless Networks* 18, no. 7 (2012): 847-860.
16. Agrawal, Deepika, Muhammad Huzaif Wasim Qureshi, Pooja Pincha, Prateet Srivastava, Sourabh Agarwal, Vikram Tiwari, and Sudhakar Pandey. "GWO-C: grey wolf optimizer-based clustering scheme for WSNs." *International Journal of Communication Systems* 33, no. 8 (2020): e4344.
17. Cai, Xingjuan, Shaojin Geng, Di Wu, Lei Wang, and Qidi Wu. "A unified heuristic bat algorithm to optimize the LEACH protocol." *Concurrency and Computation: Practice and Experience* 32, no. 9 (2020): e5619.
18. Manshahia, Mukhdeep Singh, Mayank Dave, and S. B. Singh. "Firefly algorithm-based clustering technique for Wireless Sensor Networks." In *2016 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*, pp. 1273-1276. IEEE, 2016.
19. Wang, Jin, 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* 76 (2017): 452-457.
20. Vinodhini, R., and C. Gomathy. "Fuzzy Based Unequal Clustering and Context-Aware Routing Based on Glow-Worm Swarm Optimization in Wireless Sensor Networks: Forest Fire Detection." *Wireless Personal Communications* 118, no. 4 (2021): 3501-3522.
21. Zhang, Li-Gang, Xingsi Xue, and Shu-Chuan Chu. "Improving K-Means with Harris Hawks Optimization Algorithm." In *Advances in Intelligent Systems and Computing*, pp. 95-104. Springer, Singapore, 2022.
22. Mehmood, Amjad, Jaime Lloret Mauri, M. Noman, and Houbing Song. "Improvement of the wireless sensor network lifetime using LEACH with vice-cluster head." *Ad Hoc Sens. Wirel. Networks* 28, no. 1-2 (2015): 1-17.
23. W.B. Heinzelman, A.P. Chandrakasan, H. Balakrishnan, An application-specific protocol architecture for wireless microsensor networks, IEEE Trans. Wireless Commun. 1 (4) (2002) 660–670.
24. Singh, Kamaljot. "WSN LEACH based protocols: A structural analysis." In *2015 international conference and workshop on computing and communication (IEMCON)*, pp. 1-7. IEEE, 2015.
25. Abdellah, Ezzati, S. A. I. D. Benalla, Abderrahim Beni Hssane, and Moulay Lahcen Hasnaoui. "Advanced low energy adaptive clustering hierarchy." *IJCSE) International Journal on Computer Science and Engineering* 2, no. 07 (2010): 2491-2497.
26. Wassim Jerbi, Abderrahmen Guermazi, Hafedh Trabelsi, O-LEACH of routing protocol for Wireless Sensor Netw., in: 2016 13th International Conference on Computer Graphics, Imaging and Visualization, CGiV, IEEE, 2016, pp. 399–404.
27. Huang, Jian-hua, Zi-ming Zhao, Yu-bo Yuan, and Ya-dong Hong. "Multi-factor and distributed clustering routing protocol in wireless sensor networks." *Wireless Personal Communications* 95, no. 3 (2017): 2127-2142.
28. M. Aishwarya, S. Kirthiga, Relay assisted cooperative communication for wireless sensor netw., in: 2018 Second International Conference on Advances in Electronics, Computers and Communications, ICAECC, IEEE, 2018, pp. 1–6.

29. Alnawafa, Emad, and Ion Marghescu. "IMHT: Improved MHT-LEACH protocol for wireless sensor networks." In *2017 8th international conference on information and communication systems (ICICS)*, pp. 246-251. IEEE, 2017.
30. Junping, Hu, Jin Yuhui, and Dou Liang. "A time-based cluster-head selection algorithm for LEACH." In *2008 IEEE symposium on computers and communications*, pp. 1172-1176. IEEE, 2008.
31. Amirthalingam, Krishnakumar. "Improved leach: A modified leach for wireless sensor network." In *2016 IEEE International Conference on Advances in Computer Applications (ICACA)*, pp. 255-258. IEEE, 2016.
