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Hybrid Grasshopper and Improved Bat Optimization Algorithms-based clustering scheme for maximizing lifetime of Wireless Sensor Networks (WSNs)

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Abstract: In wireless senor networks (WSNs), the process of handling the sensor nodes' restricted energy resources from the dimensions of data routing, collection and aggregation is highly challenging. These potential challenges of WSNs demand efficient energy stabilization in the network for prolonged lifetime that attributes towards improved rate of reliable data dissemination. The maximization of network lifetime is essential for attaining success in data delivery, energy conservation and scalability. Clustering schemes provide low overhead and efficiently allocates the resources for ultimate improvement in energy consumptions and minimize interfaces among the sensor nodes. Swarm intelligent meta-heuristic clustering schemes provide optimal solution for this non-deterministic polynomial (NP)-complete problem of clustering. In this paper, Hybrid grasshopper and improved bat optimization algorithm (HGIBOA)-based cluster head selection scheme is proposed for enhancing lifetime expectancy by sustaining energy stability in WSNs. This HGIBOA utilized variable coefficient-based Levy flight for enhancing the exploration potentialities of GOA. It inherited the local searching operation of bat algorithm for establishing the balance between exploitation and exploration. It further included a random strategy for employing it over high quality population with the objective of improving the capability of exploitation. It also included the fitness function evaluation based on residual energy, distance between cluster head and base station, and distance between cluster head and cluster member nodes. The simulation results confirmed that this proposed HGIBOA with different number of sensor nodes sustained residual energy by 18.21%, improved throughput by 21.84%, prolonged network lifetime by 17.92% and maintained stability of 16.28%, better than the benchmarked Cuckoo search and PSO-based QoS-aware multipath routing protocol (CSPSO), clustering scheme using firefly and modified ABC (FMABCCS) and integrated GWO and WOA-based clustering strategy (GWWOA) approaches used for investigation.

Keywords: Grasshopper optimization algorithm (GOA), Bat optimization algorithm (BOA), Network lifetime, Levy flight, Energy stability.

1. Introduction

From the decades, WSN includes a greater number of sensor nodes capable of organizing themselves in an ad hoc manner [1]. Every sensor node includes basic components that comprise of sensor unit, transceiver, memory, power supply and processing unit. The sensor nodes include an equivalent grade of detecting capability with a goal of detecting environment situations that comprise of sound, temperature and pressure [2]. The processing unit is substantial in handling the incoming signal for easing essential actions that aids in forwarding the radio signals [3]. The transceiver is responsible for sending and getting radio signals from sensor nodes with shared range of communication. The WSNs are mainly used in irrigation management in agriculture, industrial process observing and battlefield investigation in military applications and forest fire identification [4]. WSNs are extremely appropriate in fields wherein the probability of human risk is more. WSN is proficient in data collection from varied environments like seismic dimensions, tracking, civilian and observing applications that include indispensable activities to check the likelihood of disasters [5]. In addition, human life quality is found to be extremely enhanced with sensor nodes as they are used in several domains that are associated to smart learning, agriculture, health and smart home, disaster management, intelligent maintenance and construction [6]. Moreover, sensors are accountable for improving security and safety of life with the opinion to enhance the level of efficiency.

Nevertheless, the sensor nodes demand more quantity of energy in data processing, aggregation, and communication [7]. The sensor node that stays in idle state also loses energy. The sensor nodes perform error control, flow control, congestion control and routing based on the network size. The networks can be deployed in following ways: i) Static sink with mobile nodes ii) Mobile nodes with static sink iii) Mobile nodes with mobile sink and iv) Static nodes with static sinks. Static sink with mobile nodes class of network design is extremely enhanced for applying it to a wide number of applications [8]. Data aggregated from sensor nodes are conveyed to the sink node directly or the collaboration of sensor nodes of the network. Furthermore, each WSN includes a BS and a collection of sensor nodes that covers a huge region of detecting and communication. It is obvious that the likelihood of forwarding the collected data collected from the sensor to the sink through the technique of direct or single hop communication is found to be impossible. [9]. In this context, clustering mechanism is the process of grouping in which the specifically chosen CHs are solely accountable for transporting the aggregated data received from the sensors to the BS [10]. Clustering is vital for implementation of hierarchical network [11]. It deals with assigning additional roles to the sensor nodes present at the top level of network architecture. Clustering in WSN improves the likelihood of offering efficiency and optimized energy consumption. Clustering emphases on dropping the cost of transmission, thus preserving energy in WSNs. It aids the nodes to operate self-sufficiently such that they allow the provision of sending detected data to the BS in a specific way. It is also accountable for improving the lifespan of the network. The nodes in the cluster protocols exhibit two roles namely, members and CHs [12]. The energy consumption of the CHs increases quickly when compared to the member nodes, as they are loaded with more computational loads and accountability to convey messages to a lengthier distance. In general, most of the clustering algorithms are proposed without any pre-determined classification.

