Microprocessors and Microsystems 91 (2022) 104528

Contents lists available at ScienceDirect

Microprocessors and Microsystems

journal homepage: www.elsevier.com/locate/micpro

Hybridization of Pigeon inspired with glowworm' swarm optimization based clustering technique in wireless sensor networks

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ARTICLE INFO

Keywords:
Clustering
Network lifetime
Pigeon inspired optimization algorithm
Glowworm swarm optimization algorithm
CH selection

ABSTRACT

In wireless sensor networks (WSN), clustering is treated as an energy efficient technique employed to achieve maximum network lifetime. But, the process of cluster head (CH) selection for stabilized network operation and prolonged network lifetime remains a challenging issue in WSN. To resolve this issue, this paper presents a new hybridization of pigeon inspired with glowworm swarm optimization (HPIGSO) algorithm based clustering technique in WSN. The proposed HPIGSO algorithm integrates the good characteristics of pigeon inspired optimization (PIO) algorithm and glowworm swarm optimization (GSO) algorithm. The proposed algorithm operates on three major stages namely initialization, CH selection and cluster construction. Once the nodes are deployed, initialization process takes place. Followed by, base station (BS) executes the HPIGSO algorithm and selects the CHs effectively. Subsequently, nearby nodes joins the CH and becomes cluster members (CMs), thereby cluster construction takes place. Finally, the CMs send the data to CHs which is then forwarded to BS via inter-cluster communication. The proficient performance of the HPIGSO method has been evaluated and the results portrayed that the HPIGSO algorithm prolonged the lifetime of WSN over the existing clustering techniques.

1. Introduction

Recently, WSN have become a predominant one which is highly efficient in real-time applications. WSN observes the atmosphere and predicts the modifications happened in target regions. Some of the physical changes in the environment are vibration, sound, pressure, humidity, intensity, temperature, and so forth. The domains of WSN is applied in diverse areas such as armed forces, habitat monitoring [1], bio-medical sector, health observation, smart home tracking as well as inventory management system [2]. As an inclusion, clustering [3] is developed which helps in dividing the geographical region into tiny sectors. The main purpose of applying clustering is to divide the load equally to all nodes as head of cluster, termed as CH. The election of CH is one of the major task which helps in better data transmission.

Practically, the cluster contains a CH with maximum number of CM. The key objective of CH is to incorporate the nodes within a cluster [4]. However, the proper CH selection [5] with best potential is essential to manage the network's energy-efficiency. Thus, the meta-heuristic approaches as well as Computational intelligence (CI) methods like artificial bee colony (ABC), artificial immune systems (AIS), reinforcement learning (RL), and evolutionary algorithms (EA) have been applied to proceed the clustering task and to resolve NP-hard optimization problem. Transmitting data to a BS or sink from sensor node via optimal CH [6] is a complicated operation. The optimal CH selection process results in minimum power consumption, latency, distance etc. When compared with all other methods, optimal CH election process in WSN remains a challenging issue.

Various studies have been developed to determine optimal CH selection process in WSN [23–25]. Mehra et al. [7] presented a Fuzzy-Based balanced cost CH Selection method (FBECS) which has been constrained with residual energy (RE), distance and node density are considered to be the input for Fuzzy Inference System (FIS). For the selection of optimal CH, the Eligibility index has been determined for each node. Priyadarshini and Sivakumar [8] applied a load balancing by triggering the Adelson-Velskii and Landis (AVL) tree rotation clustering approaches. The developers have divided unique area network into massive clusters by novel and improved K-means clustering method. Mann and Singh [9] projected an improved ABC with optimal solution search function for improvising system efficiency. Furthermore, a population sampling algorithm has been employed for a student's

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https://doi.org/10.1016/j.micpro.2022.104528

Available online 9 April 2022

distribution. It is mainly used for enhancing the global convergence of deployed meta-heuristic approach. Elhabyan et al. [10] established a Pareto optimization-relied method for handling the problems involved in finding best network configuration. In order to estimate the efficiency, the proposed technique has assumed few metrics such as number of CH, number the clustered node, link supremacy over CMs.