32. Ikram Daanoune, Abdennaceur Baghdad, Abdelhakim Balllouk, BRE-LEACH: A new approach to extend the lifetime of wireless sensor network, in: 2019 Third International Conference on Intelligent Computing in Data Sciences, ICDS, IEEE, 2019, pp. 1–6.
33. Panchal, Akhilesh, and Rajat Kumar Singh. "EADCR: energy aware distance-based cluster head selection and routing protocol for wireless sensor networks." *Journal of Circuits, Systems and Computers* 30, no. 04 (2021): 2150063.
34. Gao, K.-Z.; He, Z.; Huang, Y.; Duan, P.-Y.; Suganthan, P.N. A survey on meta-heuristics for solving disassembly line balancing, planning and scheduling problems in remanufacturing. Swarm Evol. Comput. 2020, 57, 100719.
35. Al-Mekhlafi, Z.G.; Hanapi, Z.M.; Saleh, A.M.S. Firefly-inspired time synchronization mechanism for self-organizing energyefficient wireless sensor networks: A survey. IEEE Access 2019, 7, 115229–115248.
36. Wang, T.; Zhang, G.; Yang, X.; Vajdi, A. Genetic algorithm for energy-efficient clustering and routing in wireless sensor networks. J. Syst. Softw. 2018, 146, 196–214.
37. Mittal, N.; Singh, U.; Sohi, B.S. An energy-aware cluster-based stable protocol for wireless sensor networks. Neural Comput. Appl. 2019, 31, 7269–7286.
38. Yang, J.; Xu, M.; Zhao, W.; Xu, B. A multipath routing protocol based on clustering and ant colony optimization for wireless sensor networks. Sensors 2010, 10, 4521–4540.
39. Ari, A.A.A.; Yenke, B.O.; Labraoui, N.; Damakoa, I.; Gueroui, A. A power efficient cluster-based routing algorithm for wireless sensor networks: Honeybees swarm intelligence-based approach. J. Netw. Comput. Appl. 2016, 69, 77–97.
40. Sirdeshpande, Nandakishor, and Vishwanath Udupi. "Fractional lion optimization for cluster head-based routing protocol in wireless sensor network." *Journal of the Franklin Institute* 354, no. 11 (2017): 4457-4480.
41. Elhabyan, Riham SY, and Mustapha CE Yagoub. "Two-tier particle swarm optimization protocol for clustering and routing in wireless sensor network." *Journal of Network and Computer Applications* 52 (2015): 116-128.
42. Oladimeji, M.O.; Turkey, M.; Dudley, S. HACH: Heuristic Algorithm for Clustering Hierarchy protocol in wireless sensor networks. *Appl. Soft Comput.* **2017**, *55*, 452–461.
43. Karaboga, D.; Okdem, S.; Ozturk, C. Cluster based wireless sensor network routing using artificial bee colony algorithm. Wirel. Netw. 2012, 18, 847–860.
44. Wang, Jin, Yu Gao, Wei Liu, Arun K. Sangaiah, and Hye-Jin Kim. 2019. "An Improved Routing Schema with Special Clustering Using PSO Algorithm for Heterogeneous Wireless Sensor Network" *Sensors* 19, no. 3: 671. https://doi.org/10.3390/s19030671
45. Dwivedi, Anshu Kumar, and Awadesh K. Sharma. "I-FBECS: improved fuzzy based energy efficient clustering using biogeography-based optimization in wireless sensor network." *Transactions on Emerging Telecommunications Technologies* 32, no. 2 (2021): e4205.
