Contextual Attention Greylag Goose Neural Networks Based Efficient Energy Consumption and Fault Tolerant Method for Clustering and Reliable Routing in Wireless Sensor Network

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ABSTRACT
In the context of Wireless Sensor Networks (WSNs), fault tolerance and efficient energy usage are essential for maintaining network lifespan. For improved WSN survivability, the study presents the War strategy with Contextual Attention Greylag Goose Network based Leopard Seal Optimization (WS-CAGGN-LSO). The War Strategy Optimization (WSO) is used by the WS-CAGGN-LSO approach for cluster generation and CH selection and predicts the high energy consumption node and eliminates it. To improve network survivability, a fault-tolerant method based on Contextual Attention Greylag Goose Network (CAGGN) is taken into consideration. The parameters of the CANN is optimized by the Greylag Geese Optimization (GGO) Furthermore, WSN route selection is optimised using a Leopard Seal Optimization (LSO). Ultimately, measures such as throughput, latency, energy consumption, packet delivery ratio, network life time, survivability, and computing time can be used to assess and compare the performance of the suggested approach against the methods that are currently in use. In comparison to other available models for 100 nodes, the network using the provided model achieved a throughput of 99.95% and an average energy consumption rate of 0.021J.

Keywords: Routing, Fault tolerance, Clustering, Energy consumption, Contextual attention, Wireless sensor network

1. INTRODUCTION

Due of its many uses in fields including disaster relief, medical monitoring, military surveillance, and environmental monitoring, Wireless Sensor Networks (WSNs) have attracted a lot of interest [1-2]. The finite and often non-replaceable power sources of the sensor nodes are one of the main obstacles facing WSNs. Even replacing the sensor nodes (SN) is impractical in many applications since they operate in hostile environments. Consequently, the biggest obstacle to the long-term operation of WSNs is thought to be lowering the energy consumption (EC) of the SN [3-5]. Numerous studies have been conducted on the design of energy saving protocols, such as MAC protocols that are conscious of energy use and low-power radio communication devices. However, the two most promising areas that have received the greatest attention and study in relation to WSNs are energy efficient clustering and routing algorithm [6-8].

WSN, that are cluster-based group sensor nodes into discrete groups known as clusters, each of which is headed by a cluster head (CH). This method saves communication bandwidth by reducing repeated messages, increases network scalability by needing less routing information, and lowers energy usage by removing unnecessary and uncorrelated data [9-11]. But clustering means that CHs have to put in more effort to receive sensed data, aggregate it, and send it to the base station (BS). Among regular sensor nodes, CHs are frequently chosen, and because of this additional effort, they may use more energy [12-14]. To accomplish the same tasks as cluster heads (CHs), researchers have suggested employing unique nodes known as gateways or relay nodes with more energy. Due to their battery-operated and power-constrained nature, these gateways require careful energy management during the routing and clustering procedures [15-17]. For WSNs to operate efficiently, energy from CHs must be used properly. Environmental risks, energy loss, and device failure can all lead to sensor node failure, which can compromise network performance and lifespan. Clustering and routing (CHs) failures are disastrous because they restrict accessibility and obstruct data aggregation [18]. The challenge of developing energy-efficient routing and clustering algorithms for fault-tolerant WSNs is discussed in this study. The primar contribution of this study is given below,

- This study presents the War strategy with Contextual Attention Greylag Goose Network based Leopard Seal Optimization (WS-CAGGN-LSO).
- The War Strategy Optimization (WSO) is used by the WS-CAGGN-LSO approach for cluster generation and CH selection and predicts the high energy consumption node and eliminates it.
- To improve network survivability, a fault-tolerant method based on Contextual Attention Greylag Goose Network (CAGGN) is taken into consideration.
- The hyperparameters of the CANN are optimized by the Greylag Geese Optimization (GGO).Furthermore, WSN route selection is optimised using a Leopard Seal Optimization (LSO).
- Ultimately, measures such as throughput, latency, energy consumption, packet delivery ratio, network life time, survivability, and computing time can be used to assess and compare the performance of the suggested approach against the methods those are currently in use.

