Energy Efficient Communication In Wireless Sensor Networks Using Grey Wolf Optimization Algorithm

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Abstract- *Energy efficiency is one of the main challenges in developing Wireless Sensor Networks (WSNs). Since communication has the largest share in energy consumption, efficient routing is an effective solution to this problem. Hierarchical clustering algorithms are a common approach to routing. This technique splits nodes into groups in order to avoid long-range communication which is delegated to the cluster head (CH). In this paper, we present a new clustering algorithm that selects CHs using the grey wolf optimizer (GWO). GWO is a recent swarm intelligence algorithm based on the behaviour of grey wolves that shows impressive characteristics and competitive results. To select CHs, the solutions are rated based on the predicted energy consumption and current residual energy of each node. In order to improve energy efficiency, the proposed protocol uses the same clustering in multiple consecutive rounds. This allows the protocol to save the energy that would be required to reform the clustering. We also present a new dual-hop routing algorithm for CHs that are far from the base station and prove that the presented method ensures minimum and most balanced energy consumption while remaining nodes use single-hop communication. The proposed GWO-based approach is resulted with higher values of both clustering and routing fitness functions as compared to the existing algorithms, namely, genetic algorithm, particle swarm optimization and multi-objective fuzzy clustering.*

Keywords- Clustering, grey wolf optimizer, routing, WSN.

I. INTRODUCTION

Wireless sensor networks(WSNs) are emerging low-cost and versatile solutions that enable controlled monitoring of the environment. They generally consist of a large number of small sensing devices that are capable of data processing and wireless communication .These sensor nodes can be deployed in various environments to implement applications such as habitat monitoring ,military surveillance, home and industrial automation, and smart grids [1], [2]. Recent advances in electronic circuit design have made it possible to build lighter, cheaper and more energy efficient sensors. Wireless sensor network consisting of many sensor nodes act as a transducer which is deployed to monitor and record the conditions observed in communication infrastructure. It senses the events like temperature, pressure, sound and can be used to monitor the environment like detection of forest fire and landslide, air pollution and greenhouse emissions. It can also be used in industries to monitor the health of the machines. Many applications are found in various areas like medical, military, agriculture, structural where the sensor network is framed to observe the specific function (Jennifer Yick et al 2008) Each sensor node in a network comprises a sensing unit, a processing unit and a communication unit. The sensing unit is used to sense a situation and convert it to the required form of processing. However many research areas including energy efficiency need to be further studied [3]. In [7] and [8], network lifetime is defined in term so node life time, coverage, and connectivity. Although the use of renewable energy sources for sensor nodes are investigated in Energy Harvesting Wireless Sensors Networks (EHWSN) [9], wise use of the available energy is still required for long running WSNs. Most WSNs measure physical parameters such as temperature, humidity or location of objects. Samples of these parameters are locally correlated, therefore can be aggregated for neighbour sensors. The energy required for data transmission is several hundred times greater than the energy required for data processing [10]. Therefore it’s wise to compress data before transmission. This data compression via signal aggregation leads to a significant reduction in energy spent on communication and prolongs the network lifetime [11]. Hierarchical clustering protocols use this fact to extend network lifetime by splitting nodes into several spatial clusters in which, only one of the sensors(CH) is responsible for aggregating the signals and sending data to the base station (BS).

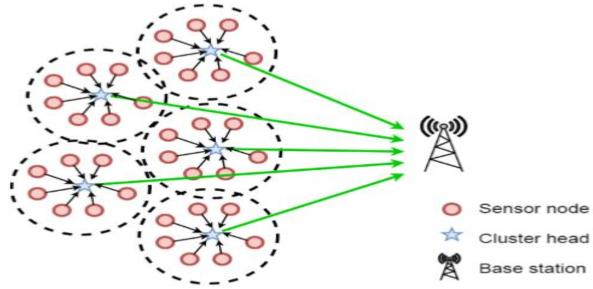

Fig 1 structure of typical WSN.

