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Original Article

Hybridization of Optimization Algorithm-Based Trust Aware Clustering Scheme for Wireless Sensor Networks

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Abstract *- Energy optimization is the most open problem in WSN. Most of the work concentrates on clustering approaches for reducing energy consumption and improving the stability period. The sensor networks include sensor nodes with restricted battery levels to monitor physical events at several locations. Data collecting is an archetypal but vital function in several Wireless Sensor Networks (WSN) applications. It can be essential to continuously operate the sensor network in an energy-effective system to collect data. This study presents a novel Hybrid Glowworm Search Optimization based Trust Aware Clustering Scheme (HGSO-TACS) technique for WSN. The presented HGSO-TACS technique aims to accomplish secure cluster communication with trust metrics. In addition, the HGSO model is designed by integrating the GSO model with Lens Oppositional Based Learning (LOBL). Moreover, the proposed HGSO-TACS method computes an objective function with multiple parameters in the network. The experimental validation of the HGSO-TACS method can be carried out under various features. The relative study revealed the improvements of the HGSO-TACS technique over other current approaches.*

Keywords *- Clustering, Stability, Trust, Wireless Sensor Networks, Stability, Energy efficiency.*

1. Introduction

The fast advancement of wireless technology and the exponential growth of wireless network services converted wireless communications into a pervasive means for transferring information over various fields [1]. In the structure of WSNs, there come several potential possibilities where WSNs are installed to support a more significant number of applications. WSN has sensors placed in remote areas for collecting and sending data back to the base station [2, 3]. Various features can classify the sensor nodes, which include power level, size, lifetime of operation, failure characteristics (denoting if the sensor has failed or is degrading gradually), movement features (representing whether the nodes are mobile or stationary), battery consumption, position features (signifying whether the nodes can be entrenched into the mechanism or independent of its surroundings) [4].

In the network, the main factor for the energy utilization was due to these two activities they are receiving and transmitting the signal. However, energy utilisation in data transmission becomes more significant than processing functions [5]. The network has mobile and stationary sensors, and their deployment will occur randomly. Wireless links can establish the data collection. Transmission of information towards the sink is impossible due to the energy holes. Figure 1 represents the overview of WSN. The nodes which are distant from the BS have faster energy depletion in the network, while single-hop routing can be employed by the SNs [6].

Energy holes will result in an uncovered zone in the sensor network, which may reduce the network lifespan. A potential solution for extending the network lifespan of the SNs is clustering. It renders many advantages like load balancing, scalability, and decreased collisions during intra-cluster transmission. It is very adaptive and is a resource-aware protocol [7, 8].

Clustering can be a broadly employed method in WSN that potentially minimizes the SN's energy utilization. In clustering, data collected by the member nodes will be sent to BS via the cluster head. In this context, the power consumed in the network through clustering methods is less than direct transmission [9]. However, in cluster-oriented routing, improper cluster formation makes certain CHs overloaded. This overload leads to high energy outflow of CHs and reduces the efficiency of WSN. Hence, CH selection and load balancing are significant concerns for clustering SNs [10].