2. LITERATURE SURVEY

Some of the recent literatures related to this work are described below,

In 2024, Tabbassum, S. et al [19] have been developed an LEACH with fuzzy logic based ANN for energy-efficient data transmission in a Wireless Sensor Network (WSN). The approach randomly places nodes in the network, allocates these functions to various nodes, and uses intrusion detection procedures to detect intruders. Fuzzy interference separates malicious nodes from legitimate ones, while an ANN separates malicious nodes from suspicious ones. The proposed classification model achieved high performance metrics, including accuracy, precision, and sensitivity.

In 2023, Moussa, N. et al, [20] developed an ACO-E-RARP method for secure data transmission in Wireless Sensor Networks (WSNs). The novel ACO algorithm uses four new parameters, including hop count, counter of weak-links, neighbour node count, and residual energy, to create high-quality paths for energy efficiency and reliability. The algorithm is compared with other protocols like showing superior performance in terms of computational time, network lifetime, and response time. The E-RARP algorithm is attractive for delay-intolerant applications like forest fire detection and is highly implementable and practical.

In 2022, Han, Y. et al [21] introduced a TAGA- routing method for trust-based and energy-aware in WSNks. It makes use of an adaptive genetic algorithm to choose safe and energy-efficient routes, thwart special trust and common routing attacks, and speed up attacker detection. To create comprehensive trust values, TAGA employs filtering methods, volatilisation factors, and adaptive penalty factors. To choose safe and high-energy nodes as CHs, an enhanced adaptive genetic algorithm with a new CH election threshold is used. Next, the algorithm is used to determine which path is best for each CH. According to simulation data, TAGA efficiently lowers the impact of malicious nodes, minimises dropped packets, and enhances network energy efficiency.

In 2023, Naderloo, A. et al, [22] proposed a fuzzy-based routing to improve energy consumption by optimizing cluster head selection. The network is divided into areas based on sensor distribution and data transmission distance. The cluster head is selected based on remaining energy, distance to the centre, and angle to the base station. The number of cluster heads in each area is defined considering living nodes. The responsibility of choosing the cluster head is on the base station, reducing the burden on other network nodes and preventing energy consumption. The method was compared with other protocols and improved results were obtained. Table 1 shows the state of art of literature survey.

Table 1: State of art of literature survey

Author and reference	**method**	**Advantage**	**Disadvantage**
Tabbassum, S. et al [19]	LEACH-FL-ANN	The proposed classification model achieved high performance metrics, including accuracy, precision, and sensitivity	Corrupted and dead network paths
Moussa, N. et al, [20]	ACO-E-RARP	The method is attractive for delay-intolerant applications	Limited accurate results
Han, Y. et al [21]	TAGA-RM	TAGA efficiently lowers the impact of malicious nodes, minimises dropped packets, and enhances network energy efficiency	Higher computational overhead and increased processing time
Naderloo, A. et al, [22]	FLBR	The method was compared with other protocols and improved results were obtained	Increased computational overhead, especially in resource-constrained sensor nodes.

2.1 Problem Statement

Creating a routing and clustering algorithm that is both fault-tolerant and energy-efficient while boosting network durability and dependability is a difficulty faced by wireless sensor networks (WSNs). This entails maximising energy usage for data processing and transmission, guaranteeing strong fault tolerance, and identifying and resolving errors. To ensure reliable network performance and data integrity, clustering methods, adaptive routing algorithms, and fault detection and recovery procedures must be in place.

3. PROPOSED METHODOLOGY

A novel War strategy with Contextual Attention Greylag Goose Network based Leopard Seal Optimization (WS-CAGGN-LSO) has been developed in this work for clustering based efficient and fault tolerant routing to increase WSN network survivability. The goal of the suggested approach is to effectively select the CHs and the most direct path to the target by using a fault-tolerant method. The suggested WS-CAGGN-LSO technique consists of three primary parts: LSO-based routing, CAGGN-based fault tolerance, and WS-based clustering and efficient energy consumption. Figure 1 shows the work flow of the proposed WS-CAGGN-LSO.