All the other nodes engage only in intra-cluster short-range communication which consumes much less energy. A CH can either send the data directly to the BS (single-hop) or use another node as a relay to deliver the data to the BS (multi-hop) [12]. The clustering protocols also divide life time of the network into several rounds and try to rotate the role of CH among all nodes in different rounds to achieve balanced energy consumption .Fig.1showsatypical structure of a hierarchical clustering over a WSN.

Another strategy to reduce the communication overhead is the use of gateways. Gateway is a device with comparatively large battery backup which works similar to CH. Use of gateways helps to avoid quick power drain of CHs. The gateways far from the BS transmit data to the gateways near to the BS. Therefore, gateways nearer to the BS carry heavy traffic load and drain their energy faster, leading to the problem of energy hole around the BS. In the case of energy hole around BS, the network becomes disconnected, and the BS loses communication with the gateways located far from it. This arises the need of load balancing management of gateways in the network to avoid the energy hole problem and to prolong the network lifetime. The concept of load balancing of gateways in WSN is schematically shown in Fig. 2 . In Fig.2, g1, g2 and g3 are gateways corresponding to 3 different clusters. As seen in Fig. 2, g1 has seven sensor nodes connected to it, whereas g2 has two and g3 has three sensor nodes within their clusters. This makes the gateway g1 to become more loaded than g2 and g3. Therefore, energy consumed by g1 is higher than g2 and g3. Higher energy consumption reduces the lifetime of g1. It leads to poor network performance and reduces the overall lifetime of the network. When g1 fails, g2 and g3 share the load of g1, as shown in the right side of Fig.2. It may further lead to early death of g2 or g3. Scientific approaches for clustering, load balancing and routing are necessary to avoid such issues in WSNs.

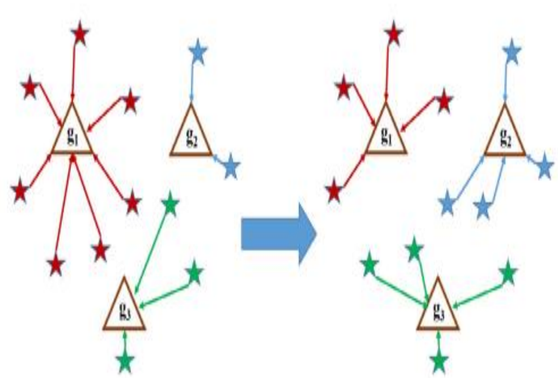

Fig 2 The concept of load balancing of gateways in WSN

In this work, applied a bio-inspired, Grey Wolf Optimizer (GWO) algorithm to WSN for routing and clustering of sensor nodes. The principle of GWO is inspired by grouping and hunting behaviour of grey wolves (Canis Lupus). The GWO performs better for the exploration and exploitation phases of swarm intelligence algorithms in the context of the standard test functions. Moreover, swarming is controlled by the leader of the group, which helps to get the optimum solution for a defined problem. GWO selects the best possible solution produced over many iterations. GWO defines a circular region around a particular solution to check its applicability to higher dimensions. The GWO-based approach serves two functions. The first one is balancing the load on gateways to avoid the energy hole problem. The second one is saving the overall energy of the network. The proposed GWO-based approach shows better performance under the conditions of equal and unequal load on sensor nodes. The proposed approach minimizes the overall energy consumption by generating an optimal routing path from gateways to BS. The proposed clustering fitness function chooses the solution in such a way that comparatively less number of sensor nodes are assigned to the gateways near to the BS, and larger number of sensor nodes are assigned to the gateways far from the BS. The selected solution minimizes the energy consumption of the gateways and sensor nodes to maximize the lifetime of the network. It avoids the energy hole problem also.

