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GWO Optimized LEACH CRT-Based Forwarding Scheme for Wireless Sensor Networks Energy Optimization

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ABSTRACT: *Wireless sensor networks (WSNs) are intelligent communication systems that assist in the industrial revolution of IoT. Sensor nodes present in WSNs often have limited battery lifetime due to their energy limits. Ability to replace or recharge the battery supply for networks in largescale or remote sites has been a major drawback. Clustering, duty cycling, data aggregation and routing has been major energy efficiency techniques employed to address energy problems. Due to the poor performance of the traditional LEACH, this paper employ the GWO CRT-based forwarding and splitting techniques to enhance the performance of LEACH. The simulation is done on MATLAB 2018a and the obtained results prove that the proposed protocol i.e., GWO CRT-based outperforms the existing models such LEACH, improved LEACH etc., with respect to energy consumption, throughput, and the lifespan of the network.*

KEYWORDS: clustering, cluster head, grey wolf optimization, Chinese remainder theorem, packet splitting and forwarding techniques, and wireless sensor networks.

INTRODUCTION

The number of intelligent connected devices in the present time, aggregate and share information in an IoT-based architecture increases significantly (Harb, Jaoude, & Makhoul, 2019). This connected devices include smart phones, smart watches, smart glasses, smart cars, etc. And consequently, the total volume of data collected over the years in many applications has surpassed petabyte and occasionally zettabyte. This amount will quadruple every two years, according to the data scientist's prediction (Harb et al., 2019). In order to optimize the data transmission from smart interconnected devices and sensing-based applications, new approaches must be proposed. IoT applications uses wireless sensor networks (WSNs) to gather and process data before transmitting it to the end user.

As shown in figure 1.0, WSNs are often composed of cheap, compact sensor nodes that monitor environmental conditions in order to distribute resources while consuming relatively little energy. Nowadays, a wide range of applications are increasingly being used for a variety of purposes, including medical applications (Han, Bozorgi, Orang, Hosseinabadi, 2020), RFID networks (Rathore, Kumar, & Garcia-Diaz, 2020), drone applications (Lee..., & Song, 2009), and disaster management (Biabani, Fotouhi, & Yazdani, 2020) involve WSN because it uses small, low-cost, and intelligent sensors to transmit control messages and instructions from the physical environment to an external Base Station (BS) (Pratha, Asanambigai, & Mugunthan, 2021). WSN is mostly used in situations where sensor nodes can assist humans in retrieving data when they are unable to do it on their own.

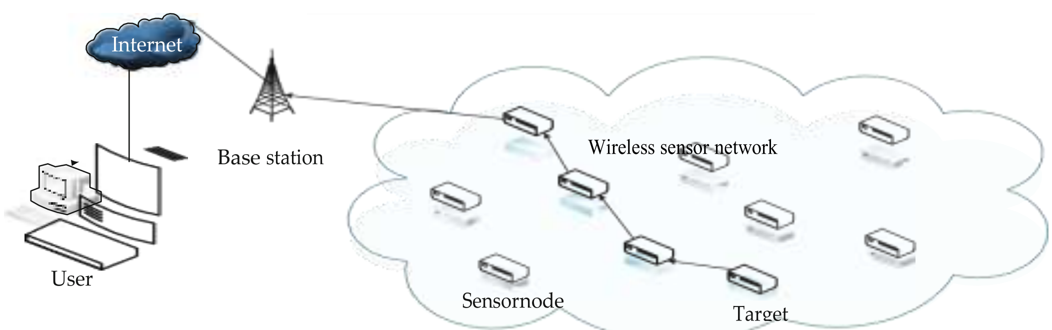

Figure 1.0: Structure of WSN (Kandris, Nakas, Vomvas, & Koulouras, 2020)

As a result, the energy in each node utilized by the sensor networks completely depends on the minimum dischargeable battery to execute activities. Numerous restrictions, including those on the battery life, memory size, communication ranges, quality of service, unpredictable latency, and processing power, put these operations in danger of being unable to establish connections (Devadas, 2022). Network nodes are commonly placed in challenging and hazardous environments, require frequent maintenance, and have a finite amount of energy they can transport. When nodes run out of energy, they die, making it impossible for them to reliably detect and track targets which makes the network's monitoring performance declines (Zheng, Zhao, Zhang, Sun, & Gao, 2022). In spite of the challenges of low power resources associated with sensor nodes, the lifetime of WSNs is always a crucial concern (Khan, Shiraz, Shaheen, Butt, Akhtar, Khan, & Changda, 2021).

Nonetheless, due to the dense deployment of nodes in WSN, which may consume a sizable amount of the sensor energy during transmission, the data that these nodes see are closely correlated. Therefore, Chinese Remainder Theorem (CRT) based packet splitting and forwarding methods are turning into a requirement in Internet of Things (IoT) and swarm intelligence applications i.e., grey wolf optimizer (GWO) based in order to spend the energy in an intelligent manner so that the network may operate for a longer length of time.

This paper's primary goal is to present a straightforward on-node prediction model that make use of a CRT-based packet splitting forwarding method and in-network aggregation technique that use redundant residue number system (RRNS). We suggest that each node communicates only the number of components on which it is divided, and that BS will reconstruct the original message based on CRT coefficient in order to conserve energy and reduce the quantity of transmitted data. With regards to in-network aggregation, this strategy tries to lessen redundant data produced by nearby nodes as well as for error detection utilizing RRNS. In order to prevent the incorrect nodes from becoming the cluster heads (CHs), we also used the grey wolf optimizer (GWO) based on fitness functions to elect the aggregators.