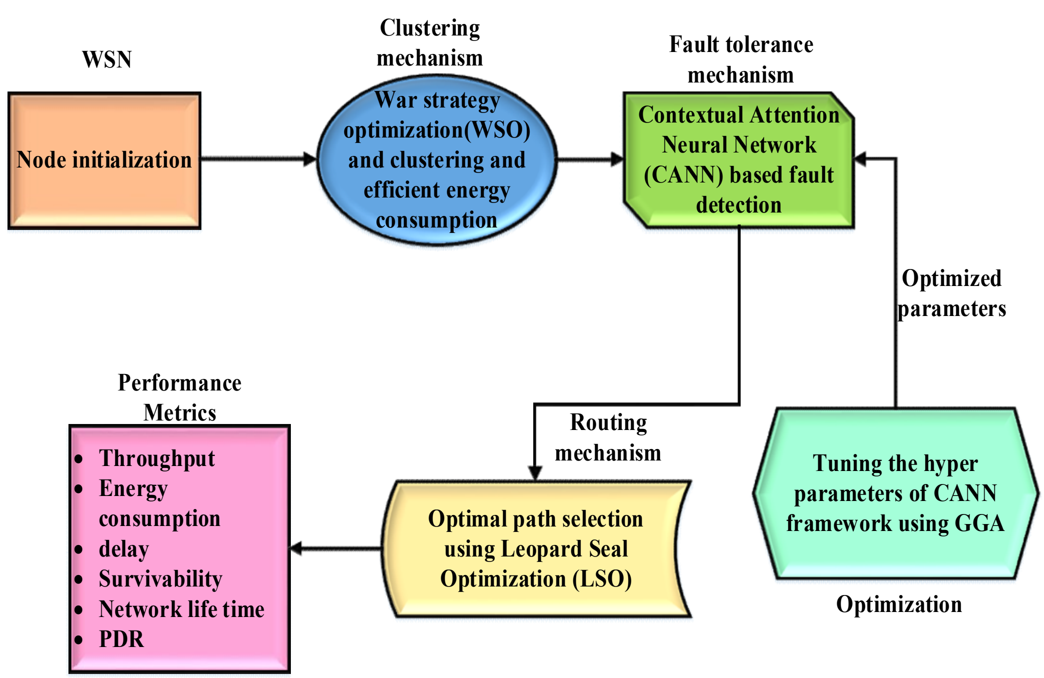


Figure 1: Workflow of the proposed OBSCN-GIA

3.1 Node creation

Develop a WSN strategy in which each SN is used arbitrarily and a few gateways are added. If it can be used, it is designed to be stationary. Wireless network nodes cannot access the networks' global data. Throughout each round, every SN gathers local data and sends it to the relevant CH. With the help of another CH serving as a following hop relay node, the gateways receive the data, aggregate it to remove redundant and uncorrelated data, and then send the combined data to the base station. In order to save energy, every node turns off its radios every two rounds.

3.2 Clustering and Efficient Energy Consumption Using War Strategy Optimization (WSO)

Employ a war strategy optimisation attack approach in the context of optimal cluster head selection, where nodes in a network adjust their placements based on the positions of a "King" and a "Commander." In this instance, the Commander stands in for a second significant node, and the King symbolises the node with the highest fitness score. Equation (1) provides the update mechanism.

$$Y_i(s+1) = Y_i(s) + 2 \times \delta \times (C - P) + rand \times (W_i - P - Y_i(s)) \tag{1}$$

Where, $Y_i(s+1)$ represents the new position of node i, $Y_i(s)$ represents the previous position, C indicates position of the commander, P represents the position of the king, W_i indicates the weight of node i. Every node starts out with the same rank and weight, but as the process goes on, those values are modified in accordance with how well their methods work. The revised position of the node is beyond the King's position $if\,(W_i > 1)$. The node gets closer to the King $if\,(W_i < 1)$. This is because the updated position lies between the King's position and the node's current position. The updated position moves very close to the Commander if W_i tends to zero, indicating the end of the selecting process. The node with the highest fitness score is chosen as the network's ideal cluster head after an adequate number of iterations.[23,24]

Similar to the attack force or fitness in a war strategy, the prediction mechanism updates each node's position based on its energy consumption. The node maintains its old place if the energy consumption in the new position E_n is greater than that in the previous position E_p. This can be represented by the equation (2).

$$Y_i(s+1) = Y_i(s+1) \times \left(\frac{E_n}{E_p} \geq 1 \right) + Y_i(s) \times \left(\frac{E_n}{E_p} < 1 \right) \tag{2}$$

One technique that can be used to remove or relocate nodes with excessive energy consumption is to replace them, much like weak soldiers. One strategy is to swap out the node that uses the most energy for a random node that is still inside the network's boundaries in equation (3).