II. RELATED WORK

The optimization algorithms like Particle Swarm Optimization (PSO) [14] and Genetic Algorithms (GA) [15] are used for improving the energy efficiency of WSN via proper load balancing. Kuila et al. have proposed an evolutionary approach termed as Novel GA (NGA) [6] in which standard deviation of a load of gate ways is used as the fitness function to measure the variations of the load on the network at each iteration. In addition, they proposed a swarm intelligence meta-heuristic PSO [7] algorithm for energy-efficient routing and clustering. Swarm intelligence algorithms preserve the search space information, whereas evolutionary algorithms like GA dispose the information of prior generations, which causes exploitation inability and impulsive convergence. Zang et al. [16] have introduced the density-based clustering algorithm called node-local density-based algorithm. It has two phases; in the first phase, sensor nodes within the communication range 'R' of only one gateway are assigned to it. In the second phase, sensor nodes which are in the distance of R/2 from gateways are assigned to their nearest gateways. Remaining sensor nodes are connected to gateways with the minimum number of sensor node connections. Gattani et al. [17] proposed a score-based load balancing algorithm in which the selection of CH is decided by its residual energy. The sensor node with maximum residual energy is considered as a CH. The score of each sensor node is calculated as a ratio of its distance from CH and its residual energy. Sensor node with the least score is considered as the best of all. Chanak et al. [18] have proposed a balanced load scheme to avoid the energy hole problem in WSN. They used energy-saving clustering and load-balanced routing technique to avoid energy holes. For CH selection, they used an on-demand selection of CH system. Morteza et al. [19] defined an algorithm with three stages. Initially, clustering is done at all levels equally. In the next step, the best node is selected by considering the residual energy and the distance between the sensor node and BS. The sensor nodes which are close to BS send their data directly to the BS. The remaining sensor nodes send data to the CHs, and CHs send received data to BS.

III. PROPOSED PROTOCOL

In the proposed protocol, the network lifetime is divided into several rounds. The operation of protocol is in two phases: setup phase and steady state phase. In the setup phase, the BS gathers information including energy and location from nodes, BS then chooses CHs by using the proposed GWO based algorithm as well as a dual-hop route between CHs and BS. In the steady state phase, nodes send collected data to CHs. CHs aggregate and send data to the BS either directly or via another CH. To improve energy efficiency, this protocol executes setup phase only if current CHs are dying soon. This saves the energy that would be required to exchange control packets necessary to form clusters.

SYSTEM MODULES

- Initialization of the wolves
- Novel fitness function for routing
- Fitness function evaluation
- Updating wolves positions
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A. Initialization of the wolves

Each solution is represented as a mapping of one gateway to another or BS. The size of the solution is equal to the total number of gateways (M). The solution provides a route from each gateway towards the BS through next succeeding gateways in the network. Each gateway is initialized with a random number

$$(X_{i,d}) = Rand(0,1) \qquad (1)$$

where $1 \le i \le N_s, 1 \le d \le M$. N_s is the number of initial solutions. The component d is a gateway number in the respective solution. It maps gateway g_k as next succeeding gateway in routing path towards the BS from g_d, indicating that g_d sends data to g_k. The mapping of the routing path is formulated in Eq.(2).

$$(g_k) = Index(SetNextG(g_d), n) \qquad (2)$$

Where $Index(SetNextG(g_d), n)$ is an indexing function which returns index of nth gateway from Set Next G and

$$n = Ceil(X_{(i,d)} \times |SetNextG(g_d)|) \qquad (3)$$

In the clustering algorithm, the size of the solution is equal to the total number of sensor nodes (N). In the initialization step, each sensor node is assigned with a random number

$$(Y_{i,d} = Rand(0,1) \qquad (4)$$

where $1 \le i \le N_c, 1 \le d \le N$. N_c is the numberof initial clustering solutions. The component d is the index of asensor node in the respective solution, and it maps to gateway g_k as a cluster head within the particular cluster, indicating s_d sends data to g_k. The mapping of the sensor node and gatewayis performed as expressed in Eq.(5)

$$g_k = Index(ComS(s_d), n) \qquad (5)$$

where Index(ComS(s), n) d is an indexing function which returns index of nth gateway from the set of $ComS(s_d)$ and $n = Ceil(Y_{i,d} \times |ComS(s_d)|)$. As the size of the solution is equal to the number of sensor nodes, insertion and omission of sensor nodes cause variation in the size of the solution inviting the need of re-clustering.