Furthermore, the aim of clustering algorithms is classified based on primary and secondary aims. The primary objectives of clustering comprise of load balancing, fault tolerance, scalability, data aggregation, scalabilityand stabilized network topology and network lifetime. The secondary objective of clustering focuses on improving connectivity, controlling control, lessening routing delay and using sleeping methods in the sensor networks [13]. In addition, the clustering schemes are categorized based on the convergence time involved in the choice of CHs. Some algorithms use the convergence time based on the node condition and network size, while the other algorithms emphases on using continuous convergence time for avoiding its dependence over the network size. In specific, the cluster head selection schemes that contribute towards effective energy management is considered as an optimization problem [14]. The process of CH choice and cluster building are the primary operations of any clustering scheme. The cluster building supports in avoiding depletion of energy sustained in WSN during direct data communication between sensor nodes and the BS. Cluster formation increases scalability and applicability of WSN in real-world applications. Likewise, selection of optimum cluster size, choice and re-selection of CHs with cluster preservation is crucial which need to be handled during the design of clustering schemes. Further, the choice of CHs and forming clusters provisioned by the clustering schemes should be capable in exploiting the usage of energy [15]. However, optimization of parameters that attribute towards efficient and effective cluster head selection process is an NP problem[16]. Meta-heuristicschemes are highly optimized for the cluster head selection process. In addition, hybrid meta-heuristic approach-that integrated GHOA and IBOA algorithm [17] is identified to be ideal and suitable for achieving predominant cluster head selection by balancing between local and global search in the clustering process.

In this paper, hybrid grasshopper and improved bat optimization algorithm (HGIBOA)-based cluster head selection scheme is proposed for enhancing lifetime expectancy by sustaining energy stability in WSNs. This HGIBOA utilized variable coefficient-based levy flight for enhancing the exploration potentialities of GOA. It inherited the local searching operation of bat algorithm for establishing the balance between exploitation and exploration. It further included a random strategy for employing it over high quality population with the objective of improving the capability of exploitation. It also included the fitness function evaluation based on residual energy, distance between cluster head and base station, and distance between cluster head and cluster member nodes. The experimental validation of the proposed HGIBOA and the benchmarked approaches is conducted using residual energy, throughput, network lifetime and packet delivery rate with respect to different number of rounds and sensor nodes.

The remaining section of the paper is structured as follows. Section 2 presents the literature review of the existing CH selection approaches with their merits and limitations. Section 3 details the complete view of the proposed HGIBOA scheme with its role in CH selection process. Section 4 demonstrates the simulation results and discussion achieved by the proposed HGIBOA scheme and the benchmarked approaches with respect to number of rounds and number of sensor nodes. Section 5 concludes the paper with major contributions and future scope of enhancement.

2. Related work

An improved ABC-based clustering algorithm was proposed by Wang et al. [18] for selecting potential heads for extending network lifetime. This improved ABC-based CH selection approach used the parameters of cluster head location, cluster head density and network cluster head energy during the clustering process. It adopted an optimal clustering method using fuzzy C-means clustering process to improved network throughput and energy efficiency during the stable transmission phase. It specifically utilized the merits of an improved ABC to facilitate energy efficient routing process between the cluster's heads and the base station. It further used the merits of improved ABC algorithm and optimized the fuzzy C-means clustering process during the network initialization period in which each nodes possesses an equal level of energy. It also inherited a polling control mechanism during intra-cluster communication to determine the idle or busy state of sensor nodes in the network during the routing process. The simulation results of this IABCCA confirmed better performance in network throughput of 21.38%, energy sustenance of 28.41%, and minimized delay of 31.18%, better to the competitive CH selection approaches. Then, gravitational search algorithm (GSA)-based clustering scheme was proposed by Lalwani et al. [19] for better optimized routing through potential CH selection process. GSACS was proposed for preventing the degree of overheads incurred by CHs in a two-tired WSN architecture, such that the process of receiving and aggregating data packets from sensor member nodes is made easy during the process of transmitting them to the base station. It was proposed with the focus to select CHs to completely target and sustain the network lifetime with maximized optimality. It used inter-cluster routing strategy to transmit data to the BS after the construction of clusters, which aided in high extension of network lifetime. It adopted a CH selection approach using an efficient encoding scheme that adopted the benefits of CH balancing factor, intra-cluster distance and residual energy during the computation of fitness function. It also optimized the parameters using distance and residual energy during the process of routing data. The results of GSACS confirmed its excellence in maintaining energy stability by 23.28%, enhanced network lifetime of 21.98% and improved network A teaching and learning optimization-based throughput of 29.21%, on par with the existing works of the literature.