The remainder of this essay is divided into the following sections. A brief summary of relevant research on clustering, swarm intelligence, and residue number systems is presented in Section 2. Techniques for GWO and CRT are described in Section 3. The suggested strategy is covered in Section 4. Section 5 discusses the analysis and simulation results. Finally, Section 6 introduces the conclusion and future work.

RELATED WORK

The energy used during the data sensing, collection, and transmitting in WSNs is continuous in nature. However, several studies have established that data transmission accounts for the majority of energy consumption, so energy conservation plans have been put forth to reduce radio interface energy consumption. In addition, efficient data transfer is another problem faced in WSNs due to mismanagements that led to increase in the packet payload size, which directly increases the probability of dropping data packets. Consequently, the retransmission of the data packets consume more energy as well (Shehadeh, Idna Idris, Ahmedy, Ramli, & Mohamed Noor, 2018; Raj, Ahmedy, Idna Idris, & Md Noor, 2022). The corporate architecture, routing strategy, power management processes, security concerns, and sensor node sensing capabilities are only a few of the study directions that are available for WSNs (Khan et al., 2021).

Over the years, several researchers have put forth a number of energy-efficient optimization strategies. They include duty cycling, routing, clustering, and data aggregation, among others (Chowdhury & Hossain, 2020). One of the best techniques for wireless sensor network energy optimization has been clustering (Agrawal, Qureshi, Pincha, Srivastava, Tiwari, & Pandey, 2020).

Furthermore, clustering chooses the cluster head (CHs) based on the residual energy of the member nodes. The selection of the CHs, however, presents a number of difficulties in this clustering operation. Furthermore, low energy adaptive clustering hierarchy (LEACH) is a well-known, classic clustering algorithm that is utilized to maximize energy efficiency in a network of wireless sensors (Agrawal et al., 2020). To select a random number between 1 and 0, this LEACH employs a probabilistic approach. The chosen number becomes the cluster head (CH) once it falls below the predetermined threshold T(n). However, this approach has a number of drawbacks, including poor performance and the risk that a node with less energy will take over as the cluster head (Agrawal et al., 2020). Multiple strategies have been suggested to address the LEACH problem. This include stable election procedure (SEP), the low energy adaptive clustering hierarchy (LEACH-C) centralized, and the energy efficient heterogeneous clustering (EEHC). These protocols are not suited for WSNs because of the heterogeneity, unbalanced load sharing in the networks, and residual energy for CH selection. Figure 2.0 illustrates the basic communication hierarchy of LEACH routing protocol.

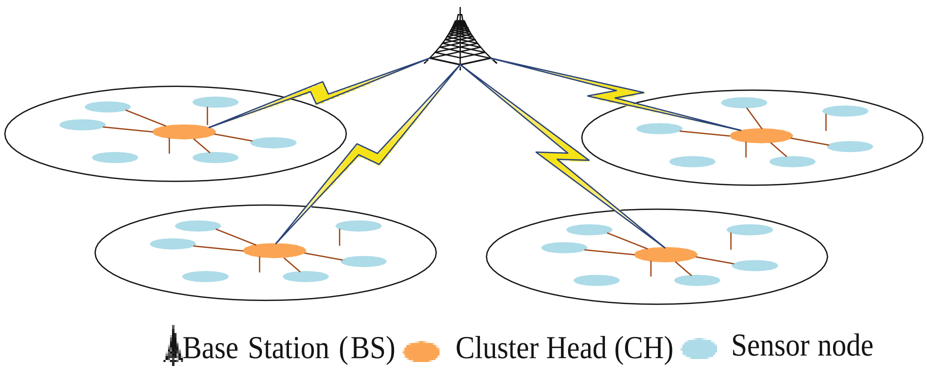

Figure 2.0: LEACH communication architecture (Khan, Shiraz, Shaheen, Butt, Akhtar, Khan, & Changda, 2021).

The T(n) is given in the next Equation (1):

$$T(n) = \begin{cases} \dfrac{p}{1-p*[r \bmod (\frac{1}{p})]} & if\ n \in G \\ 0 & else \end{cases} \tag{1}$$

where: p is the percentage of choosing cluster heads; r is the current round; G is the set of sensor nodes that have not been cluster heads in 1/p rounds; and T(n) is the threshold value.

In addition, Raji, Gbolagade, and Taofeek-Ibrahim (2018) proposed using a modified TDMA schedule and a 2D elliptical Gaussian distribution function to address the issue of conventional LEACH limitations. They describe a novel method to improve energy balance in the cluster between all sensor nodes. Two approaches of improvement form the foundation of the suggested strategy. The first one is the cluster head selection mechanism, which has been altered to guarantee a consistent generation of cluster heads among all sensor nodes in WSN. The TDMA schedule, which has been altered, is the second technique to prevent smaller clusters from using more energy than larger clusters.

The position of the base station and the sensor nodes is determined using the 2D Elliptical Gaussian Distribution function. The network lifetime is improved and energy balance is attained using the Gaussian distribution approach. The outcomes demonstrate how well this strategy may cut down on the network's energy usage.