B. Novel fitness function for routing

The fitness function measures the quality of the solution with respect to the parameters involved in it. It helps to update alpha, beta and delta solutions at each iteration. Here, our novel fitness function is designed for generating an efficient routing path from each gateway to the BS. The overall distance (D) traversed by gateways is defined in Eq.(6)

$$D = \sum_{i=1}^{m} dist(g_i, NextG(g_i)) \qquad (6)$$

The total number of gateway hops in the network is defined in Eq.(7)

$$H = \sum_{i=1}^{m} NextGCount(g_i)) \qquad (7)$$

Routing is carried out by considering the minimum distance traversal and the minimum number of hops. Therefore, the smaller the overall distance traversed, and the number of hops, the higher the fitness value for the solution. The solution with the highest fitness value is the best solution in the population. The proposed fitness function is formulated in Eq.(8).

$$Routing\ Fitness = \frac{K_1}{(w_1 * D + w_2 * H)} \quad (8)$$

where $(w_1, w_2) \in [0,1]$ such that, $w_1 + w_2 = 1$ and K_1 is a proportionality constant. Routing fitness function balances the overall distance and the total number of hops in the network.

C. Fitness Function Evaluation

The gateway consumes energy to perform operations like receiving data from sensor nodes within respective clusters, aggregating the received data and finally transmitting the aggregated data either directly to the BS. or other gateways in the routing path. Therefore, the energy consumed by the gateway g_i connected with a n_i number of sensor nodes to perform the different inter-cluster activities in one round is expressed in Eq.(9).

$$E_{cluster}(g_i) = n_i * E_r + n_i * E_{da} + E_t(g_i, NextG(g_i)) \quad (9)$$

where $E_r, E_{da},$ and E_t are the energies consumed for receiving the data, data aggregation and transmitting aggregated data to the next gateway in the routing path, respectively. On the other side, any arbitrary gateway g_i consumes energy to forward the incoming data from other gateways also. Therefore, energy consumed to receive the incoming data from another gateway can be recursively formulated.

$$InData(g_i) = \begin{cases} 0 & NextG(g_i) \neq g_j \forall g_j \in G \\ \sum\{InData(g_j) | NextG(g_j) = g_i, g_j \in G\} & Else \end{cases} \quad (10)$$

The incoming data is received by gateway g_i and further forwarded to another gateway in the routing path. Therefore, the energy required to forward incoming data is calculated in Eq.(11).

$$E_f(g_i) = InData(g_i) * E_t(g_i, NextG(g_i)) + InData(g_i) \times E_r \quad (11)$$

Finally, the total energy consumption of the gateway is the summation of energy required to do operations in the respective cluster and to forward the data received from other gateways. Total energy consumption of the gateway can be expressed as in Eq.(12).

$$E_{gateway}(g_i) = E_{cluster}(g_i) * E_f(g_i) \quad (12)$$

$$L(g_i) = \frac{E_{residual}}{E_{gateway}} \quad (13)$$

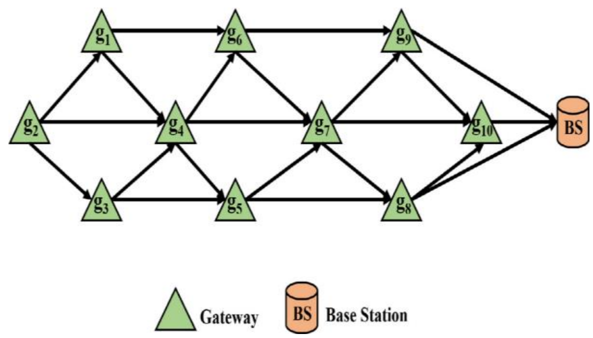

Fig 3 WSN Gateway

To measure the quality of the solution, proposed a novel fitness function for clustering to avoid the energy hole problem around BS by balancing the load of gateways in the network. In this fitness function, the load on the gateway is distributed depending on the distance between the gateway and the BS. The gateways nearer to the BS are connected to less number of sensor nodes, whereas the gateways far from the BS are connected to a large number of sensor nodes. The gateways located near the BS transfer data coming from the gateways located far from the BS. Hence, own load of a gateway is minimized as it is connected to less number of sensor nodes.