Cluster head selection technique (TLO-CHST) was proposed by Yadav et al. [20] for estimating the optimal cluster head count in the field of sensor network monitoring. This TLO-CHST completely focused on the minimization of energy consumption with prolonged network lifetime expectancy. It is also combined with LEACH and termed as LEACH-T for the objective of considering residual energy as the vital parameter for cluster head selection. The simulation results of TLO-CHST confirmed its superiority in reducing packet loss rate and percentage of dead nodes in the network. An uneven dynamic clustering protocol using PSO was proposed by Ruan and Huanget al. [21] for maximizing network lifetime by handling the issue of unbalanced energy consumption introduced by the hotspot problem. It facilitated dynamic change in the distribution of clusters for preventing the failure of sensor nodes resulting in their earlier death. It adopted PSO algorithm for determining the region in which the necessitated candidate CH nodes are located. This adaptive method of clustering performed better cluster distribution and, balanced energy consumption to the required level. It determined the most suitable next-hop node during the route construction method for establishing a connecting line between the CH nodes and the BS. It was also identified to improved energy efficiency during multi-hop data transmission. It was further identified to balance energy consumption in the network with better scalability independent of their varying network sizes.

An integrated GWO and WOA-based clustering strategy (GWWOA) was proposed by Rathoreet al. [22] for attaining energy balance during the problem of hotspot with prolonged network longevity. This GWWOA approach was proposed integrated the exploitation characteristics of GWOA and exploration potentialities of WOA for increasing the effectiveness involved during the process of clustering. The capabilities of exploration and exploitation associated with GWWOA algorithm was determined to be better than the existing hybrid meta-heuristic algorithms used for CH selection process. It adopted the phases of cluster formation and cluster head selection in a more dynamic manner to prevent unnecessary energy consumptions in the network. Another clustering scheme using Firefly and Modified ABC (FMABCCS) was proposed by Sengathir et al. [23] for guaranteeing prolonged network lifetime and energy stability. This FMABCCS approach minimized delay and inter-node distance based on the characteristics of firefly optimization algorithm to dynamically generate new updated positions that are not exploited well during the scout bee phase. It facilitated the option of incorporating firefly optimization algorithm into the traditional ABC to prevent the problem of premature convergence that introduces the possibility of solution to enter the local optimal point. It specifically adopted the benefits of modified ABC to enhance the feasible dimensions through which the rate of exploration and exploitation can be better balanced in the search process. The results of FMABCCS confirmed enhanced energy stability improved network lifetime and minimized network latency on par with the baseline CH selection approaches.

A hybrid cuckoo search and PSO-based QoS-aware multipath routing protocol was proposed by Mohanadevi and Selvakumar[24] for attaining optimized network routing. This CSPSO-based routing protocol selected multiple stable paths based on the selection of optimal CHs that aided in transmitting the data through multi-hop communication. It completely relied on the routing paths that do not influence QoS unlike the existing protocols during the process of data transmission. It achieved the selection of CHs periodically using the factors of residual energy and optimal number of paths during the data transmission for the objective of ensuring extended network lifetime. Moreover, CSPSO-based clustering approach guaranteed maximized QoS factors of network lifetime, end-to-end delay, packet delivery ratio and throughput better than the competitive CH selection approaches. Hybrid sea lion optimization and PSO-based clustering protocol (HSLO-PSOCP) was proposed by Yadav and Mahapatra[25] for attaining optimized routing based on optimized selection of CHs in the network. This HSLO-PSOCP was proposed for attaining a new energy-aware CH selection framework to facilitate hierarchical routing in WSN. It carried out CH selection based on the factors of QoS, delay, distance, and energy. It explored and exploited multi-dimensional parameters that attributed towards better CH selection in the network with minimized computational complexity involved during its implementation.

The limitations of the existing works contributed to the literature are listed as follows.

i) Most of the CH selection schemes failed in balancing the trade-off between the rate of exploration and exploitation.
ii) Majority of the existing clustering approaches failed in incorporating comprehensive set of factors that prevented frequent selection of CH in the network.
iii) The conventional schemes were either better in energy stability or augmented network lifetime, but not both.

3. Proposed hybrid grasshopper and improved bat optimization algorithm (HGIBOA)-based cluster head selection scheme

In the proposed HGIBOA-based CH selection algorithm, the primitive grasshopper optimization algorithm (GROA) is utilized for attaining optimized sensor node as CHs in the network. This traditional GROA algorithm completely mimics the foraging characteristics of grasshopper. This foraging principle of grasshopper is equivalent to the searching phenomenon adopted by the search agents that perform the phases of exploration and exploitation. In general, the grasshoppers have the potentiality of exhibiting small steps movement during the larval phase, and move on a long range during their adulthood. This larval and adulthood movement of grasshopper is similar to the movements exhibited by the search agents that move in small steps during exploitation and move abruptly during the exploration process. The mathematical model that depicts the characteristic properties of GROA is presented as follows.

$$GR_{(i)} = IS_{(i)} + FG_{(i)} + A_{W(i)} \quad (1)$$

Where, $GR_{(i)}$ and $IS_{(i)}$ represents the search agents' (grasshopper) initial position and social interaction factor. Moreover, $FG_{(i)}$ and $A_{W(i)}$ indicates the factor of gravity and wind advection coefficient.