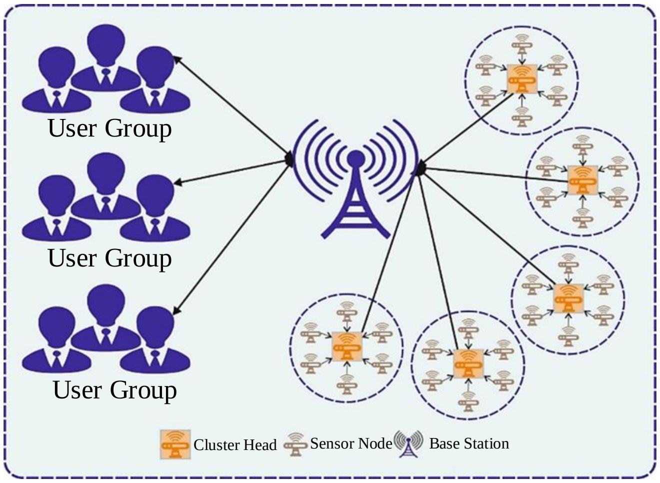

Fig. 1 Overview of WSN

This study presents a novel Hybrid Glowworm Search Optimization based Trust Aware Clustering Scheme (HGSO-TACS) technique for WSN. The presented HGSO-TACS technique aims to accomplish secure cluster communication with trust metrics. In addition, the HGSO model is designed by integrating the GSO model with Lens Oppositional Based Learning (LOBL). Moreover, the proposed HGSO-TACS method computes an objective function with multiple parameters in the network. The experimental validation of the HGSO-TACS method can be carried out under various features. The relative study revealed the improvements of the HGSO-TACS technique over other current approaches.

2. Literature Review

Kaushik et al. [11] present a Distance-Based Stable Connected Dominating Set technique employing a metaheuristic GWO (DBSCDS-GWO) to accomplish a steady, balancing, and energy-effective CDS-related WSN. The authors presented a distance-based stable clustering technique employing DBSCDS-GWO to enhance the efficiency of cluster-related WSNs. Hegde and Dilli [12, 13] examined an Improved type of GWO (IGWO) technique for overcoming the premature convergence of fundamental GWO technique, and it can be executed in optimizing the CH selective from WSNs for maximizing the network lifespan.

The enhancement of the IGWO technique was dependent upon RE, sink distance, average intra-cluster distance, and CH balance factor. In [14, 15], a Hybrid Grasshopper and Differential Evolution-oriented Optimization Algorithm (HGDEOA) were presented to achieve energy constancy and prolonged networking lifespan. This HGDEOA integrates an adaptive approach to DE to enhance the global searching ability in optimisation. It can be presented to enhance the convergence efficacy and retain population diversity. In [16, 17], GA-related Optimized Clustering (GAOC) protocol was planned to optimize the selection of CH by combining the RE parameter, distance to sink, and node density in their expressed fitness function. In addition, to deal with the hotspot issue and reduce the transmission distance in the nodes to sink, Multiple data Sinks based GAOC (MS-GAOC) were presented. In [18, 19], a unique clustering methodology called Energy Centers searching utilizing PSO (EC-PSO) was projected to avoid this energy hole and search energy centres to CHs selective.

The CHs were chosen to employ a geometric approach for an initial period. Afterwards, the energy of networks is heterogeneous, and EC-PSO was implemented to cluster. Kaur and Grewal [20, 21] examined a PSO-based Dual Sink Mobility (PSODSM) approach for reducing the SN's energy expenditure.

PSODSM has the paramount concentration on the CH selective dependent upon the combination of vital features: "ratio of RE to primary energy," node centrality, node degree, separating feature betwixt the SN and sink, CH number, and energy consumption rate. If the CHs were chosen, two opposite sinks would be developed for moving near the selective CHs for data gathering.

3. The Proposed Model

The present article formulated a new HGSO-TACS method for secure communication in the WSN. The presented HGSO-TACS method aims to accomplish secure cluster communication with trust metrics. In addition, the HGSO algorithm is designed by integrating the GSO algorithm with the LOBL concept.

3.1. Design of HGSO Algorithm

In addition, the HGSO algorithm is designed by integrating the GSO algorithm with the LOBL concept. GSO is a novel SI technique projected by Krishnanand and Ghose [22]. GSO is primarily employed for optimizing multi-modal purposes with uneven or corresponding strategy function values. During the GSO, $the\ S$ glowworm swarm, including the m glowworm, was dispersed in the Objective Function (OF) searching space.