A fractional ABC dependent based multi-objective CH selection (FABCMOCHS) approach has been presented as energy effective clustering model to expand the sensor nodes' duration with improved network power [11]. FABC-MOCHS is mainly utilized for the managing the convergence present in ABC by adding fitness function (FF) along with latency, travelling distance and power application to reduce the problem. Followed by, combination of ACO and ABC model-based clustering scheme (ACO-ABCA-CS) was presented for effective CH election under the mutual prevention of limitations [12]. The problem of stagnation in ACO and delayed convergence of ABC can be solved by mutual modification in exploitation and exploration phases. A dynamic scour bee-based CS (DSB-CS) has been projected for increasing the scout bee and maintain the count of active nodes as well as CH power in a system [13]. It is highly applicable due to the advantages of ABC and FABC for increasing the duration of a network and power by using best CH election approach. The concatenated Simulated Annealing as well as differential evolution-based CH selection (SADE-CHS) model has been established to enhance the power effectiveness by using clustering [14]. The SADE-CHS is mainly used for eliminating the overload of sensor nodes which is related with CH, as it is a major reason for immediate death of sensor nodes that leads to improper CH election process. It highly focuses on the network extension by removing the possibility of premature death of CH.

A combined PSO as well as HSA-based CH selection approach has been applied to retain the energy balance as well as network duration [15]. PSO-HSA-CHS method was presented by integrating the dynamic ability of PSO and higher exploring potential of HSA meta-heuristic approach for selecting the best CH in a system.

A hybrid PSO and Tabu search (TS)-relied CH selection (PSO-TS-CHS) technology has been projected to increase the network lifetime with equal network energy efficiency [16]. PSO-TS-CHS model is highly important in best path election by routing the objective of maximizing network duration. It has been due to the advantages of TS which solve the problems of poor local optimal issue that is typical in PSO-based CH election modules. A synchronous firefly algorithm-based CH selection (SFA-CHS) approach was presented under the application of merits of changed heuristics for improving the network function by power applications [17]. An ABC-based CH selection (ABC-CHS) scheme has been deployed for energy optimization in a system and enhances the network lifespan [18]. The ABC-CHS approach has used a FF with distance from BS, intra-cluster distance as well as RE. The FF applied in ABC-CHS has highly concentrated on parameters optimization which has played a significant role in best CH election process.

A grey wolf optimization algorithm-based CH selection (GWOACHS) method has been employed to maximize the network lifetime along with energy efficiency [19]. The GWOA-CHS approach applied FF to offer higher coverage and induced as input to optimization method which facilitates best performance. Additionally, a firefly cyclic GWO-based CH selection (FCGWO-CHS) scheme has been developed for clustering hat optimizes power stability, delay reduction as well as distance limitation over sensor nodes [20]. FCGWO-CHS approach has eliminated the worst exploitation value of GWOA and poor global exploration of FF using mutual enhancement and extend the system' lifespan.

To maximize the network lifetime, this paper presents a new HPIGSO algorithm based clustering technique in WSN. The proposed HPIGSO algorithm incorporates the benefits of two PIO algorithm and GSO algorithm. The proposed algorithm operates on three major stages namely initialization, CH selection and cluster construction. The proposed HPIGSO algorithm involves an objective function using residual energy, distance and energy. The proposed method has the ability to select the CHs in an optimal way; thereby network lifetime can be maximized. The proficient performance of the HPIGSO algorithm has been evaluated and the results portrayed that the HPIGSO algorithm prolonged the lifetime of WSN over the existing clustering techniques.

The upcoming parts of the study are formulated as given below. Section 2 discusses the HPIGSO algorithm and Section 3 discusses the experimental validation. Finally, Section 4 draws the conclusion.