$$IS_{(i)} = \sum_{\substack{j=1 \\ j \neq i}}^{N_{SA}} s\left(d_{ij(GR)}\right) \frac{GR_{(j)} - GR_{(i)}}{d_{ij(GR)}} \quad (2)$$

Where,$d_{ij(GR)}$ represents the inter-distance between two search agents (grasshoppers) estimated based on $d_{ij(GR)} = \left\| GR_{(j)} - GR_{(i)} \right\|$. Further, the function $\left(d_{ij(GR)}\right)$ determined for the purpose of defining the social factor as expressed in Eq. (3)

$$s\left(d_{ij(GR)}\right) = A_{Int} e^{-\frac{r}{A_{LS}}} - e^{-r} \quad (3)$$

Where, A_{Int} and A_{LS} represents the attraction intensity and scale of attractive length with e^{-r}as the exponential function. These factors of $A_{Int}$and A_{LS} is identified to introduce a direct impact on the social interaction parameter. The justification that confirms the influence of $A_{Int}$and A_{LS} over social interaction factor is presented in the literature [26]. In this context, the force of gravity function ($FG_{(i)}$) is computed based on Eq. (4).

$$FG_{(i)} = -g\widehat{e_{uv}} \quad (4)$$

Where, '$\widehat{e_{uv}}$'and 'g' refers to the unity vector towards the center and constant of gravity.Moreover, the value of wind advection coefficient $A_{W(i)}$ is computed based on Eq. (5).

$$A_{W(i)} = D_{Const}\widehat{e_{UW}} \quad (5)$$

Where, $\widehat{e_{UW}}$ and D_{Const} indicates the unity vector representing the wind direction and drift constant, respectively.

At this juncture, the positions of search agent (grasshopper) are updated based on Eq. (6).

$$GR_{(i)} = \sum_{\substack{j=1 \\ j\neq i}}^{N_{SA}} s\left(d_{ij(GR)}\right) \frac{GR_{(j)}-GR_{(i)}}{d_{ij(GR)}} - g\widehat{e_{uv}} + D_{Const}\widehat{e_{UW}} \quad (6)$$

The problem of CH selection is considered as an optimization problem. Thus, the mathematical model considered for solving the process of CH selection is computed as follows.

$$GR_{(i)} = C_{IW} \sum_{\substack{j=1 \\ j\neq i}}^{N_{SA}} C_{AZC} \frac{UL_d-LT_d}{2} s\left(d_{ij(GR)}\right) \frac{GR_{(j)}-GR_{(i)}}{d_{ij(GR)}} + \widehat{OP_{Sol}} \quad (7)$$

Where, C_{IW} and C_{AZC} is computed based on Eq. (8).

$$C_{IW} = C_{Max} - Iter_{Curr} \frac{(C_{Max}-C_{Min})}{Iter_{Max}} \quad (8)$$

Where, $UL_d$and LT_drepresents the upper and low threshold in d −dimensions with '$\widehat{OP_{Sol}}$' referring to the optimal solution. Further,C_{IW} and C_{AZC} refers to the inertia weight and attraction zone controlling parameter. Furthermore, C_{Max} and C_{Min} indicates the minimum and maximum value of C_{IW} . In addition, $Iter_{Curr}$ and $Iter_{Max}$ represents the current and maximum number of iterations considered for the implementation process. The above-mentioned Eq. (7) aids in identifying the successive positions of each search agent depending on the current position, target position and the complete position of all the other search agents.

3.1 Improved bat optimization algorithm (IBOA)

In this section, the complete view of IBOA integrated into GROA is presented with the factors of levy flight and adjustment factors responsible for establishing better exploitation in the search space [27]. The position vector associated with the search agent (bat) is represented based on Eq. (9).

$$B_{Pos(i,j)} = B_{Pos(LT)} + r_{nd}\left(B_{Pos(UT)} - B_{Pos(LT)}\right), \quad 1 \leq i \leq n \text{ and } 1 \leq j \leq d \quad (9)$$

Where i and j represents the number of search agents (n) and the dimensions (d) used for searching the optimized solution in the search space. The above-mentioned position vector representing the global optimal solution is not known in priori in the search space, this IBOA algorithm initializes the search agents randomly. Moreover, $B_{Pos(UT)}$ and $B_{Pos(LT)}$indicates the lower and upper limits of the dimensions (d) with 'r_{nd}' highlighting the random number that ranges between 0 and 1.