Each glowworm $g_j (j = 1 \ldots m)$ was assigned a random place p_j within the offered function, searching space. The glowworm g_j transmits their luciferin level L_j and is the vision range termed as local decision range rd_j. The luciferin level was dependent upon glowworm place and OF values. In each place of the luciferin level upgrades, the OF was evaluated at the present glowworm place (p_j) and the luciferin level to all the glowworms was employed to a novel OF value. The L_j luciferin levels were upgraded by Equation (1):

$$L_j(t) = (1 - \rho)L_j(t - 1) + \gamma F\left(p_j(t)\right) \qquad (1)$$

Where $L_j(t-1)$ stands for the earlier luciferin level to glowworm j; γ implies the luciferin improvement fractions; p demonstrates the luciferin decay constant ($\rho \in (0,1)$), and $F(p_j(t))$ refers to the OF for glowworm j at the current glowworm place (p_j); t indicates the current iteration. Afterwards, every j glowworm searches its neighbourhood area to remove the neighbour which is higher luciferin levels by employing the succeeding rules [23]:

$$z \in N_j(t) \; iff \; d_{jz} < rd_j(t) \; and \; L_Z(t) > L_j(t) \tag{2}$$

Whereas d defines the distance and Z demonstrates the neighbouring glowworm to glowworm j, $N_j(t)$ denotes the neighbourhood setting, d_{jz} refers to the Euclidean distance betwixt glowworms j and z, $rd_j(t)$ implies the local decision range to j glowworm and $L_Z(t)$ & $L_j(t)$ stands for the luciferin level to glowworm z and j correspondingly. Afterwards, for choosing an optimum neighbour in the neighbourhood setting, the possibility of all the neighbours is evaluated by Equation (3):

$$prob_{jz} = \frac{L_Z(t) - L_j(t)}{\sum_{k \in N_j(t)} L_k(t) - L_j(t)} \tag{3}$$

Assume that z is the neighbourhood set $N_j(t)$ of glowworm j. Next, every glowworm chooses the direction of motion with the roulette wheel technique. However, the glowworm with a higher chance is a superior probability than that chosen in the neighbourhood set. Afterwards, the glowworm place (p_j) was changed based on the chosen neighbour place (p_z) as in the following:

$$p_j(t) = p_j(t-1) + s\frac{p_z(t) - p_j(t)}{Distance_{jz}} \tag{4}$$

Constant, and d_{jz} Indicate the Euclidean Distance between glowworms j and z. At last, the local decision range rd_j was changed utilizing Equation (5):

$$rd_j(t) = \min\left\{rs, \max\begin{bmatrix} 0, rd_j(t-1) + \\ \beta\left(nt - \left|N_j(t-1)\right|\right)\end{bmatrix}\right\} \tag{5}$$

$rd_j(t-1)$ refers to the previous rd_j, r_s implies the radial sensor range constant, β defines the constant, nt stands for the constant variable employed to limit the neighbourhood set size, and $|N_j(t)|$ represents the real neighbourhood set size. During this projected technique, it could be relaxed the local decision range upgrading stage and set the value of rd_j that is similar to the r_s Constant. However, the nt and β parameters were also relaxed. If X_i has a decoder to obtain cluster centres C and evaluate fuzzy partition matrix U, the fitness function of i^{th} glowworm is defined as:

$$f_i = J_{GSO-FEC}$$

The minimized of f_i is the same as minimized OF $J_{GSO-FEC}$ which results in an optimal partition. Figure 2 implies the GSO flowchart. Lens imaging is a phenomenon of physical optics that represents that objects are positioned at two or more primary focal lengths farther from the convex lens, and smaller and inverted images are generated on opposite sides of the lens. Considering the 1D search space, there exists a convex lens with focal length f fixed at the base point O (search range mid-point [lb, ub]). In addition, the p object with h height is positioned on the coordinate axis, and the projection is GX (the candidate solution). Distance from the objects to the lens u is greater than twice f. By employing the lens imaging operation, a reversed image p' of height h^* is achieved, which is predicted by GX^* (reverse solution) on the x-axis. Accordingly, to the similar triangle rules and lens imaging, the geometrical relationship attained is given by:

$$\frac{(lb+ub)/2 - GX}{GX^* - (lb+ub)/2} = \frac{h}{h^*} \tag{6}$$

In Equation (6), consider the scale factor $n = h/h^*$, the reverse solution GX^* is computed by transmitting the following:

$$GX^* = \frac{lb+ub}{2} + \frac{lb+ub}{2n} - \frac{GX}{n} \tag{7}$$

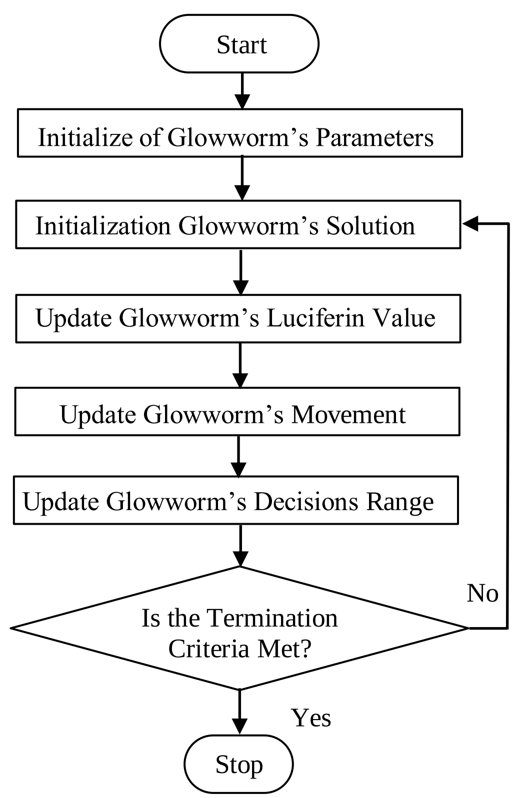

Fig. 2 GSO flowchart

It is apparent that if $n = 1$, it is expressed as follows:

$$GX^* = lb + ub - GX \tag{8}$$

Now, it considers the OBL approach as an unusual LOBL case. Contrary to OBL, the latter consents obtaining dynamic reversal solutions and a wide search range by tuning the scale factor n.

Usually, it is prolonged into D-dimension space:

$$GX_j^* = \frac{lb_j+ub_j}{2} + \frac{lb_j+ub_j}{2n} - \frac{GX_j}{n} \tag{9}$$

Whereas lb_j and ub_j Indicate the $j\text{-}th$ parameter's lower and upper bounds; subsequently, $j = 1, 2, \cdots D$, GX_j^* symbolizes the inverse solutions of GX_j in the $j\text{-}th$ parameter. No agreement exists after creating a novel inverse solution, often better than the present candidate solution. As a result, it is crucial to assess the candidate's fitness value and inverse solutions later; the fitter one would be chosen for continuous participation in the ensuing utilization phase that is shown below:

$$GX_{next} = \begin{cases} GX^*, & if F\ (GX^*) < F(GX) \\ GX, & otherwise \end{cases} \tag{10}$$

Whereas GX^* represent the reverse solution produced using LOBL, GX indicates the present candidate solution, GX_{ext} denotes the selected gorilla to update the subsequent location continuously, and F represents the fitness function.

3.2. Process Involved in Clustering Technique

The presented HGSO-TACS technique computes an objective function with multiple parameters in the network. This study exploits a novel HGSO-TACS technique for selecting CH and creating clusters. Then, the FF is formulated using four different variables: Residual Energy (RE), number of hops, trust, and distance [24, 25].

Trust: In selecting CH, trust is considered a crucial variable in FF to increase safety. The mutual trust created at a particular time is applied to accomplish the communication.