$$Y_w(s+1) = L_b + rand \times (U_b - L_b) \tag{3}$$

Alternatively, convergence and overall network performance can be enhanced by moving the node with the highest energy consumption closer to the median position of all nodes in equation (4)

$$Y_w(s+1) = -(1 - rand\, n) \times (Y_w(s) - median(Y)) + P \tag{4}$$

where the node with the highest energy consumption is represented by Y_w, the lower and upper bounds of the network are represented by L_b and U_b, random numbers are represented by $rand$ and $rand\,n$, and the node with the optimal energy consumption is represented by K (similar to the King in the war strategy). By following these procedures the optimal cluster head selection and efficient energy consumption has been performed.[25,26]

3.3 Fault Mechanism Using Contextual Attention Greylag Goose Network (CAGGN)

A contextual attention module is proposed to detect fault nodes and adaptively manage fault tolerance. Every group of nodes should have a relative importance to the job at hand. As a result, the two-level normalisation processes listed below are used in our suggested module: It performs spatial normalisation to highlight specific long-range contextual dependencies within the node set after recalibrating the representation for a node-level fault understanding. Define the channel-wise normalisation weights T_{ch} as follows after applying the squeeze and excitation method given equation (5).

$$T_{ch} = \sigma(L_2 \alpha(L_1 GAP(f))) \tag{5}$$

Where GAP stands for the global average pooling operation that is done to the node features

(f), learning parameters are represented by L_1 and L_2, and the ReLU and Sigmoid activation functions are represented by α and σ, respectively. The normalised features are formed by: $f' = T_{ch}.f$. Add the fault representation to the normalised feature in order to highlight the fault area: $\widetilde{f} = f' + B$.

The fault feature's goal is to highlight probable fault-prone areas and direct the model to accurately pinpoint them. Next, carry out spatial normalisation using the feature set that was obtained from the Transformer module. To scale the representation according to regional relevance, first multiply the RIC coefficient by the appropriate areas in $\widetilde{f}$ is $f_{sn} = RIC.\widetilde{f}$.

The ICR representation should be concatenated with f_{sn} to further incorporate long-range dependency. Next, non-linear aggregation should be performed using an activation function, batch normalisation (BN), and a convolutional kernel I given in equation (6).

$$\widetilde{f}_{sn} = \alpha(BN(Conv(ICR, f_{sn}))) \tag{6}$$

To identify fault nodes, the resulting feature set is carefully integrated from local semantic and global contextual representations. Next, utilise the decoder block on the features that were extracted in order to forecast the failure mask: $Y' = D(\widetilde{f}_{sn}; \gamma)$. During training, the following joint objective loss function is optimised in equation (7)

$$Lo_{joint} = \lambda_1 Lo_{fault} + \lambda_2 Lo_{boundary} + \lambda_3 Lo_{RIC} \tag{7}$$

Whereas the MSE loss between the distribution of fault nodes in each region and the corresponding predicted one is calculated by Lo_{RIC}, the binary cross-entropy loss for boundary prediction is displayed by $Lo_{boundary}$, and the cross-entropy loss between the predicted mask and the ground truth is computed by Lo_{fault} . To weight each loss, utilise coefficients $\lambda_i, i \in \{1,2,3\}$. By following these procedures fault mechanism has been performed.

3.4 Optimizing the hyperparameters CANN using Greylag Goose Optimisation (GGO)

The migratory habits of Greylag geese serve as the basis for the Greylag Goose Optimisation (GGO) algorithm, an optimisation method inspired by nature. It is applied to many challenges to enhance performance and optimise loss functions. The step-by-step processes to optimize these hyperparameters using the GGO are given below in Algorithm 1.

Algorithm1: CANN-GGO

Step1: Initialization

Initialize the population of geese and set GGO parameters for optimizing CANN

$$x_i (i = 1,2,....N)$$

Step 2: Random distribution

$$x_i = rand(LB, UB) \quad for \quad i = 1,2,....N$$

Step 3: Fitness function

Evaluate the fitness (or loss) of each goose's position

$$F_i(x_i) = fitness(Loss(X_i))$$

Step 4: Select Best Geese

Identify the best-performing geese (those with the lowest loss).