Each search agent (bat) in the d-dimensional search space is responsible for updating the position vector ($B_{Pos(i)}^{(t)}$), velocity vector ($B_{Vel\,(i)}^{(t)}$) and its frequency ($B_{f(i)}$) depending on Eqs. (10-12).

$$B_{Pos(i)}^{(t)} = B_{Pos(i)}^{(t-1)} + B_{Vel\,(i)}^{(t)} \quad (10)$$

$$B_{Vel\,(i)}^{(t)} = B_{Vel\,(i)}^{(t-1)} + \left(B_{Pos\,(i)}^{(t)} - B_{C-Best}\right) B_{f(i)} \quad (11)$$

$$B_{f(i)} = B_{f(Min)} + \left(B_{f(Max)} - B_{f(Min)}\right)\beta_{rnd[0,1]} \quad (12)$$

Where, $\beta_{rnd[0,1]}$ represents the random number that lies between 0 and 1. Further, B_{C-Best}represents the current global best solution which is used for updating the position and velocity depending on the change of the frequency. Moreover, this IBOA facilitates the process of local search (exploitation) for updating the position based in Eq. (13).

$$B_{f(New)} = B_{f(Old)} + \epsilon[-1,1]A_{LD(i)} \quad (13)$$

Where, $\epsilon[-1,1]$ is the randomly generated constant that lies between -1 and 1. In specific, the value of $\epsilon[-1,1]$ is set to 0.001 in this proposed CH selection approach [28]. Moreover, $A_{LD(i)}$ indicates the mean loudness determined in the current iteration.

Improvement of IBOA using levy flight

In the primitive BOA algorithm, the search mechanism of levy flight is incorporated for modifying the position vector of the search agent and update the position vector depending on Eq. (14).

$$B_{Pos(i)}^{(t)} = Levy\ (d)\ B_{Pos(i)}^{(t-1)} + B_{Vel\ (i)}^{(t)} \quad (14)$$

Where, the value of $Levy\ (d)$ is computed based on Eq. (15).

$$Levy\ (d) = 0.01 \frac{r_{nd(1)}\delta}{|r_{nd(2)}|^{\frac{1}{\alpha}}} \quad (15)$$

In this context, $r_{nd(1)}$ and $r_{nd(2)}$ represents the random number that ranges between 0 and 1, respectively. Further, α indicates the constant equal to the value of 1.5. Furthermore, the value of δ is computed based on Eq. (16).

$$\delta = \left(\frac{\gamma(1+\alpha)Sin\left(\frac{\pi\alpha}{2}\right)}{\gamma\left(\frac{1+\alpha}{2}\right)\alpha 2\left(\frac{\alpha-1}{2}\right)}\right)^{\frac{1}{\alpha}} \quad (16)$$

In addition, the adoption of inertial weight levy flight plays an anchor role in introducing large steps suddenly after a series of small steps. It improves the capability of the search agent such that they introduce the ability to jump suddenly to prevent the problem of premature convergence. This process of preventing premature convergence increases the possibility of achieving maximized global searching potentiality during CH selection process.

3.2 Hybrid GOA and BOA-based CH selection process

The pseudo code of the hybrid GOA and BOA-based CH selection process is explained as follows.

Algorithm: Hybrid GOA and BOA-based CH selection process

Step *1:*Initialize the population of search agents, maximum number of iterations ($\mathrm{Iter_{Max}}$), current iteration ($\mathrm{Iter_{Curr}}$), inertia weight ($\mathrm{C_{IW}}$), attraction zone controlling ($\mathrm{C_{AZC}}$) parameter, Maximum ($\mathrm{C_{Max}}$) and minimum ($\mathrm{C_{Min}}$)value of $\mathrm{C_{IW}}$.

*Step 2:*Select the best sensor nodes through the search agent (grasshopper) from the complete set of sensor nodes depending on their estimated fitness value

*Step 3:*While ($\mathrm{Iter_{Curr}} < \mathrm{Iter_{Max}}$)

- Update the value of C_{IW} and C_{AZC} depending on the current position of search agents
- For each search agent ($GR_{(i)}$)

Use Eq. (14) for updating the variable coefficient using levy flight.

Determine the normalized distance between search agents ($\mathrm{GR_{(i)}}$) and ($\mathrm{GR_{(j)}}$).

Utilize Eq. (15) for updating the positions of current search agent ($\mathrm{GR_{(i)}}$)

Terminate the search agents out of the available boundaries.

End for

- If ($r_{nd} > r_i$)

Select the position from the complete set of existing best positions.

Use Eq. (12) for generating a local solution

If ($\mathrm{r_{nd}} < \mathrm{A_{W(i)}}$&$\mathrm{f(GR_{(i)})} < \mathrm{f(\widehat{OP_{Sol}})}$)

Update the new position of the exploited search agents

Update the value of $\mathrm{r_i}$ and $\mathrm{A_{W(i)}}$

End If

- Use the fitness values of the search agents and randomize their positions

Use Eq. (16) and generate the new position of the search agents

- If ($f(GR_{(New)}) < f(\widehat{OP_{Sol}})$)

Identify the new position as the exact location of the search agent

End If.

- $Iter_{Curr} = Iter_{Curr} + 1$

End while

Select the output $\mathrm{OP_{Sol}}$ as the location of CH sensor node with their best fitness value

In addition, Fig. 1 presents the flowchart depicting the comprehensive steps involved in the implementation of the proposed HGOBOA scheme in the network.