Direct Trust (DT) is established on the estimated time of transmission amongst $the\ i^{th}$ node and d^{th} destination n. DT is evaluated by the gaps on the list of actual and predictable times of i^{th} nodes for validating the public key formulated using the d^{th} terminus. Henceforth, DT comprising i^{th} node and d^{th} the terminus is shown below,

$$DT_i^d(\tau) = \frac{1}{3}\left[DT_i^d(\tau - 1) - \left(\frac{\tau_{appx} - \tau_{est}}{\tau_{appx}}\right) + \omega\right] \tag{11}$$

Now, τ_{appx} determines the estimated time and τ_{est} defines the predictable time to validate the public keys. Likewise, τ_{appx} and τ_{est} denote the predictable time for getting and directing the public keys through the terminus and the node. ω indicates the opinion parameter of these nodes. The node with the opinion variable is planned according to the DT. But the node without witness variable is validated using the Indirect Trust (IDT) as shown below,

$$IDT_i^d(\tau) = \frac{1}{r}\sum_{i=1}^{r} D\,T_i^d(d) \tag{12}$$

Here, r indicates the overall neighbours of node i.

Recent Trust (RT) is evaluated using the DT and IDT together with the essential legitimacy and admits the sink or terminus that is shown below

$$RT_i^d(\tau) = \alpha^* DT_i^d(\tau) + (1-\alpha)^* IDT_i^d(\tau) \tag{13}$$

Whereas $\alpha = 0.3$.

$$g_1 = DT_i^d(\tau) + IDT_i^d(\tau) + RT_i^d(\tau) \tag{14}$$

Distance: It defines the distance (g_2) between the CH to BS and next-hop nodes. Because the power utilization of the node can be proportionated to the transmission path distance. Subsequently, defining the transmission path using less distance is crucial to diminish power usage. Remaining energy: The candidate CH using the highest RE (g_3) is significantly desired during CH selection. Meanwhile, the CH should implement distinct processes like data aggregation, transmission, and collection.

$$g_3 = \sum_{i=1}^{a} E_{CH_i} \tag{15}$$

From the expression, E_{CH_i} demonstrates the RE of CH.

Some hops: the typical node that belongs to the particular CH is defined using certain hops. The power consumption of CH is smaller once it contains a smaller amount of hops. Consequently, the CH having smaller hops was considered in the number of hops (g_4) and CH election was expressed as.

$$g_4 = \sum_{i=1}^{a} I_i \tag{16}$$

Now, the quantity of typical nodes for the certain CH is denoted by I_i. The abovementioned objective value was transformed into a single objective associated with the weighted sum model.

$$f = \delta_1 \times g_1 + \delta_2 \times g_2 + \delta_3 \times g_3 + \delta_4 \times g_4 \tag{17}$$

In Equation (17), the δ_1, δ_2, δ_3, and δ_4 indicate the weights allocated to all the FF values.

4. Results and Discussion

The investigational validation of the HGSO-TACS approach is evaluated under various features. Table 1 and Figure 3 follow the NOAN evaluation of the HGSO-TACS method with other models [26].

The outputs stated that the HGSO-TACS technique on 1000 rounds, the HGSO-TACS technique has attained a higher NOAN of 100 while the ETSSEP and RBETSSEP models have shown lesser NOAN of 97 and 99 correspondingly.

Table 1. NOAN evaluation of the HGSO-TACS technique with other models in different rounds

Number of Alive Nodes			
Number of Rounds	ETSSEP	RBETSSEP	HGSO-TACS
1	100	100	100
1000	97	99	100
2000	95	98	99
3000	93	97	99
4000	87	95	98
5000	84	91	97
6000	82	90	95
7000	82	86	90
8000	71	76	84
9000	58	63	72
10000	42	45	53
11000	21	23	35
12000	0	0	0