2. The proposed HPIGSO algorithm

Fig. 1 depicts the workflow of the presented HPIGSO algorithm. When the nodes are developed in the region which has to be sensed, BS telecasts a beacon signal to complete system. A node receives the beacon signal and measures the approximate distance to sink relied on RSSI. Then, sensor nodes telecast a handshaking message inside the transmission range to collect data regarding the neighbors. The handshaking message like node ID, link supremacy, residual power level, and the distance to sink. For example, if a neighboring node j gains a handshaking message from node i, it saves the obtained information and responses the corresponding data to node i. Then, node i upgrades the Node Degree (ND) by one and measures the distance to the neighboring node j under the application of node j's distance to sink and saves the data of node j. Likewise, node i receives data from neighboring nodes, then ND and distance to neighbors are measured. Under the application of this strategy, a node collects data regarding neighbors and upgrades the data and clustering process is simulated. Once the nodes are deployed, initialization process takes place. Followed by, BS executes the HPIGSO algorithm and selects the CHs effectively. Subsequently, nearby nodes join the CH and becomes CMs, thereby cluster construction takes place. Finally, the CMs send the data to CHs which is then forwarded to BS via intercluster communication. The intercluster communication finds helpful to achieve energy efficiency by transmitting the data to BS via multiple hops.

The presented approach exploits an objective function using residual energy, distance and delay for CH selection. Based on the objective method of CH election, distance among nodes and decided CHs as well as delay to forward the data among nodes which has to be minimum. Hence, the RE in a system has to be maximum where it has to consume minimum power at the time of data transmission. Followed by, an objective function of newly developed cluster election is provided in Eq. (1), in which β measure has to be within $0<\beta<1$ and f_a and f_b represent the functions as given in Eqs. (2) and (3). The constraint parameters are relied on distance, power as well as latency as σ_1, σ_2 and σ_3. The principle of these variables is obtained as $\sigma_1+\sigma_2+\sigma_3=1$. In Eq. (3), X^x-B_s signifies the distance from normal node and sink, f_a implies the cumulative FF which integrates the distance, power and latency, f_b showcases the FF which shows the relevance from non-CH and BS.

$$F_n=\beta f_b+(1-\beta)f_a \tag{1}$$

$$f_a=\sigma_1^* f_i^{dis}+\sigma_{2^*}f_i^{ene}+\sigma_{3^*}f_i^{del} \tag{2}$$

$$f_b=\frac{1}{n}\sum_{x=1}^{n}\parallel X^x-B_s\parallel \tag{3}$$

Eq. (4) implicates the FF for distance, where $f_{(a)}^{dis}$ has been related with data transmission from normal node to CH and again from CH to BS. The score of f_i^{dis} has to be within $[0,1]$. The score of f_i^{dis} is gradually increased, if the distance from normal node and CH becomes maximum.

$$f_i^{dis}=\frac{f_{(a)}^{dis}}{f_{(b)}^{dis}} \tag{4}$$

$$f_{(a)}^{dis}=\sum_{x=1}^{N_x}\left[\parallel C_x-B_s\parallel+\sum_{y=1}^{N_y}\parallel C_x-X_x\parallel\right] \tag{5}$$