Best Goose: x^* is the position of the goose with the minimum fitness value

$$Best\ \ fitness = \min(f(x_i))$$

Step 5: Mitigation and Update

Update the positions of geese based on migration behavior.

$$x_i^{(t+1)} = x_i^{(t)} + C1.rand.(x^* - x_i^{(t)}) + C2.rand.(x_{local} - x_i^t)$$

Step 6: Boundary check

Ensure geese positions stay within the defined search space boundaries.

$$x_i^{(t+1)} = clip(x_i^{(t+1)}, LB, UB)$$

Step 7: Termination

Check if the stopping criterion is met.

the maximum number of iterations t are satisfied

If not, go back to Step 3

Step 7: Output

Return the best solution found

3.5 Routing Mechanism Using Leopard Seal Optimization (LSO)

The hunting stages (seeking, encircling, and attacking) of the Leopard Seal Optimisation (LSO) algorithm must be modified to meet the unique requirements of data routing in order to adapt it for secure data transfer by choosing the best routes. This means that in addition to minimising the objective function (such delay or cost), the chosen paths must also guarantee secure data transfer by eliminating susceptible nodes and paths. A modified method for choosing the best path for safe data transfer that incorporates the LSO phases is shown below:

3.5.1 Searching for optimal paths

The searching phase of routing for safe data transfer concentrates on examining several routes throughout the network to identify probable best routes that minimise latency and maximise security. This is one way to modify the search phase:

Every node, like a leopard seal, looks for possible routes on its own, taking into account different network parameters including latency, bandwidth, and security flaws. Randomly start each node's position in the network topology so that it symbolises a search agent. Nodes travel randomly throughout the network to investigate various routes, resembling the erratic, rotating motion of leopard seals. The position update using the equation (8).

$$Y_i^{\alpha}(L_m) \mid \forall \alpha \in \{2,3,4....,\Im - 1\} = B_i(L_m).e^{bf_\alpha \cos(2\pi f\alpha)} + Y_i^{\Im}(L_m) \qquad (8)$$

Where, $B_i(L_m)$ represents between nodes, and f_α controls the movement based on the iteration number. Use a fitness function to assess the paths according to parameters like bandwidth, latency, and security precautions given in equation (9).

$$F(Y_i) = latency + \cos t - \sec urity \qquad (9)$$

Where better pathways are indicated by lower latency and cost in conjunction with increased security.

3.5.2 Encircling Potential Optimal Paths

Nodes utilise encircling approaches to improve and secure prospective paths that they find during the searching phase. This stage is all about encircling and verifying the paths to make sure they satisfy security and performance standards. The path with the best fitness score is chosen as the leader is given equation (10).

$$Y_{prey} = position[\arg\ \max(validation[F(L_m)]\forall L_m \in S \qquad (10)$$

For additional analysis, a selection of top pathways is selected, and their average position is used, which is given in equation (11).

$$Y_{prey} = \frac{1}{k}\sum_{i=1}^{k} Y_i \tag{11}$$

Based on their fitness scores, paths are assigned a weight. The top paths are weighted averaged to create the forecast path is given in equation (12).

$$Y_{prey} = \frac{\sum_{m=1}^{k} W(L_m).Y_m}{\sum_{m=1}^{k} W(L_m)} \tag{12}$$

Using the following equations (13), (14), update the node placements to get closer to the expected optimal paths:

$$B_i(L_m) = \| Y_{prey} - Y_i(L_m) \| \tag{13}$$

$$Y_{i+1}(L_m) = Y_{prey} - A.B_i(L_m) \tag{14}$$

Where, the coefficients A and C change the movement according to the iteration phase.