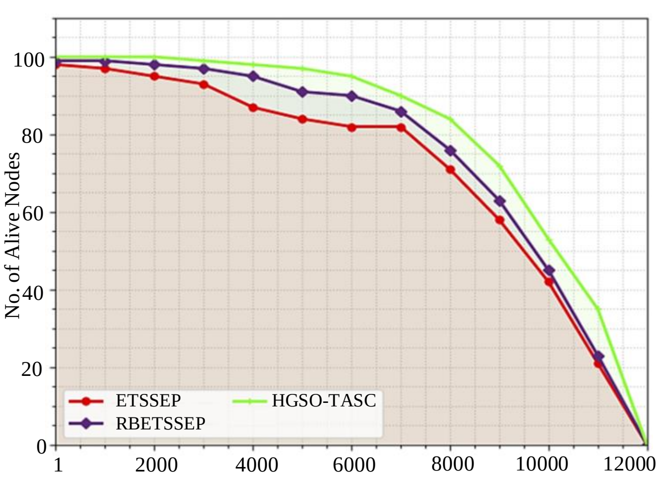

Fig. 3 NOAN evaluation of the HGSO-TACS model in different rounds

Also, on 5000 rounds, the HGSO-TACS technique achieved a higher NOAN of 97, whereas the ETSSEP and RBETSSEP techniques exhibited lower NOAN of 84 and 91 correspondingly. Additionally, on 7000 rounds, the HGSO-TACS approach has accomplished a greater NOAN of 90, while the ETSSEP and RBETSSEP approaches have shown lower NOAN of 82 and 86.

Table 2. NODN evaluation of the HGSO-TACS technique with other models in diverse distinct rounds

Number of Dead Nodes			
Number of Rounds	ETSSEP	RBETSSEP	HGSO-TACS
1	0	0	0
1000	3	1	0
2000	5	2	1
3000	7	3	1
4000	13	5	2
5000	16	9	3
6000	18	10	5
7000	18	14	10
8000	29	24	16
9000	42	37	28
10000	58	55	47
11000	79	77	65
12000	100	100	100

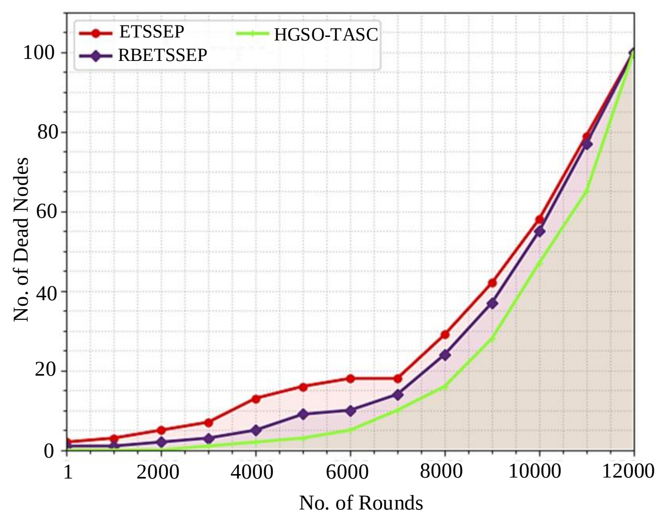

Fig. 4 NODN evaluation of the HGSO-TACS model in different rounds

A comparative NODN assessment of the HGSO-TACS method under diverse rounds is given in Table 2 and Figure 4. The outputs depicted the improvement of the HGSO-TACS method over other models. As a sample, on 1000 rounds, the HGSO-TACS model has revealed a minimum NODN of 0, whereas the ETSSEP and RBETSSEP models have correspondingly portrayed higher NOADN of 3 and 1. Moreover, on 4000 rounds, the HGSO-TACS method has revealed a minimal NODN of 2, whereas the ETSSEP and RBETSSEP techniques have depicted increased NOADN of 13 and 5 correspondingly. Furthermore, on 10000 rounds, the HGSO-TACS technique has manifested a minimal NODN of 47, whereas the ETSSEP and RBETSSEP approaches have shown increased NOADN of 58 and 55 subsequently.