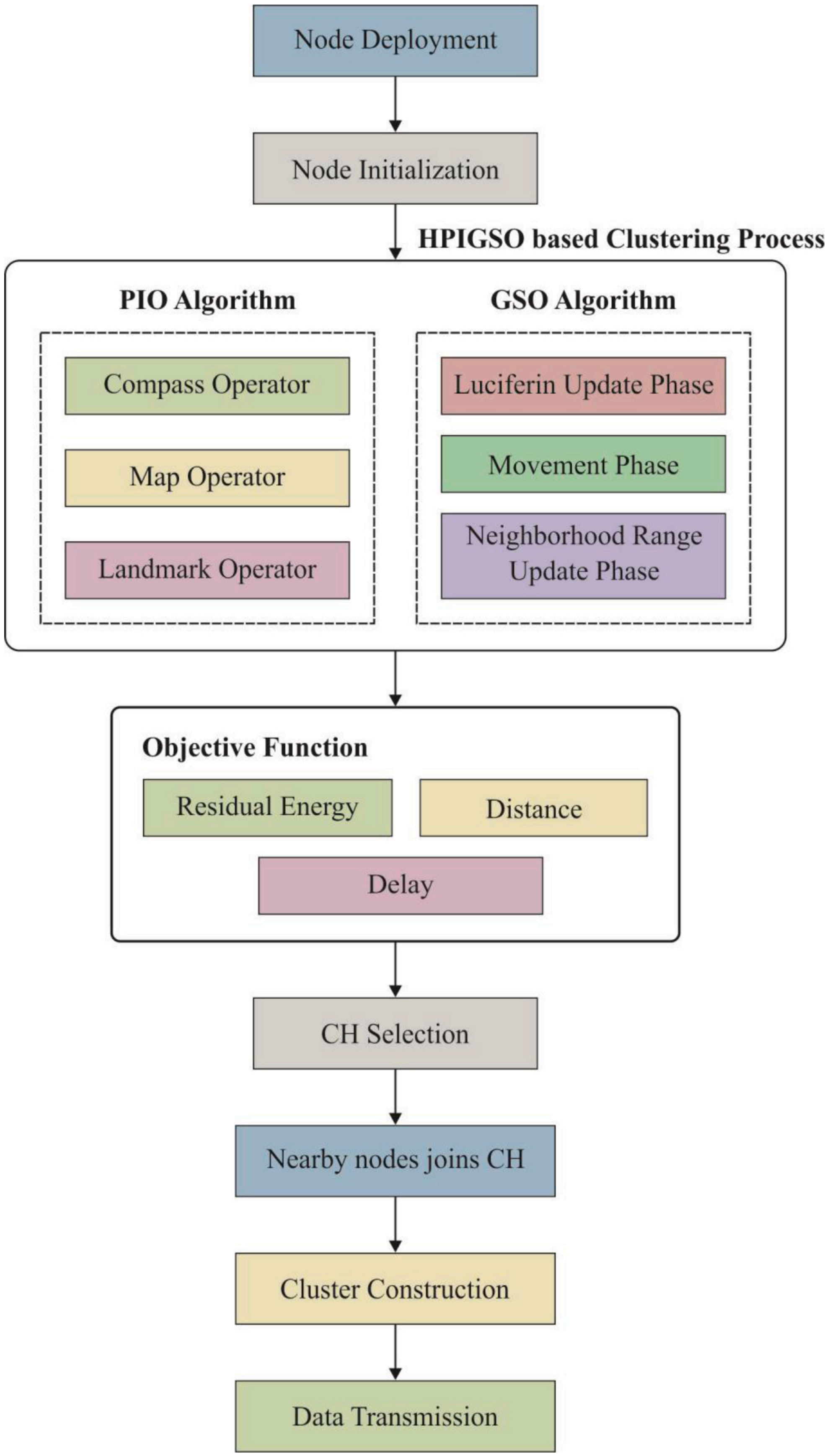

Fig. 1. Block diagram of HPIGSO algorithm.

$$f_{(b)}^{dis} = \sum_{x=1}^{N_x} \sum_{y=1}^{N_y} \| X_x - X_y \| \tag{6}$$

The formulation of $f_{(a)}^{dis}$ and $f_{(b)}^{dis}$ is depicted in Eqs. (5) and (6), where C^x is CH of x-th cluster, X_x demonstrates the normal node which comes under x-th cluster, $C_x - B_s$ denotes the distance from CH and BS, $C_x - X_x$ signifies the distance between CH and normal node as well as $X_x - X_y$ refers the distance among 2 normal nodes N_x and N_y represents the number of nodes which does not comes under the x-th and y-th cluster.

The FF of power is expressed in Eq. (7). The measure of f_i^{ene} becomes high when compared while the whole CH cumulative $f_{(a)}^{ene}$ and $f_{(b)}^{ene}$ considers power to be higher and CH's value should be higher.

$$f_i^{ene} = \frac{f_{(a)}^{ene}}{f_{(b)}^{ene}} \tag{7}$$

Eq. (8) illustrates the FF of delay that is directly proportional to overall number of nodes which comes under a cluster. Hence, delay is lower if cluster is composed of enough count of nodes. In Eq. (8), the higher number of clusters is consumed for limiting the delay. The denominator N_N shows overall value of nodes.

$$f_i^{del} = \frac{\max\left(\| C_x - X_x \| \right)_{x=1}^{N_c}}{N_N} \tag{8}$$

The value of f_i^{del} must be within the range $[0, 1]$.