Additionally, Zheng, Zhao, Zhang, Sun, and Gao (2022) built an ellipse monitoring area where the moving target caused real-time changes to the area's size, shape, number of nodes, and working nodes. The size and form of an elliptical monitoring area were predicted using the extended kalman filter (EKF), two-step linearization, and the linearized nonlinear dynamic state. However, by reducing the number of work nodes, this strategy was able to cut back on the energy usage of redundant nodes on the network. A new cluster head selection threshold is suggested based on the working node set and the shifting target state forecast. However, the simulation results demonstrate that the residual network energy corresponding to each of the four algorithms (LEACH, LEACH-DBCH, LEACH-RARE, and LEACH-MTC) decreases with an increase in running time, but the residual network energy corresponding to the LEACH-MTC algorithm is higher than the other three algorithms mentioned, which can save network energy more effectively and extend the life cycle of the network.

But Elshrkawey, Elsherif, and Wahed (2017) provided a simple and adaptable energy-efficient sector clustering approach. To balance the cluster head's energy dissipation, they divided the network into virtual sectors and created an unequal sector cluster using the sector decomposition approach. Each node in the cluster calculates its own priority based on the total communication distance, residual energy, and local node density. The cluster head node is determined by its priority. Based on the results of the simulation, it can be concluded that the suggested method improves network stability and maximum lifetime. The smaller sector helps to increase network lifetime by producing better energy, balancing consumption, and preventing excessive node energy loss.

It takes O(n2) to process a message. Energy efficiency is impacted by probability-based clustering algorithms' propensity to create uneven clustering patterns. To accomplish the best possible selection of CHs, several strategies have, nevertheless, been put forth throughout the years. Among them were fuzzy logic, genetic algorithms, ant colony optimization, particle swarm intelligence, harmony search algorithm, grey wolf optimizer, etc. (Agrawal et al., 2020).

To overcome WSN problems, other swarm intelligence optimization methods were applied. One of these, particle swarm optimization, offers a better solution while using more efficient computing. In terms of throughput and network longevity, it also exhibits superior performance when compared to LEACH-C and LEACH (Agrawal et al., 2020). Particle swarm optimization-based energy efficient cluster head selection (PSO-ECHS), fitness value-based improved grey wolf optimization (FIGWO), and routing protocol with the aid of Tabu PSO are a few other protocols that have been proposed, though they have large energy consumptions and load balancing among the CHs (Srinivasa Rao, Jana, & Banka 2016; Zhao, Zhu, Aleksic, & Gao 2018; Vijayalakshmi & Anandan, 2018).

For wireless sensor networks, Agrawal et al. (2020) proposed GWO-based clustering. Compared to the various clustering protocols used for comparisons, the proposed protocol converges in the shortest possible amount of iterations to arrive at the answer. Decision factors and search space are both continuously reduced as a result of GWO. Additionally, local optima are avoided. In terms of performance measures, GWO-based clustering was able to produce superior outcomes. But the proposed approach can only be put into practice and tested for WSNs with static sensor nodes, i.e., nodes that can't change their positions in real time. O (Np) + O (Np) + O (Tr Np m) is the algorithm's total complexity. Additionally, each time a new CH is elected, the distance needed to transmit data is recalculated. As stated by Agrawal et al. (2020), it struggles to evenly distribute the workload across the CHs.

Additionally, the packet-Splitting algorithm used by Campobello, Leonardi, and Palazzo (2012) is based on the Chinese Remainder Theorem (CRT), which is characterized by a straightforward modular division between integers. According to the results of the simulation, using the CRT-based technique dramatically lowers the amount of energy used by each node, extending the lifetime of the network.

Raji, Asaju-Gbolagade, & Gbolagade (2021) proposed CRT-based packet splitting forwarding method. This strategy included splitting the sensed messages into many packets so that each node in the network would only transfer small sub-packets to the sink and afterwards reconstruct back to the original message. To find the sensor nodes and the BS, they employed a 2D elliptical Gaussian distribution function. The simulation results demonstrate that the suggested algorithm outperforms conventional approaches in terms of security, reliability, energy usage, simplicity, and decrease in end-to-end time.

The Low-Energy Adaptive Clustering (LEACH) protocol technique and CRT-based packet splitting were additional ideas put forth by Mohan (2016). In order to divide up sensed data by each node and transmit proportional deposits to the cluster head (CH), Local Closet First (LCF) was utilized to select the closest neighbors and moduli set $\{2^{n+1} - 1, 2^n, 2^n\text{-}1\}$ to break sensed data by every node and send proportional deposits to the cluster head (CH). While traveling to the base station (BS), the CH uses LCF to communicate the remaining sensed data to other CHs that are nearby. Utilizing the moduli set and the message ID, the BS reconstructs the residues from the original messages. In comparison to the other two algorithms (Shortest Path Algorithm and MRHC-LEACH Algorithm), the suggested CRT-LEACH findings exhibit greater performance. CH could disappear for the shortest amount of time. They rely on the hubs to communicate with one another until the message reaches the BS, which is the reason for this.

Thus, how to efficiently optimize the selection of CHs and obtain a faster convergence rate with shortest optima routes are the important problem to be addressed. However, this paper introduce GWO CRT-based to resolve the problem of LEACH and provide better enhancements with the help of residue number system.