Table 3. NOPSTBS evaluation of HGSO-TACS technique with other methods under distinct rounds

Number of Packets Transmitted to Base Station			
Number of Rounds	ETSSEP	RBETSSEP	HGSO-TACS
1	5429	6131	12803
1000	9116	10169	23864
2000	13856	15963	31414
3000	22108	25620	42123
4000	31940	34574	48971
5000	40017	43352	55467
6000	43879	53184	59329
7000	45108	55467	62139
8000	45284	57398	62841
9000	45284	58452	63719
10000	45284	58452	64245
11000	45284	60207	64948
12000	45635	61787	65299

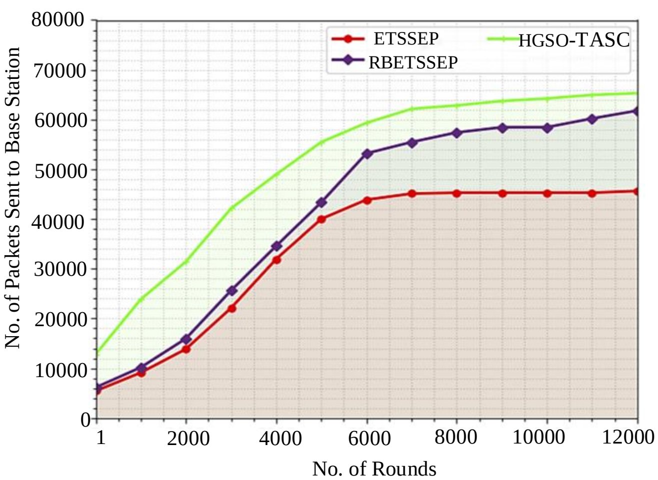

Fig. 5 NOPSTBS evaluation of the HGSO-TACS technique under distinct rounds

Table 3 and Figure 5 portray the NOPSTBS review of the HGSO-TACS approach with other techniques. The results highlighted that the HGSO-TACS approach has displayed higher NOPSTBS values. For example, on 1000 rounds, the HGSO-TACS method has reached a higher NOPSTBS of 23864, while the ETSSEP and RBETSSEP methods have exhibited lower NOPSTBS of 9116 and 10169 appropriately. Similarly, on 5000 rounds, the HGSO-TACS technique has achieved higher NOPSTBS of 55467, while the ETSSEP and RBETSSEP techniques have shown lesser NOPSTBS of 40017 and 43352 subsequently. Also, on 7000 rounds, the HGSO-TACS method achieved higher NOPSTBS of 62139, while the ETSSEP and RBETSSEP methods displayed lower NOPSTBS of 45108 and 55467 appropriately.

Table 4 offers a brief lifetime investigation of the HGSO-TACS method with current models. Figure 6 illustrates a relative FND investigation of the HGSO-TACS method with current approaches. These outputs illustrated that the ETSSEP technique has reported poor achievement with the least FND of 960 rounds. Next, the RBETSSEP technique has revealed closer outcomes with an FND of 1000 rounds. However, the HGSO-TACS model has shown its supreme lifetime with a maximum FND of 2000 rounds.