4. Simulation results and discussion

The proposed HGIBOA and the competitive

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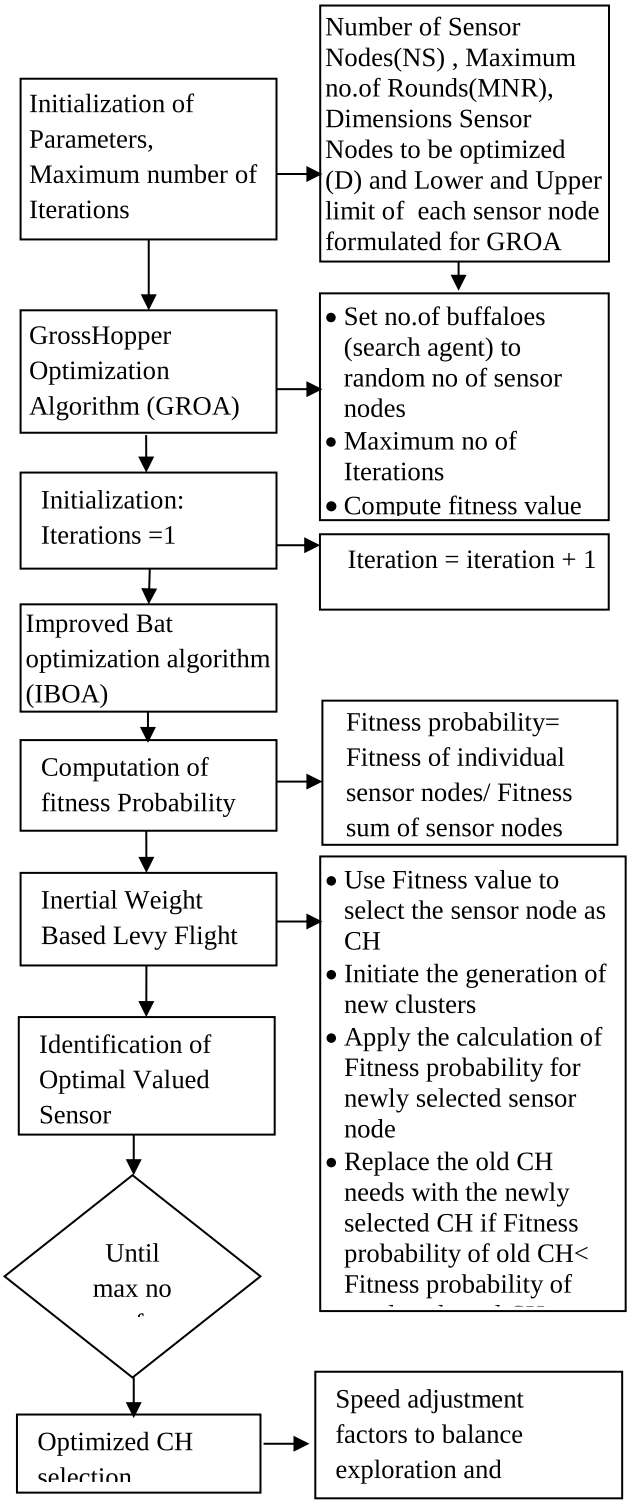

Figure.1 Flowchart of the proposed HGOBOA-based CH selection scheme

CSPSO [24], FMABCCS [23] and GWWOA [22] schemes are implemented using ns 2.35 simulator. The parameters considered for simulating the proposed HGIBOA and its benchmarked approaches is presented in Table 1. The complete simulation is carried out in homogeneous and heterogeneous

Table. 1 Simulation parameters

Simulation Parameters	Value used
Maximum number of iterations	2000
Area of Simulation	500 x 500 meters
Type of antenna	Omnidirectional
MAC type	IEEE 802.15.4
Radio propagation model	Two-ray ground refection model
Number of sensor nodes	300
Time used for simulation	500 seconds
Data rate	250 kbps
Radio frequency	2.5 GHz
Size of the data packets	128 Bytes
Nodes initial energy	3 Joules
Size of the control packets	32 Bytes
Power consumed for transmission	0.002 Joules
Power consumed for reception	0.02 Joules

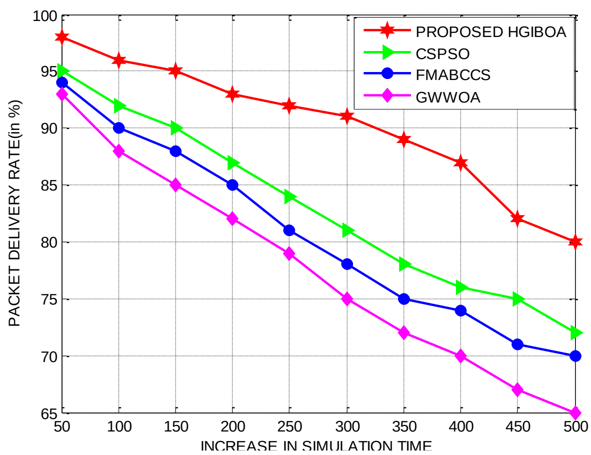

Figure. 2 Proposed HGIBOA- packet delivery rate with increasing simulation time

sensor network. In the homogeneous network scenario, the energy possessed by the sensor nodes at the start of CH selection is equal. On the other hand, the energy possessed by the sensor nodes are completely different during the initial phase of CH selection. In the simulation environment, the sensor nodes are randomly deployed on the network area of 500 x 500 meters with the number of sensor nodes varied from 50 to 250 during the process of simulation. The initial energy of sensor node is assigned to 3 Joules with the data packets' size set to 128 bytes.