2.1. PIO algorithm

The PIO algorithm is a newly developed swarm based optimization algorithm which is stimulated from the homing characteristics of pigeons. A pigeon is a familiar bird commonly employed for message passing by Egyptians, also by military forces. For idealizing the homing features of pigeons, 2 operators were developed by utilizing few principles:

1) Map and compass operator: the pigeons predict the earth using magneto reception to design the map mentally. It considers the altitude of the sun as range to alter the way.
2) Landmark operator: If the pigeons fly near to a target, it relies on landmarks. When it is well-known with the landmarks, then it flies to the target. When it is distant from the target and unknown to the landmarks, it is following the pigeons that are well-known through the landmarks.

2.1.1. Map and compass operator

It determines the position X_u and velocity V_u of pigeon u in a D-dimension search space which are updated for all iterations. A novel position X_u and velocity V_u of pigeon u at the z-th iteration is computed with the subsequent equations [21]:

$$V_u(z) = V_u(z-1) \cdot e^{-Rz} + rand \cdot \left(X_g - X_u(z-1) \right) \tag{9}$$

$$X_u(z) = X_u(z-1) + V_u(z) \tag{10}$$

where R implies map and extent factor, *rand* is an arbitrary number, and X_g is the present global optimal position, and that is attained by relating every the positions between each pigeon.

While an optimal position of each pigeon is assurance by utilizing map and compass. With relating each domain positions, it can be apparent which the right-centered pigeon's location is optimized. All the pigeons alter the flying direction by subsequent and particular pigeon based on Eq. (9) that is illustrated by dark arrows. A thin arrow refers the former flying way that has relative to $V_u(z-1) \cdot e^{-Rz}$ in Eq. (9). A vector value of these 2 arrows is its subsequently flying way.

2.1.2. Landmark operator

Here, maximum pigeons are reduced by N_p in all generations. But, the pigeons are until distant from the target, and it is different through the landmarks. Assume $X_c(z)$ be the center of any pigeon's position at the z-th iteration, and assume all pigeons are flying directly to the target. A position updating rule to pigeon u at the z-th iteration is provided by:

$$N_P(z) = \frac{N_P(z-1)}{2} \tag{11}$$

$$X_c(z) = \frac{\sum X_u(z) \cdot fitness(X_u(z))}{N_P \sum^f itness(X_u(z))} \tag{12}$$

$$X_u(z) = X_u(z-1) + rand \cdot (X_c(z) - X_u(z-1)) \tag{13}$$

where *fitness* () is the efficiency of a pigeon. Followed by, it selects $f\imath tness(X_u(z)) = \frac{1}{f\nu(X_u(z)) + \varepsilon}$. To maximum optimization problems, it is select $itness\ (X_u(z)) = f_{mx}(X_u(z))$. To all individuals pigeon, a better position of the Nc-th iteration is indicated with X_p, and $X_p = \min\ (X_{u1}, X_{u2}, \ldots, X_{uNc})$. The center of each pigeon is their aim in all iterations. The half of each pigeon which are distant from their target is following the pigeons which are near to their target that also implies that 2 pigeons can be at the similar position. A pigeons that are near to their target (a pigeons in encircle) would fly to the required place with sufficient speed.

2.2. Conventional GSO algorithm

The GSO algorithm is an efficient swarm based optimization algorithm, which is based on the the flashing nature of glowworms. Here, a swarm of glowworms are organized in a random manner on the solution space. A brighter individual implies an optimal position. Utilizing a probabilistic method, all agents are inspired by a neighbor with better luciferin intensity in local-decision filed. A density of a glowworm's neighbors influences its decision radius and defines the size of its local-decision filed: if the neighbor-density is minimum, a local-decision filed is extended; else, it may be limited to enable the swarms to divide into lesser groups. The above procedure is followed till reaching the termination criteria. Currently, maximum individuals collect brighter glowworms. Followed by, the GSO contains 5 important stages: luciferin-update stage, neighborhood-select stage, moving probability-computer stage, movement stage, and decision radius update stage [22].