PROPOSED WORK

The methodology for the proposed technique is a hybrid of GWOCRT based packet splitting and forwarding scheme. This method consists of two phases: Phase-1, for optimized selection of Cluster Head using Grey wolf optimization algorithm. Phase-2, in which, cluster size for routing is optimized using CRT packet splitting and forwarding scheme. However, this two techniques are fitness function and reverse conversion techniques

Energy Model

In this model, when the threshold distance (d_0) is greater than the propagation distance (d) then the consumption of energy of a node is directly proportional to d^2. The overall consumption of energy of each node to transmit the *l-bit* packet of data is specified by the following equations:

$$E_{TX(K,d)} = E_{TX-elec^{(K)}} + E_{TX-amp^{(K,d)}}$$
$$= \begin{cases} K * E_{elec} + K * \varepsilon_{fs} * d^2, & d < d_0 \\ K * E_{elec} + K * \varepsilon_{mf} * d^4, & d > d_0 \end{cases} \tag{2}$$
$$E_{RX}(\text{k}) = E_{RX-elec}(\text{k}) = \text{k} * E_{elec} \tag{3}$$

Where,

E_{TX} required energy utilization for packet transmission.

E_{elec} is electronic energy that counts on the filtering, modulating the digital coding and spreading of the signal.

E_{RX} required energy utilization for packet receiving.

d_0 is equal to the square root of the dividing E_{DA} free space model by multipath fading model.

Grey Wolf Optimization

GWO algorithm imitates grey wolf behavior including hunting, searching, encircling and attacking the prey. Grey wolves, the apex predators in the food chain, typically reside in packs of 5 to 12 individuals. There are four different wolf group types represented in the hierarchy consists: alpha (α), beta (β), gamma (δ), and omega (ω) wolves. Wolves use advisers provided by other wolves to help them make key hunting decisions. The β are replaced by α when α becomes old. The leaf of the tree is ω wolves and they are controlled by δ wolves. The δ wolves provides information to the α and β wolves.

The Mathematical Equations for Grey Wolf Optimization

During hunting, the grey wolves enclose in and surround the prey. This enclosing behavior of wolves can be depicted mathematically as follows

$$\vec{D} = |\, \vec{C} \cdot \vec{X}_{p(t)} - \vec{X}_{(t)} \,|, \tag{4}$$
$$\vec{X}_{(t+1)} = \vec{X}_{p(t)} - \vec{A} \cdot \vec{D}, \tag{5}$$

Where t represents current iteration, $\vec{A}$ and $\vec{C}$ are the coefficient-vectors, $\vec{X}_p$ is the vectors position of the prey, and $\vec{X}$ is the vector position of the grey wolf. The vectors, $\vec{A}$ and $\vec{C}$ can be computed as follows:

$$\vec{A} = 2\,\vec{a}\,.\,\vec{r}_1 - \vec{a}\,, \tag{6}$$
$$\vec{C} = 2.\,\vec{r}_2\,, \tag{7}$$

Where $\vec{r}_1$ and $\vec{r}_2$ are the random vectors in [0, 1] and components of $\vec{a}$ are decreased linearly from 2 to 0 over repeated iterations. The hunting process is lead by the best candidate solutions alpha and beta and the least important members, i.e., omegas update their position according to the information made available by the best search agents viz alphas and betas (Agrawal et al., 2020)

The mathematical equations for this purpose are modeled as follow:

$$\vec{D}\alpha = |\,\vec{C}_1 \cdot \vec{X}\alpha - \vec{X}\,|,\quad \vec{D}\beta = |\,\vec{C}_2 \cdot \vec{X}\beta - \vec{X}\,|,\quad \vec{D}\delta = |\,\vec{C}_3 \cdot \vec{X}\delta - \vec{X}\,|, \tag{8}$$

$$\vec{X}_1 = \vec{X}\alpha - \vec{A}_1 \cdot (\vec{D}\alpha), \tag{9}$$
$$\vec{X}_2 = \vec{X}\beta - \vec{A}_2 \cdot (\vec{D}\beta), \tag{10}$$
$$\vec{X}_3 = \vec{X}\delta - \vec{A}_3 \cdot (\vec{D}\delta), \tag{11}$$
$$\vec{X}_{(t+1)} = \frac{\vec{X}1 + \vec{X}2 + \vec{X}3}{3} \tag{12}$$

The final step in the process of hunting is the attack. The process of attacking can be mathematically defined using the operators stated above. This is done by decreasing the value of $\vec{a}$ and also reducing the range of variation of A in the range of [−2a, 2a] while a is reduced from 2 to 0 over the iterations. If the values of $\vec{A}$ lie in [−1,1], the position of the search agent will be between the current position and the prey's position. If |A| < 1, the wolves attack the prey. Thus, it can be seen that according to the GWO algorithm, the search agents update their positions according to the positions of the alpha, beta, and delta members (Agrawal et al., 2020). The search for prey starts when the wolves diverge from each other to find the prey. This search is also dependent on the positions of the alpha, beta, and delta members. According to the conditions for search or attack are dictated by the values of A as follows: |A|>1=> diverge and search; and |A|<1=> converge and attack (Agrawal et al., 2020).

Fitness function = $x_1 * f_{n1} + x_2 * f_{n2} + x_3 * f_{n3} + (1 - x_1 + x_2 + x_3) * f_{n4}$ (13)

Where x_1, x_2, and x_3 are constant value and $x_1 + x_2 + x_3 = 1$

Chinese Remainder Theorem (CRT)

According to Chinese Remainder Theorem (CRT), the moduli set $\{m_i\}_{i=1,n}$ with dynamic range M = $\prod_{i=1}^{n} m_i$, the residue number $(x_1, x_2, x_3, \ldots, x_n)$ can be converted to decimal number X as follows (Harb et al., 2019):

$$X = |\textstyle\sum_{i=1}^{n} M_i |\, M_i^{-1}\, x_i \,|\, m_i|_M \tag{14}$$

Where M = $\prod_{i=1}^{n} m_i$, $M_i = \frac{M}{m_i}$, and M_i^{-1} is the ;multiplicative inverse of M_i with respect to m_i. The Chinese Remainder Theorem uses a simple modular division is applied to the packets.