46. Guleria, K. and Verma, A.K. (2018), "An energy efficient load balanced cluster-based routing using ant colony optimization for WSN", International Journal of Pervasive Computing and Communications, Vol. 14 No. 3/4, pp. 233-246. https://doi.org/10.1108/IJPCC-D-18-00013
47. Guleria, K., Verma, A.K. Meta-heuristic Ant Colony Optimization Based Unequal Clustering for Wireless Sensor Network. *Wireless Pers Commun* **105,** 891–911 (2019). https://doi.org/10.1007/s11277-019-06127-1
48. Rajakumar, R., K. Dinesh, and T. Vengattaraman. "An energy-efficient cluster formation in wireless sensor network using grey wolf optimisation." *International Journal of Applied Management Science* 13, no. 2 (2021): 124-140.
49. Mittal, N., Singh, U., Salgotra, R. *et al.* A boolean spider monkey optimization-based energy efficient clustering approach for WSNs. *Wireless Netw* **24,** 2093–2109 (2018). https://doi.org/10.1007/s11276-017-1459-4

50. Sahoo, Biswa Mohan, Hari Mohan Pandey, and Tarachand Amgoth. "GAPSO-H: A hybrid approach towards optimizing the cluster-based routing in wireless sensor network." *Swarm and Evolutionary Computation* 60 (2021): 100772.
51. Mahesh, N., and S. Vijayachitra. "DECSA: hybrid dolphin echolocation and crow search optimization for cluster-based energy-aware routing in WSN." *Neural Computing and Applications* 31, no. 1 (2019): 47-62.
52. Sengathir, J., A. Rajesh, Gaurav Dhiman, S. Vimal, C. A. Yogaraja, and Wattana Viriyasitavat. "A novel cluster head selection using Hybrid Artificial Bee Colony and Firefly Algorithm for network lifetime and stability in WSNs." *Connection Science* 34, no. 1 (2022): 387-408.
53. Dattatraya, Kale Navnath, and K. Raghava Rao. "Hybrid based cluster head selection for maximizing network lifetime and energy efficiency in WSN." *Journal of King Saud University-Computer and Information Sciences* (2019).
54. Shankar, T., S. Shanmugavel, and A. Rajesh. "Hybrid HSA and PSO algorithm for energy efficient cluster head selection in wireless sensor networks." *Swarm and Evolutionary Computation* 30 (2016): 1-10.
55. Pitchaimanickam, B., and G. Murugaboopathi. "A hybrid firefly algorithm with particle swarm optimization for energy efficient optimal cluster head selection in wireless sensor networks." *Neural Computing and Applications* 32, no. 12 (2020): 7709-7723.
56. Subramanian, P., J. Martin Sahayaraj, S. Senthilkumar, and D. Stalin Alex. "A hybrid grey wolf and crow search optimization algorithm-based optimal cluster head selection scheme for wireless sensor networks." *Wireless Personal Communications* 113, no. 2 (2020): 905-925.
57. J. Xu, W. Liu, F. Lang, Y. Zhang, and C. Wang, "Distance measurement model based on RSSI in WSN," Wireless Sensor Netw., vol. 2, no. 8, pp. 606–611, 2010.
58. P. S. Rao and H. Banka, "Energy efficient clustering algorithms for wireless sensor networks: Novel chemical reaction optimization approach," Wireless Netw., vol. 23, no. 2, pp. 433–452, 2017.
59. P. S. Rao, P. K. Jana, and H. Banka, "A particle swarm optimization-based energy efficient cluster head selection algorithm for wireless sensor networks," Wireless Netw., vol. 23, no. 7, pp. 2005–2020, 2017.
60. Mirjalili, Seyedali, Seyed Mohammad Mirjalili, and Andrew Lewis. "Grey wolf optimizer." *Advances in engineering software* 69 (2014): 46-61.
61. Tizhoosh HR. Opposition-based learning: a new scheme for machine intelligence. In: Proceeding of the international conference on computational intelligence for modeling, control and automation, Austria. p. 695–701.
62. Roy PK, Paul C, Sultana S. Oppositional teaching learning-based optimization approach for combined heat and power dispatch. Int J Elect Power Energy Syst 2014;57: 392–403.
63. Roy PK, Mandal D. Oppositional biogeography-based optimization for optimal power flow. Int J Electr Power Energy Syst 2013;53: 123–34.