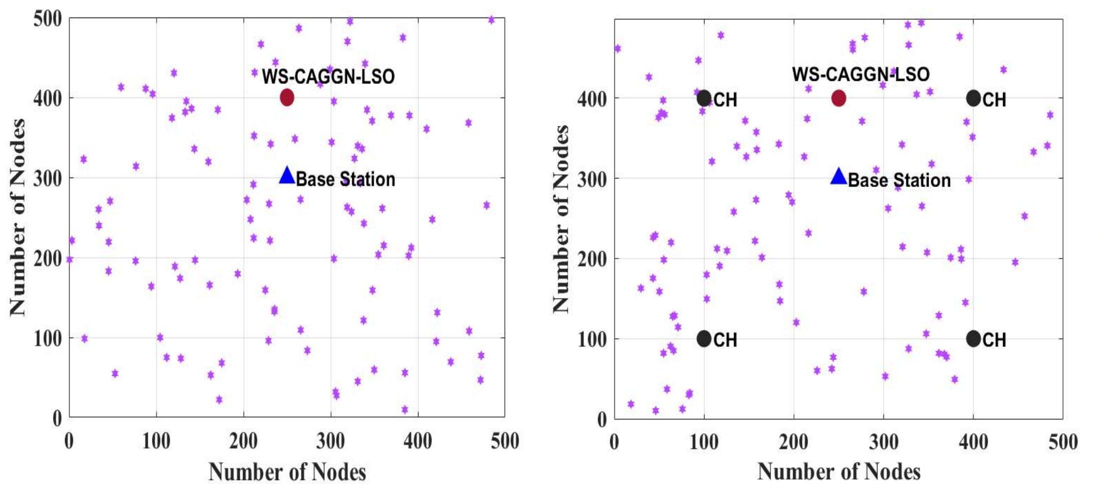
3.5.2 Path Validation

The final pathways chosen are thoroughly verified during the attacking phase to guarantee secure data transfer. In order to defend against attacks, this entails assessing the pathways for potential security flaws. Furthermore, by employing encryption and other security mechanisms, the nodes improve the security of these pathways and guarantee data integrity and confidentiality during the transfer process.

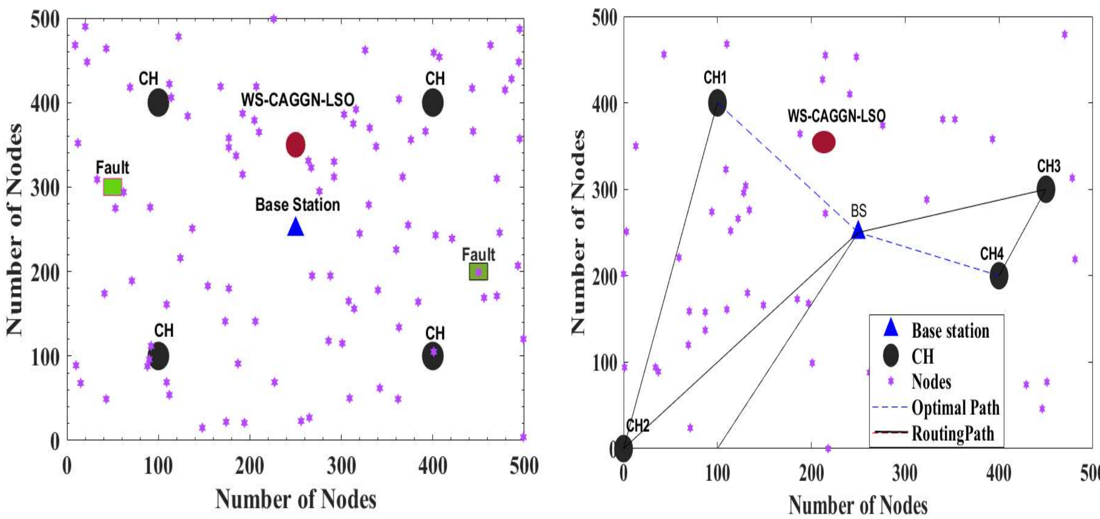
It is possible to guarantee that the paths chosen are both highly efficient in terms of performance and safe from possible threats by adapting the LSO algorithm to the secure data routing scenario.

4. RESULT AND DISCUSSION

The suggested WS-CAGGN-LSO approach is evaluated in Ns3. Monitoring and ideal characteristics were incorporated in the first deployment of the crucial nodes in the communication environment. In this work, 500 moving nodes are included in a WSN simulation configuration. The NS3 simulator will be used to conduct the simulation on a Windows 10 computer.



a) b)



c) d)

Figure 2: a) node initialization b) optimal cluster head selection c) fault detection

d) Optimal path finding

The node construction in the WSN environment in the NS3 is depicted in Figure 2a. In this case, 500 nodes are the initialised number. It was possible to make a 500*500 moving node. Figure 2b) shows the ideal choice of cluster head. The ideal cluster head is represented by the black node. The ideal cluster head is identified using the War strategy function. Here, the ideal heads are determined by factors including the distance to the base station, the last movement, the remaining energy, and the accessible area for an alternate node. Figure 2(c) illustrates how to discover faultss. CANN-GGO can be used in this situation to identify the fault node. The fault node is represented by the green node. Additionally, figure 2d) shows how to choose the best path for data transfer using LSO. The best course is indicated by the black line.