For illustration purpose, let us consider the traditional moduli set {7, 6, 5} (Mohan, 2016), with residue representation (1,2,3), thus

m=1 mod 7,
m= 2 mod 6,
m =3 mod 5.

Then by CRT, m= 8 (decimal value). However, it is worth mentioning here that in the above illustration, 4 bits are required to represent X, while maximum of 2 bits are required to represent each xi.

$$\text{MERF} = \frac{\text{w} - \text{w}\, CRT_{max}}{w} \tag{15}$$

Consequently, if instead of X, xi number with xi = X mod xi are forwarded in wireless sensor networks. However, based on the equation of energy reduction factor as stated in equation 15. Therefore, it could be deduced that certain percentage can be saved using CRT-based forwarding technique.

$$\text{MERF} = (\frac{4-2}{4} * 100)$$

$$\text{MERF} = 50\%$$

The energy consumption based on CRT forward technique further enhance the energy reduction using (Mohan, 2016) traditional moduli set {7, 6, 5} as compared to (Raji et al.,2021)

Algorithm

The algorithm of the proposed protocol is given as follows:

Input: Set of alive sensor node in a round

Number of Packs N_P

Number of cluster heads in pack: 10% alive sensor node whose residual energy is greater than the average residual energy is selected as the cluster head for each pack.

Output: Optimal choice of cluster heads CH = {$CH_1, CH_2, CH_3, \ldots, CH_n$}

a. Step 1: Initialize packs Pi , choose 10% alive sensor node whose residual energy is greater than the average residual energy.
b. Step 2: for I =1 to Np do
    1. Calculate MERF (P_i) using equation 15
    2. $CRTbest_i = P_i$

    End for
c. Step 3: MINbest = {$CRTbest_i$ | MERF ($CRTbest_i$) = min(MERF($CRTbest_i$), I, 1<i$\leq Np$)}
    i. z=P with the minimum ERF
d. Step 4: for t =0 to T_R //Maximum number of iterations
    i. for i= 1 to N_p do
    ii. for m = 1 to the size of N_p do
        1. Calculate MERF (P_i) //Using equation 15
        2. Select the leader node $\alpha, \beta, and\ \delta$ according to the best MERF value
        3. Update the position of the prey using eqns. 9, 10, and 11
        4. Take an average of the 3 solutions and update position for the cluster head

5. Find the nearest sensor node to be selected as new cluster head.

iii. End for
iv. if MERF (P_i) < MERF ($CRTbest_i$) then
   1. $CRTbest_i = P_i$
v. End if
vi. If MERF (P_i) < MERF (MINbest) then
   1. MINbest = P_i
   2. Z = i
vii. End if
viii. End for
ix. End for

e. Step 5: CH = Set of sensor nodes in P_i
f. Step 6: Stop

CRT packet splitting and forwarding scheme

a) CRT Packet Splitting

To ensure that each network node only transmits little subpackets, the original messages are split up into many packets. Implementing the splitting process involves the CRT algorithm, which is distinguished by a simple modular division between integers. The sink node will recombine all sub packets known as CRT components by reassembling the original messages once every sub packet known as CRT component has been properly received by the BS. Additionally, the broadcasting forwarding mechanism makes copies of a packet and broadcasts them over a number of lines in an effort to reach every device connected to the network. A further consequence of the redundancy utilized is that many copies of the same packet must be sent, which uses more energy. These multiple copies of the same packet must travel along multiple pathways. The initialization phase algorithm is given as below:

Initialize SN = 1 //Sequence No 1 is reserved to identify a failure or reset an already initialized network.

While initialization message (IM) is send to node
Do //perform the initialization message
If CL_{ID} = 1 // Assume that sink is the only node in CL_{ID} =1
Then transmit IM with SN =2 to the next CL_{ID} at startup
Increase SN =SN +1
Else
Transmit IM to the next CL_{ID}
Increase SN = SN + 1
All nodes that receives the IM with SN=I assume to belong to CL_{ID} = j

b) CRT-Based Forwarding Technique

The most successful energy-efficient technique for WSNs, Low Energy Adaptive Clustering Hierarchy (LEACH), was improved by merging GWO CRT-based in order to maximize LEACH and eliminate data aggregation. The packet splitting forwarding mechanism is the main method for transferring data between systems on a network. The maximum number of bits per packet that a node must send is decreased by partitioning the messages transmitted by the sensor nodes using the moduli set, extending the network's lifespan. Using the CRT, a simple technique that only requires plunging integers into modules, the splitting operation is carried out. Without taking network dependability for granted, this is achievable with very minimal equipment, such as sensor nodes (Raji et al., 2021). Energy used for transmission can be saved by reducing the number and size of packets delivered across the network. Energy utilization can be preserved by giving the CHs fewer tasks to finish. By using the GWO CRT-based packet splitting technique, the residues would be broadcast in place of the original message, rendering the data packet invisible to outsiders.

Initialize SN = 1 //Sequence No 1 is reserved to identify a failure or reset an already initialized network.