Initially, the experimental investigation of the proposed HGIBOA scheme and the compared CSPSO, FMABCCS and GWWOA schemes are conducting using packet delivery rate and throughput with increasing simulation time.

From Fig. 2, It is identified that the PDR representing the ratio between the number of data

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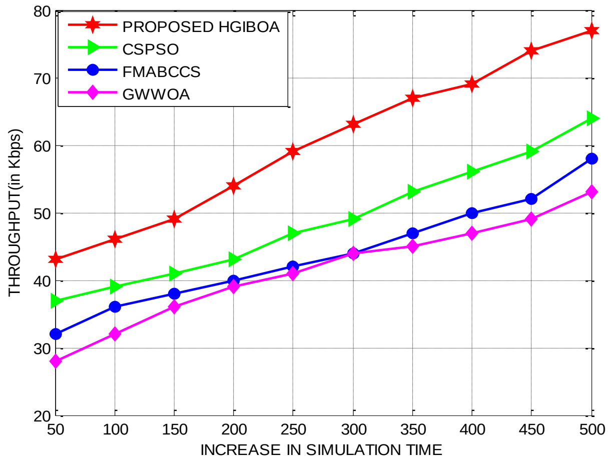

Figure. 3 Proposed HGIBOA- throughput with increasing simulation time

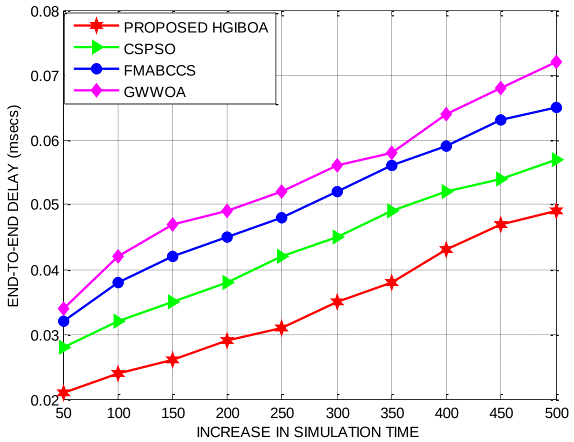

Figure. 4 Proposed HGIBOA- end-to-end delay with increasing simulation time

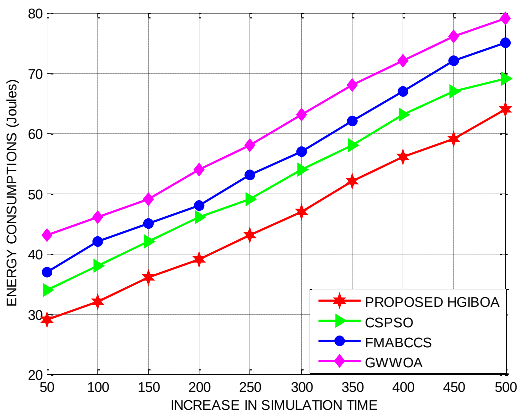

Figure. 5 Proposed HGIBOA- energy consumptions with increasing simulation time

packets delivered to the sink nodes and the number of packets sent by the source node is comparatively high during the implementation of the proposed HGIBOA protocol. This increased PDR is attained by the proposed HGIBOA is mainly due to the inertial weight levy weight factor included into IBOA for enforcing maximized degree of exploitation. It also balanced energy in the network by utilizing the fitness function that always identified potential sensor nodes as CHs during the process of data transmission. This PDR attained by the proposed HGIBOA scheme is improved by 14.21%, 17.84% and 19.32%, better than the compared CSPSO, FMABCCS and GWWOA protocols. On the other hand, Fig. 3 depicts the throughput guaranteed by the proposed HGIBOA scheme enhanced with increasing simulation time, since impotent sensor nodes are completely prevented from being selected as CH in the network. Thus, the throughput achieved by the proposed HGIBOA scheme is enhanced by 13.84%, 16.21% and 18.682%, better than the compared CSPSO, FMABCCS and GWWOA protocols.