The proposed algorithm constructs a novel fitness function with distributed mean load μ over all gateways according to the distance between gateways and BS. The proportionality constant K_2 is used in Eq. (14).The proposed clustering fitness function for the gateway is formulated in Eq.(14).

$$Clustering\ Fitness(g_i) = K_2 \times |load(g_i) - dist(BS, g_i) * \mu| \quad (14)$$

$$\mu = \frac{\sum_{i=1}^{m} load(g_i)}{m} \quad (15)$$

where, $load(g_i)$ is the data received by gateway g_i and $dist(BS, g_i)$ is the distance between BS and gateway g_i. Calculated clustering fitness for the network as the average I of all clustering fitness of gateways as expressed in Eq. (16)

$$Clustering\ Fitness = \frac{\sum_{i=1}^{m} Clustering\ Fitness(g_i)}{m} \quad (16)$$

D. Updating Wolves' Positions

To reach to the prey (optimum solution), each wolf (solution) needs to update its position depending on the positions of alpha, beta and delta wolves as formulated. In GWO-based approach, the alpha wolf is the global solution in the solution set; the beta wolf is the best solution from the previous iteration, and the delta wolf is the best solution from the current iteration. To update the positions of omega wolves, refer to the average of updated positions of alpha, beta and delta wolves. In this way, the updation of the position leads to the optimal solution for the optimization problem. Now, it is possible that updated positions might be negative or greater than 1 because of the algebraic addition and subtraction. However, the $(X_{i,d})$ is expected to be in the range [0,1].

1. If $(X_{i,d} \leq 0)$, then $(X_{i,d}) = (r_1 \leq r_2 ? (r_1 \leq r_3 ? r_1 : r_3) : (r_2 \leq r_3 ? r_2 : r_3))$.

where r_1, r_2 and r_3 are the random numbers selected for predicting positions of alpha, beta and delta wolves respectively. Here, $(X_{i,d})$ is the minimum value among r_1, r_2 and r_3.

2. If $(X_{i,d} \geq 1)$, then $(X_{i,d}) = 1$.

All the solutions are re-evaluated with the help of fitness function after assigning new positions. The updation of velocity and position of wolves is carried out in a manner similar to the routing algorithm. Here, the positions of alpha, beta, and delta wolves are computed from the fitness function and omega wolves update their position referring to the mean of positions of alpha, beta, and delta wolves.

CLUSTERING BASED ON GREY WOLF OPTIMZER

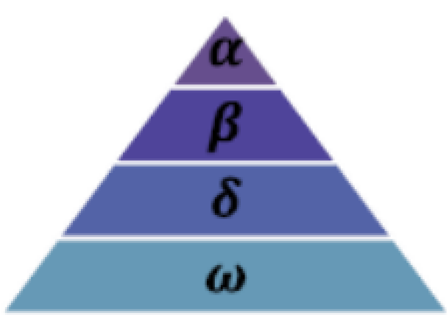

Fig 4 Hierarchy of Grey-Wolf

1) It needs very few parameters.
2) It is simple, scalable and easy to use.
3) It has a special ability to achieve the right balance between exploration and exploitation.
4) It uses less memory than PSO.

A. GREY WOLF OPTIMIZER OVERVIEW

The inspiration for GWO is the natural behavior and social structure of grey wolves in chasing prey. Each pack of wolves is governed by a hierarchical structure. The most powerful wolf is the alpha, which leads the entire pack. In absence of the alpha wolf, the second most powerful wolf, known as beta wolf, takes the role of the alpha wolf. The delta and omega wolves are the less strong wolves. Fig.6 shows the hierarchical structure of wolf packs. The grey wolves have a specific intelligent method in chasing and hunting the ir prey which includes chasing ,encircling, harassing ,and attacking the prey .In order to model this social structure, the GWO considers the fittest solution the alpha, and second and third best solutions the beta and the delta .The rest of the solutions in the population are considered omega. In this algorithm, the optimization is guided by alpha, beta, and delta wolves while omega wolves follow these three .The algorithm starts by generating a random initial population and repeatedly updates the position of the individuals in the population until a termination criterion is met. Then the best solution which is the alpha wolf is returned as the output of the algorithm. The procedure of updating wolf positions in each iteration involves these steps:

1- Encircling the prey:
To mathematically model the encircling of the prey, the GWO employs the following formula:
X (t +1) =X (t)−A.D (17)
where X(t+1) is the next location of the wolf and X(t) is its current location. A is a coefficient matrix and D is a vector that depends on the approximated location of the prey which is calculated by the following formula:
D=|C.Xp (t)−X (t)| (18)
Where C =2×r2 and Xp(t) is the current location of the prey andr2 is a randomly generated vector whose components are inrange0-1. Using these two equations, the wolf will relocate itself on a hyper sphere around the prey. The random values are used to simulate different movement speeds of the wolves. To let wolves chase and approach the prey the vector A is defined as:
A=2a×r1−a (19)
Components of a are linearly decreased from 2 to 0 over the course of iterations. r1 is a random vector with components in the range 0-1. The effects of applying these equations to update the position of wolves is that, wolves encircle the prey and change their distance to the prey to achieve both exploration and exploitation. Fig. 7 shows this process.
2- Hunt
To simulate the social structure, omega wolves should follow the alpha, beta and delta wolves. As the position of the prey is not known, it is assumed that alpha, beta and delta wolves,

being the there best solutions found, have better knowledge about the location of prey. Therefore the location of prey is approximated by considering the location of alpha, beta and omega wolves and the other wolves are obliged to update their position using the following formula:

$X(t+1) = X1+X2+X3 \div 3$ (20)

where $X1 = X\alpha(t) - A1.D\alpha$

$X2 = X\beta(t) - A2.D\beta$

$X3 = X\delta(t) - A3.D\delta$ (21)

And

$D\alpha = |C1.X\alpha - X|$

$D\beta = |C2.X\beta - X|$

$D\delta = |C3.X\delta - X|$ (22)

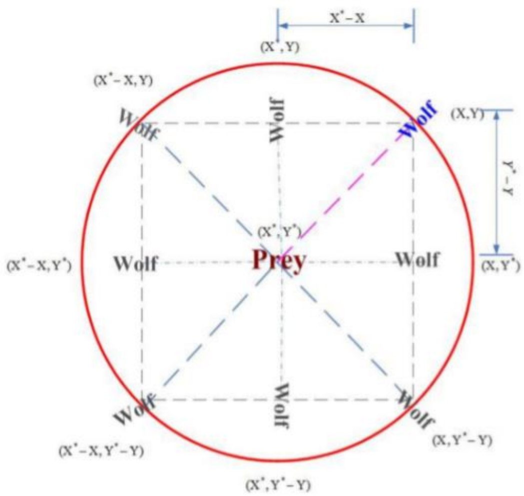

Fig 5 2D position vectors and possible next locations.

IV. CONCLUSION

Thus, GWO-based approach is proposed for routing and clustering operations in WSN. The proposed approach improves the lifetime of the network and also addresses the energy hole problem in the network. It is based on two novel fitness functions for both routing and clustering. These fitness functions considered the parameters such as residual energy, the distance of gateway from BS, and load on the gateway. The global best solution from the population, the local best solution from the previous iterations and the best solution from the current iteration are fetched to improve the quality of all the remaining solutions in the population. The best solution among the population is selected for routing and clustering. Simulations are performed under different evaluation parameters such as energy consumption, load balancing, and the number of heavily loaded sensor nodes to evaluate the performance of GWO-based approach. The performance under different network lifetime parameters such as the first gateway die for both equal and unequal load, first sensor node die and half of the nodes alive in the network is analysed. GWO-based approach is observed to be more sustainable than other algorithms.

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