While initialization message (IM) is send to node

Do //perform the initialization message

If $CL_{ID} \neq 1$ // Assume that sink is the only node in CL_{ID} =1

Then transmit IM with SN =2 to the next CL_{ID} at startup

Increase SN =SN +1

Else

Transmit IM to the next CL_{ID}

Increase SN = SN + 1

All nodes that receives the IM with SN=I assume to belong to CL_{ID} = j

PERFORMANCE EVALUATION AND SIMULATION RESULTS

WSN are evaluated using the following performance metrics: Residual energy, throughput, and packet loss.

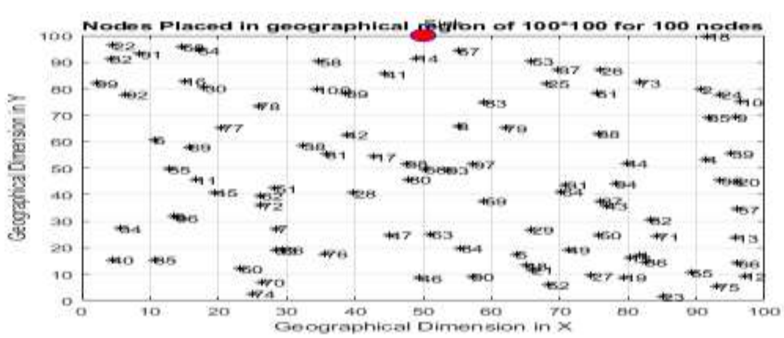

Figure 3.0 Network Generation.

Energy Consumption

The proposed algorithm outperforms the LEACH method in terms of energy consumption. Figure 4.0 shows that the GWO based LEACH extend the lifespan by balancing the load among the nodes compared to LEACH protocol.

Table 1 Total Residual Energy

No of Rounds	**10**	**50**	**100**	**150**	**200**	**250**	**300**	**350**	**400**	**450**	**500**
LEACH	**49.88**	**43.78**	**37.57**	**31.36**	**25.18**	**19.06**	**13.28**	**8.346**	**4.604**	**2.362**	**1.07**
GWO Optimized LEACH	**49.99**	**49.74**	**49.46**	**49.22**	**48.96**	**48.69**	**48.42**	**48.15**	**47.89**	**47.62**	**47.36**
CRT	**50.49**	**50.24**	**49.96**	**49.72**	**49.46**	**49.19**	**48.92**	**48.65**	**48.39**	**48.12**	**47.86**

Table 2 The Mean and Standard deviation for Residual Energy

Technique	**Mean**	**Standard Deviation**
LEACH	**21.02**	**15.31**
GWO Optimized LEACH	**48.68**	**0.7641**

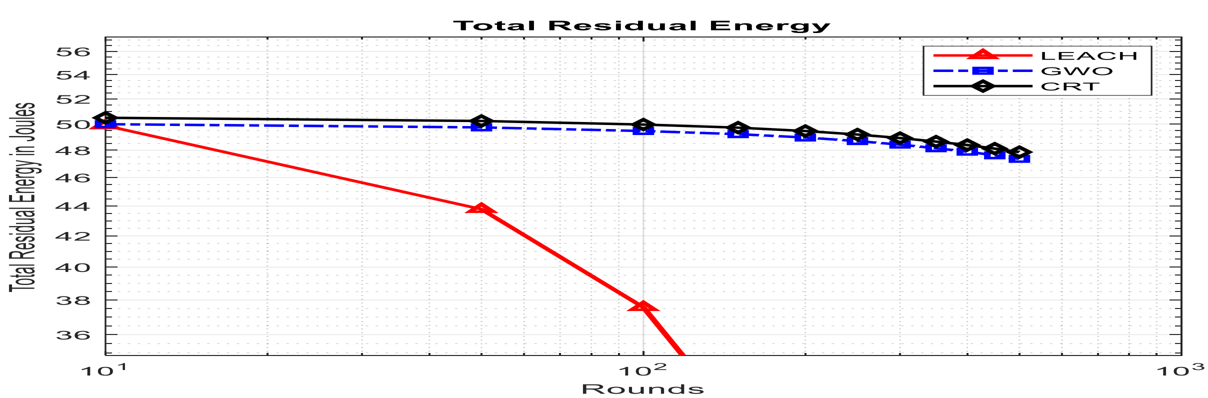

Figure 4.0 Total Residual Energy

Total number of Alive nodes in each round

This evidently shows in figure 5.0 that the number of alive node at each round for the GWO is higher than the LEACH protocol.

Table 3 Total number of alive nodes in each round

NO	100	200	250	300	350	400	450	500
LEACH	100	99	98	90	75	52	30	17
GWO Optimized LEACH	100	100	100	100	100	100	100	100

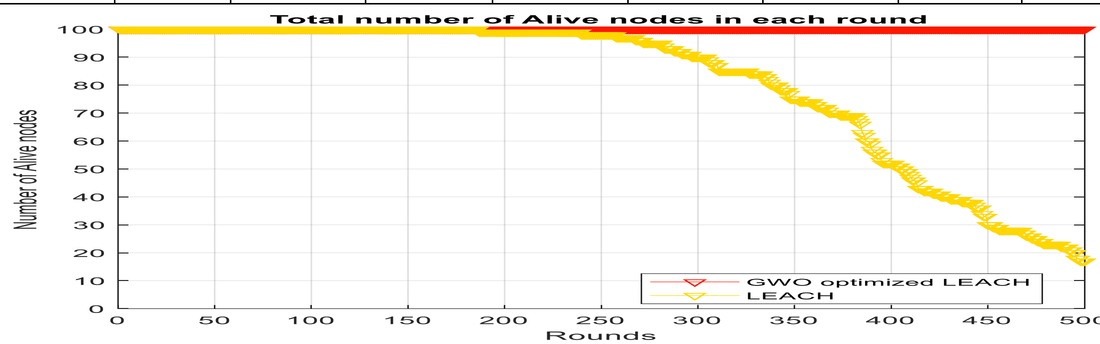

Figure 5.0 Total Number of Alive Nodes in Each Round

Total number of packet drops in each round

Figure 6.0 evidently shows that no packet(s) lost during iteration at each round for the two protocols. No packet is lost in transition