Fig. 4 and Fig. 5 demonstrates the end-to-end delay and energy consumptions incurred by the proposed HGIBOA scheme compared to the competitive CSPSO, FMABCCS and GWWOA protocols. It is realized that that the end-to-end of the proposed HGIBOA scheme is highly minimized as they adopted some adjustment factors that evaluated the potential of sensor nodes in multiple dimensions that attribute towards better data transmission. Moreover, the energy spent by the sensor nodes is highly sustained and balanced as it dynamically handled the issue of hotspot problem that prevented the overhead in the network both in terms of communication and computation. The end-to-end delay incurred by the proposed HGIBOA scheme with increasing simulation time is perceived to be minimized by 11.98%, 13.49% and 16.52%, better than the compared CSPSO, FMABCCS and GWWOA protocols. In addition, the energy consumptions spent by the proposed HGIBOA scheme with increasing simulation time is perceived to be minimized by 11.98%, 13.49% and 16.52%, better than the compared CSPSO, FMABCCS and GWWOA protocols.

Then, Fig. 6 and Fig. 7 depicts the end-to-end delay and residual energy maintained during the implementation of the proposedHGIBOA-based CH scheme on par with the competitive techniques used for evaluation. In this context, the number of clusters formed in the network through the proposed HGIBOA scheme with increasing sensor nodes is confirmed to be minimized by 12.32%, 15.48% and 18.42%, better than the compared CSPSO, FMABCCS and GWWOA protocols. Moreover, the packet loss ratio identified under the proposed HGIBOA scheme with different sensor nodes is determined to be minimized by 11.64%, 14.86% and 17.36%, better than the compared CSPSO,

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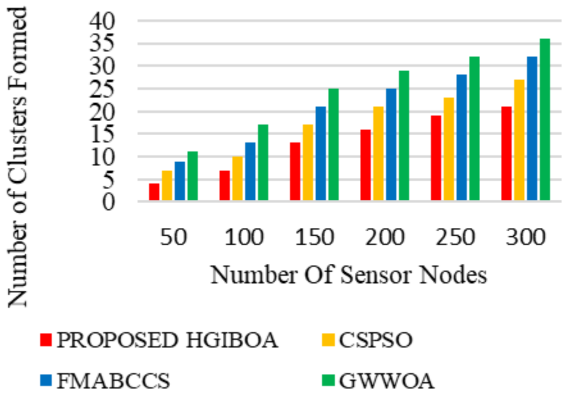

Figure. 6 Proposed HGIBOA- number of cluster formed with number of sensor nodes

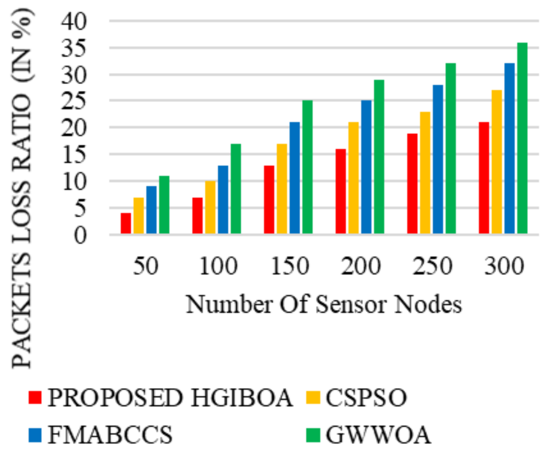

Figure. 7 Proposed HGIBOA- packet loss ratio with number of sensor nodes

FMABCCS and GWWOA protocols. This potential performance of the proposed HGIBOA-based CH scheme with respect to number of clusters formed and the packet loss rate is mainly due to the inertial weight levy flight parameters with adjustment factors considered for balanced exploration and exploitation.

5. Conclusion

The proposed HGIBOA-based CH scheme improved lifetime expectancy with maximized energy stability during the process of data routing between the CHs and the BS in the dynamically changing WSNs. It adopted a variable coefficient-based levy flight and confirmed for enhancing the exploration potentialities of GOA. It inherited the local searching operation of bat algorithm for establishing the balance between exploitation and exploration. It further included a random strategy for employing it over high quality population with the objective of improving the capability of exploitation. It also included the fitness function evaluation based on residual energy, distance between cluster head and base station, and distance between cluster head and cluster member nodes. The simulation results confirmed that this proposed HGIBOA sustained residual energy by 18.21%, improved throughput by 21.84%, prolonged network lifetime by 17.92% and maintained stability of 16.28%, better than the benchmarked approaches used for investigation. As the part of future work, hybrid symbiosis and whale optimization-based CH selection scheme is planned to be proposed and implemented.

Conflicts of interest

"The authors declare no conflict of interest."

Author contributions

Conceptualization, G. Rajeswarappa and Vasundra S; methodology, G. Rajeswarappa; software, G. Rajeswarappa; validation, G. Rajeswarappa and Vasundra S; formal analysis, G. Rajeswarappa; investigation, G. Rajeswarappa; resources, G. Rajeswarappa and Vasundra S; data curation, G. Rajeswarappa; writing—original draft preparation, G. Rajeswarappa; writing—review and editing, Vasundra S; visualization, G. Rajeswarappa; supervision, Vasundra S;

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