Table 4. Lifetime evaluation of the HGSO-TACS technique with recent methods

Analysis	ETSSEP	RBETSSEP	HGSO-TACS
FND (1%)	960	1000	2000
HND (50%)	8460	9730	9972
LND (100%)	11768	11892	11993

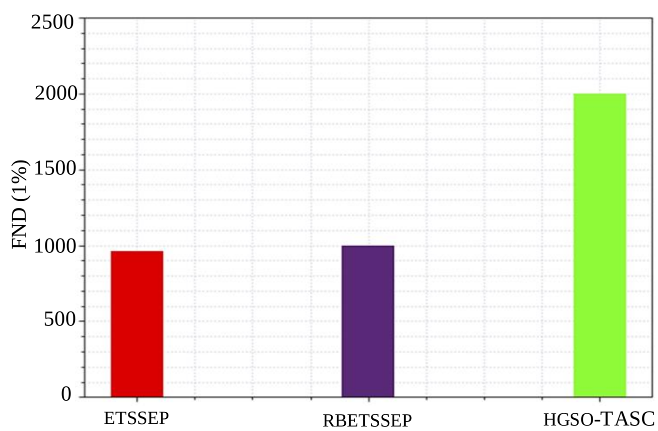

Fig. 6 FND evaluation of the HGSO-TACS technique with recent methods

Figure 7 exemplifies a short HND inspection of the HGSO-TACS technique with recent models. These results showed that the ETSSEP approach performs poorly with the least HND of 8460 rounds.

Then, the RBETSSEP method revealed closer outcomes with an HND of 9730 rounds. However, the HGSO-TACS technique has exposed its supreme lifetime with a maximal HND of 9972 rounds.

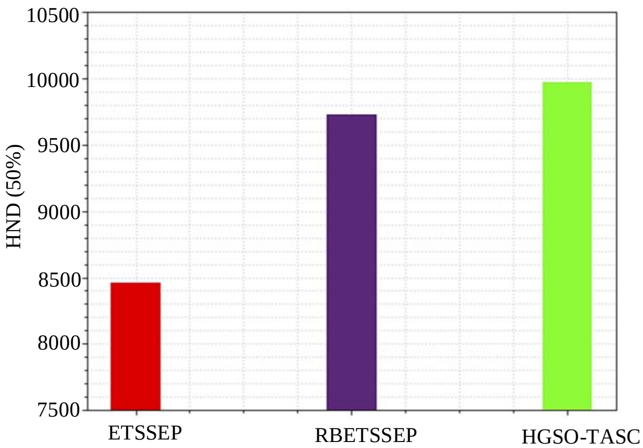

Fig. 7 HND evaluation of the HGSO-TACS technique with recent methods

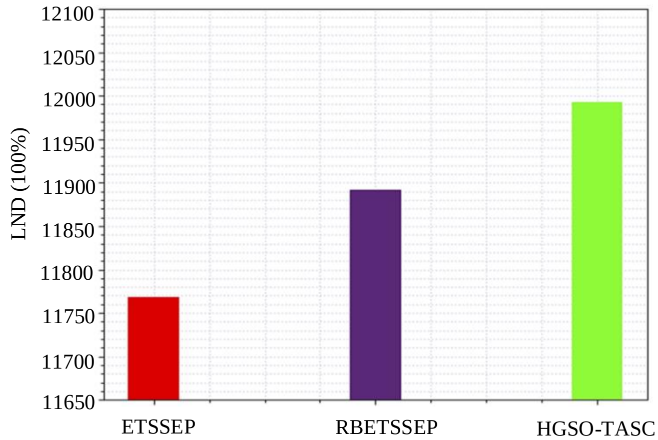

Fig. 8 LND analysis of the HGSO-TACS system with recent approaches

Figure 8 establishes the detailed LND study of the HGSO-TACS methodology with current techniques. These results emphasized that the ETSSEP approach has reported poor performance with the least LND of 11768 rounds. Consequently, the RBETSSEP method has shown closer outcomes with an LND of 11892 rounds.

However, the HGSO-TACS technique has exhibited its supreme lifetime with a maximum LND of 11993 rounds. Thus, the HGSO-TACS model can accomplish stability and energy efficiency in WSNs.

5. Conclusion

The present article proposed a new HGSO-TACS method for safe communication in the WSN. The presented HGSO-TACS method aims to accomplish secure cluster communication with trust metrics. In addition, the HGSO model is designed by integrating the GSO model with the LOBL concept. Moreover, the presented HGSO-TACS technique computes an objective function with multiple parameters in the network. The experimental validation of the HGSO-TACS technique can be carried out under various features. The relative study revealed the improvements of the HGSO-TACS methodology over other current approaches.

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