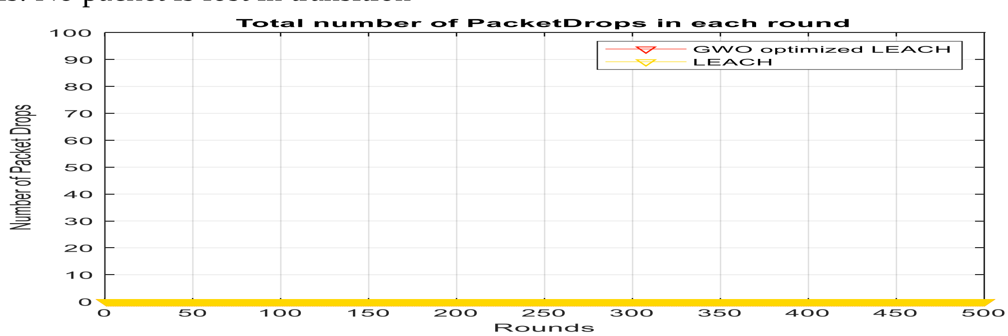

Figure 6.0 Total Number of Packet Drops in Each Round

Total number of packet received in each round

Figure 7.0 evidently show a significant increase in the number of packet starting from 300 rounds and above.

Table 5 Total number of packet received in each round

NO	50	100	200	300	400	500
LEACH	3.2e+5	6.4e+5	1.28e+6	1.912e+6	2.397e+6	2.627e+6
GWO Optimized LEACH	3.2e+5	6.4e+5	1.28e+6	1.92e+6	2.56e+6	3.2e+6

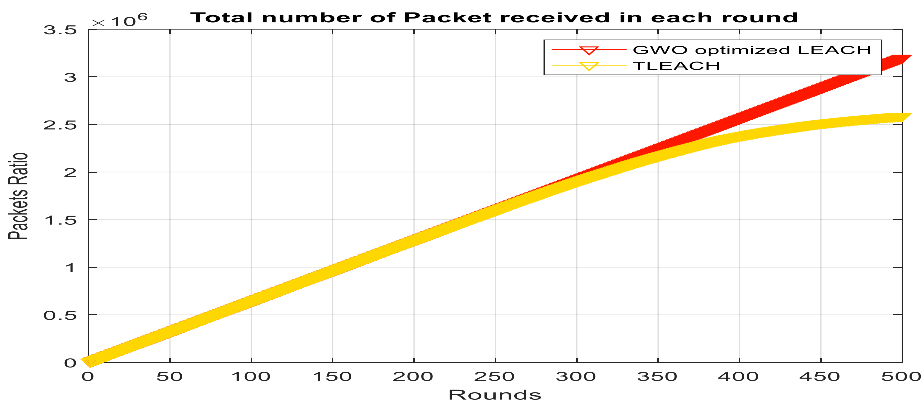

Figure 7.0 Total Number of Packet Received in Each Round

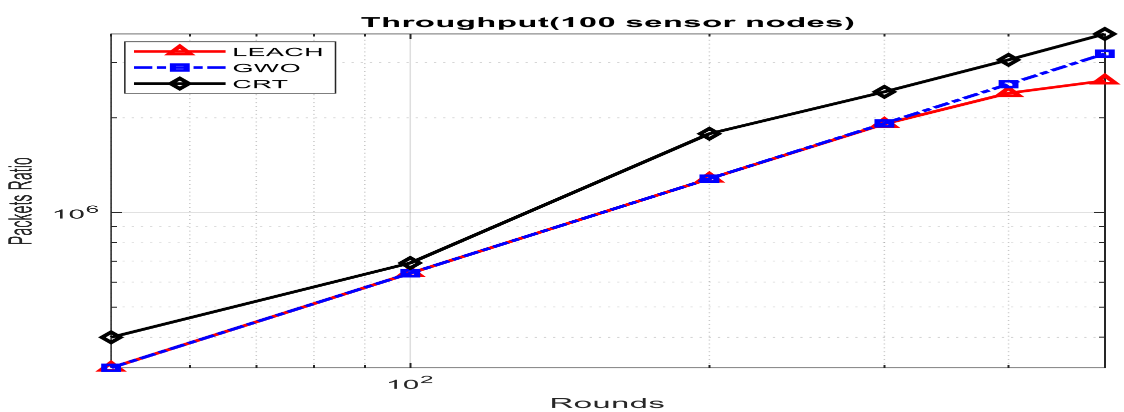

Figure 8.0 Comparison of the three algorithms in terms Throughput

Figure 8 shows that the number of packet in GWO LEACH Optimize is effectively transmitted without any drop in packet as compared to LEACH and Improved LEACH