4.1 Performance Validation

The requisite node is used to test the suggested WS-CAGGN-LSO approach on the Ns3 platform and in a WSN. Many network parameters, including throughput, latency, energy consumption, network lifetime, packet delivery ratio, survivability analysis, and computing time, are used to confirm the efficacy of the suggested WS-CAGGN-LSO. The current techniques are LEACH-FL-ANN [8], ACO-E-RARP [9], TAGA-RM [10], and FLBR [12].

Table 2: comparison analysis of throughput, delay, and energy consumption

Metrics	**No of nodes**	**LEACH-FL-ANN**	**ACO-E-RARP**	**TAGA-RM**	**FLBR**	**WS-CAGGN-LSO (proposed)**
Throughput (%)	100	63.9	64	66	69	99.95
	200	65.6	70	77	70	99.95
	300	77.9	69	78	77	99.87
	400	79.4	69.2	79.5	80	99.81
	500	80.5	77.7	80.7	81	99.64
Delay (sec)	100	0.0338	0.0328	0.0324	0.0309	0.0202
	200	0.0347	0.049	0.0332	0.0311	0.0204
	300	0.0369	0.0356	0.0338	0.0318	0.0205
	400	0.0374	0.0380	0.0353	0.0326	0.0208
	500	0.04252	0.0398	0.0367	0.028	0.036
Energy Consumption (J)	100	0.0574	0.665	0.4219	0.845	0.0253
	200	0.2406	1.4271	0.903	1.9854	0.1283
	300	0.2809	2.0048	1.2323	2.5633	0.194
	400	0.4238	2.331	1.627	2.9686	0.1693
	500	0.488	2.69	2.089	3.573	0.215

Table 2 presents a comparison of current approaches on a network with 500 nodes increasing from 100. While most existing approaches suffer some performance loss as the network scales, the suggested WS-CAGGN-LSO method stands out, attaining near perfect throughput of 99.95 at 100 nodes and the lowest delay and energy usage across all network sizes.

Table 3: comparison analysis of Network lifetime, PDR, and Survivability

Metrics	No of nodes	LEACH-FL-ANN	ACO-E-RARP	TAGA-RM	FLBR	WS-CAGGN-LSO (proposed)
Network lifetime (sec)	100	62	38	56	117	206
	200	217	62	112	281	338
	300	273	88	227	365	405
	400	318	118	271	421	456
	500	376	153	302	468	488
Packet delivery ratio (%)	100	72	75	85	84	99
	200	87	72	84	82	99
	300	84	73	82	79	98
	400	83	66	76	74	97.99
	500	81	63	73	69	97.81
Survivability (%)	100	80.4	86	87.3	90.22	94.54
	200	81.73	86.53	88.47	91.47	95.21
	300	83.22	85.73	89.48	92.68	96.11
	400	84.16	89.32	91.71	94.96	97.40
	500	85.77	90.37	92.79	95.33	98.89

Table 3 presents a comparative analysis between the suggested approach and the current approaches in terms of network longevity, packet delivery ratio, and survivability for varying numbers of nodes (100, 200, 300, 400, and 500). For varying numbers of nodes, the suggested approach yields the best results across all metrics.

5. CONCLUSION

WSNs face obstacles related to fault tolerance and energy efficiency. However, this paper's integration of clustering and dependable routing technique presents a viable answer to these issues. A novel War strategy with Contextual Attention Greylag Goose Network based Leopard Seal Optimization (WS-CAGGN-LSO) has been developed in this work for clustering based effiecient and fault tolerant routing to increase WSN network survivability. The goal of the suggested approach is to effectively select the CHs and the most direct path to the target by using a fault-tolerant method. The suggested WS-CAGGN-LSO technique consists of three primary parts: LSO-based routing, CAGGN-based fault tolerance and the GGO optimize the hyperparameters of the CANN, and WS-based clustering and efficient energy consumption. In conclusion, a comparison is made between the suggested approach and the current approaches' performance. The model that was given resulted in a network throughput of 99.95%, and the average energy consumption rate for 100 nodes was 0.025J lower than that of the other models that were previously available. Future work should focus on creating sophisticated fault-tolerant routing protocols that can manage diverse environments and more intricate network topologies.

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