2.2.1. Luciferin-update stage

A luciferin update is based on the FF of preceding luciferin value, and regulation is provided by

$$l_u(z+1) = (1-\rho) l_u(z) + \gamma\ Fitness\ (x_u(z+1))\ . \tag{14}$$

where, $l_u(z)$ indicates the luciferin measure of glowworm u at time z,ρ represents the luciferin decompose constant,

γ implies the luciferin improvement constant,

$x_u(z+1) \in R^M$ is the position of glowworm u at time $z+1$, and

Fitness $(x_u(z+1))$ signifies the value of the fitness at glowworm u's position location at time $z+1$.

2.2.2. Neighborhood-select phase

The neighbors $N_u(z)$ of glowworm u at z time have the brighter ones and are expressed as

$$N_u(z) = \left\{ v\ : d_{uv}(z) < r_d^u(z); l_u(z) < l_v(z) \right\}. \tag{15}$$

where, $d_{uv}(z)$ signifies the Euclidean distance among glowworms u and v at time z, and $r_d^u(z)$ signifies a decision radius of glowworms u at time z.

2.2.3. Moving probability-computer phase

The glowworm utilizes a possibility rule in order to send other glowworms containing superior luciferin level. A possibility $P_{uv}(z)$ of glowworm u move towards the neighbor v is expressed by:

$$P_{uv}(z) = \frac{l_v(z) - l_u(z)}{\sum_{k \in N_u(z)} l_k(z) - l_u(z)}. \tag{16}$$

2.2.4. Movement phase

Assume glowworm u chooses glowworm $v \in N_u(z)$ with $P_{uv}(z)$; the discrete-time method of glowworm u is offered by (17)

$$x_u(z+1) = x_u(z) + s\left(\frac{x_v(z) - x_u(z)}{x_v(z) - x_u(z)}\right). \tag{17}$$

where, $\| \cdot \|$ signifies the Euclidean norm operator, and s is the step-size.

2.2.5. Decision radius update phase

During all updates, the decision radius of glowworm u is provided as following:

$$r_d^u(z+1) = \min\left\{r_s,\ \max\left\{0,\ r_d^u(z) + \beta(n_z - |N_u(z)|)\right\}\right\}. \tag{18}$$

where, β shows a constant, r_s indicates the sensory radius of glowworm u, as well as n_z refers an attribute for balancing the adjacent value.

2.3. Hybridization of PIO and GSO algorithms

This section discusses the HPIGSO algorithm, which integrates PIO and GSO algorithms. Actually, the GSO algorithm has the ability to deal with non-linear, multimodal issues. But it gets stuck to solve high dimensional problems and fails to convergence faster. At the same time, the PIO algorithm has the ability of faster convergence.

At this point, the validation of the objective function is carried out initially and the evaluated fitness gets sorted. Then, find the optimal five fitness values and chose an index. If it is higher than five, execute the PIO algorithm update, otherwise execute the GSO update. Through the hybridization, the multi-objective CHs election leads to minimum delay, and maximum energy saving. Besides, the negative searching ability is discarded by the HPIGSO technique, whereas the enhanced searching capability can be used for faster convergence. Therefore, the HPIGSO algorithm has achieved better CH selection process. The processes involved in HPIGSO method is illustrated in Fig. 2.

3. Performance validation

This section investigates the experimental outcome of the HPIGSO technique under different dimensions. The presented HPIGSO technique has been simulated using MATLAB. Moreover, a set of measures applied to examine the results are network lifetime, network stability, count of active nodes as well as number of inactive nodes. The parameter settings involved in the experimentation are given in Table 1.

3.1. Alive nodes analysis of HPIGSO technique on varying node count

Fig. 3 portrays the results analysis of HPIGSO technique in terms of count of alive nodes under the node count of 100. The figure exhibited that the FFOA model has resulted to a least number of alive nodes over the compared methods. In line with that, the GOA and ALO algorithms have led to certainly higher and closer number of alive nodes. On continuing with, PIOA-DS algorithm has started to show moderate network lifetime with somewhat supreme number of alive nodes. Simultaneously, the QOGSO algorithm has tried to exhibit near optimal results with the higher count of alive nodes. At last, the proposed HPIGSO technique has shown better outcome by attaining high alive nodes. For example, with the execution round of 1000, the HPIGSO technique has attained higher count of 51 alive nodes whereas the lowest of 42, 32, 16, 12 and 4 alive nodes are attained by QOGSO, PIOA-DS, ALO, GOA and FFOA algorithms. Likewise, with the execution round of 2000,the HPIGSO model has displayed a massive number of 18 alive nodes whereas the minimum of 14, 11, 6, 4 and 0 alive nodes are attained by QOGSO, PIOA-DS, ALO, GOA and FFOA algorithms.