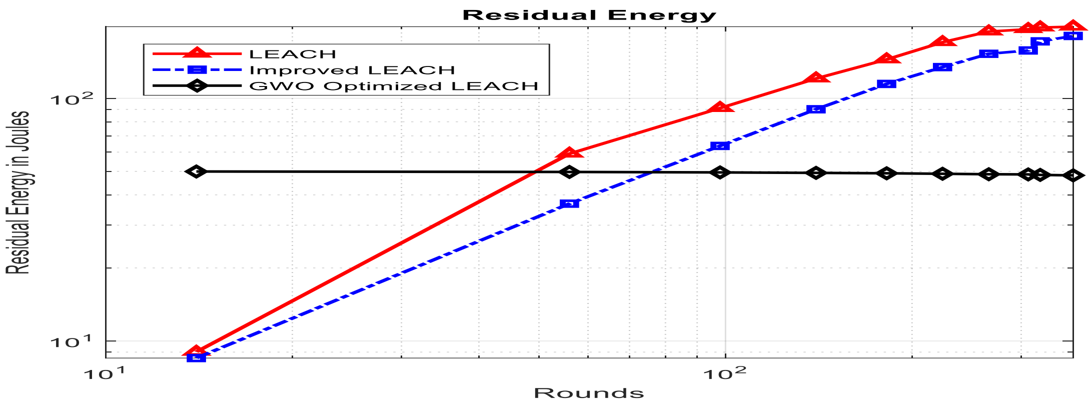

Figure 9.0 Comparison of three algorithms in terms of Residual Energy

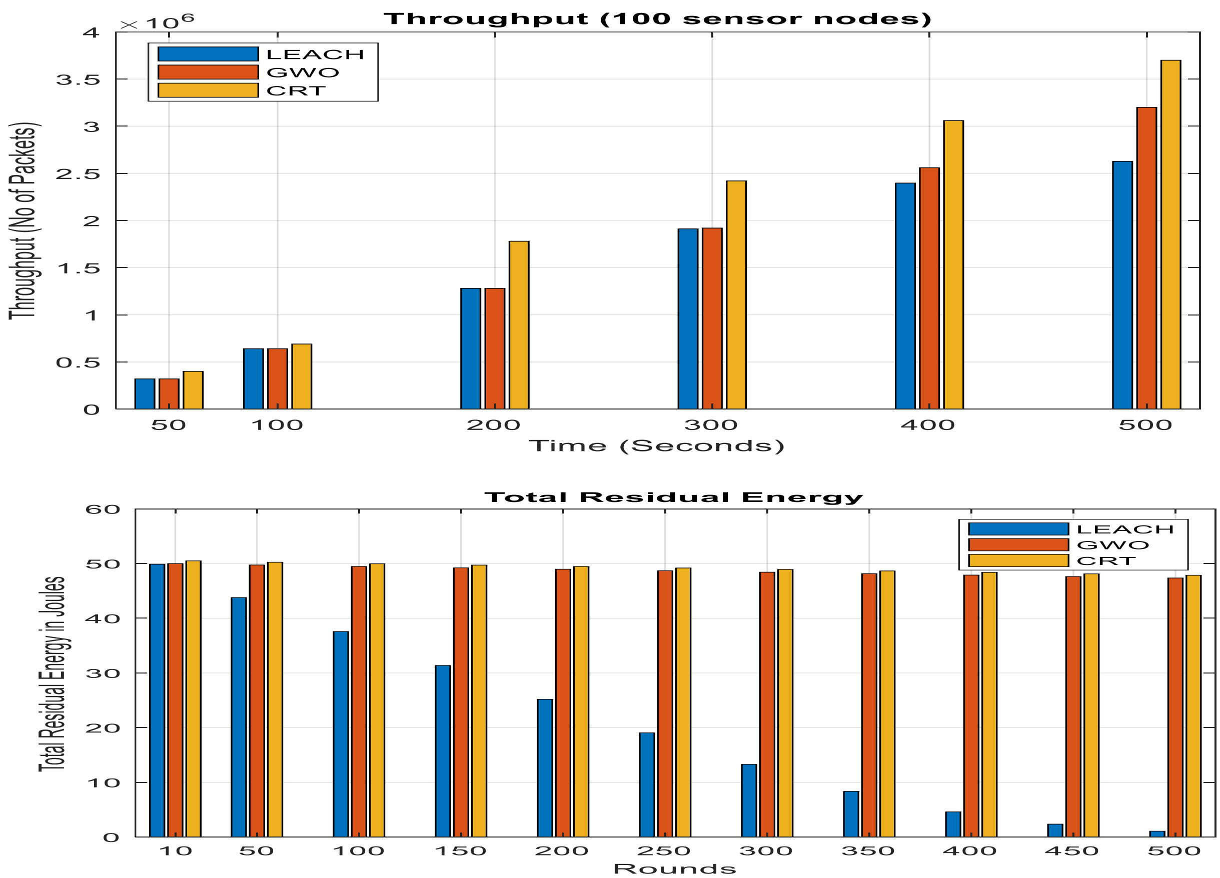

Figure 10.0 Residual Energy of LEACH, Improved LEACH, and GWO

CONCLUSION AND FUTURE WORK

The proposed algorithm is able to address the problem unbalance load sharing, and nodes with lesser energy becoming the cluster head. Also, this algorithm is able to converge faster and can also optimize a complex networks with a very large range. Fitness function is applied to each round to select the cluster head. The simulation shows better results in term of residual energy, total number of alive nodes in each round, total number of packet drops in each round, and the total number of packet received at each round. However, due to time constraint, the authors could not apply Chinese Remainder Theorem to further enhance the performance of the network. The work will further be expanded to other techniques such as Residue number system time.

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