Fig. 4 depicts the results analysis of HPIGSO model with respect to count of alive nodes under the node count of 300. The figure implied that the FFOA method produced lower number of alive nodes than other technologies. Similarly, the GOA and ALO methodologies resulted in better and identical count of alive nodes. In line with this, PIOA-DS technology has invoked to demonstrate gradual network duration with considerable maximum count of active nodes. At the same time, the QOGSO technology has attempted to showcase closer nearer outcomes with maximum living nodes. Finally, the presented HPIGSO approach has depicted reasonable outcome by reaching numerous count of alive nodes. For instance, with the implementation round of 1000, the HPIGSO methodology has accomplished maximum count of 129 active nodes while the minimum 113, 168, 81, 40 and 8 active nodes are reached by QOGSO, PIOA-DS, ALO, GOA and FFOA models. Similarly, using the execution round of 2000, the HPIGSO approach has depicted maximum of 25 alive nodes whereas while the lower of 22, 18, 0, 0 and 0 active nodes are achieved by QOGSO, PIOA-DS, ALO, GOA and FFOA methods.

Fig. 5 displays the results analysis of HPIGSO model by means of count of active nodes under the node count of 500. The figure showcased that the FFOA approach has shown a minimum number of alive nodes than the earlier technologies. Likewise, the GOA and ALO methodologies resulted to maximum and identical count of alive nodes. Similarly, PIOA-DS model has initialized to demonstrated manageable network lifetime with better count of living nodes. At the same time, the QOGSO approach has attempted to show closer and best results with the higher number of alive nodes. Eventually, the presented HPIGSO approach has showcased moderate results by reaching more number of alive nodes. For instance, with the execution round of 1000, the HPIGSO model has reached enormous count of 224 alive nodes while the least of 191, 168, 81, 40 and 8 alive nodes are reached by QOGSO, PIOA-DS, ALO, GOA and FFOA methodologies. In line with this, with the execution round of 2000, the HPIGSO model has displayed showcased maximum count of 73 alive nodes and lower of 57, 12, 0, 0 and 0 alive nodes are reached by QOGSO, PIOA-DS, ALO, GOA and FFOA approaches.

3.2. Dead nodes analysis of HPIGSO technique on varying node count

Fig. 6 demonstrates the results analysis of HPIGSO approach by means of number of inactive nodes under the node value of 100. The figure illustrated that the FFOA technique has provided a reasonable number of dead nodes than the previous modules. On continuing this, the GOA and ALO models have resulted in least and closer number of dead nodes. Similarly, PIOA-DS algorithm has initialized to showcase better network lifetime with normal lower number of inactive nodes. Meanwhile, the QOGSO approach has attempted to show near best results with minimum number of dead nodes. Finally, the projected HPIGSO approach has exhibited moderate outcome by accomplishing lower count of dead nodes. For sample, with the execution round of 1000, the HPIGSO model has achieved minimum number of 49 dead nodes while the maximum of 58, 68, 84, 88 and 96 dead nodes are reached by QOGSO, PIOA-DS, ALO, GOA and FFOA methodologies. In line with this, with the execution round of 2000, the HPIGSO scheme has depicted a lower number of 82 dead nodes and the maximum of 86, 89, 94, 96 and 100 dead nodes are achieved by QOGSO, PIOA-DS, ALO, GOA and FFOA algorithms.

Fig. 7 displays the results analysis of HPIGSO method by means of count of dead nodes under the node count of 300. The figure illustrated that the FFOA approach has led to a higher number of dead nodes over the earlier approaches. On continuing this, the GOA and ALO methodologies have resulted in minimal and identical count of dead nodes. In line with this, PIOA-DS framework has initiated to demonstrate gradual network lifetime with considerable number of dead nodes. At the same time, the QOGSO method has attempted to show closer optimal results

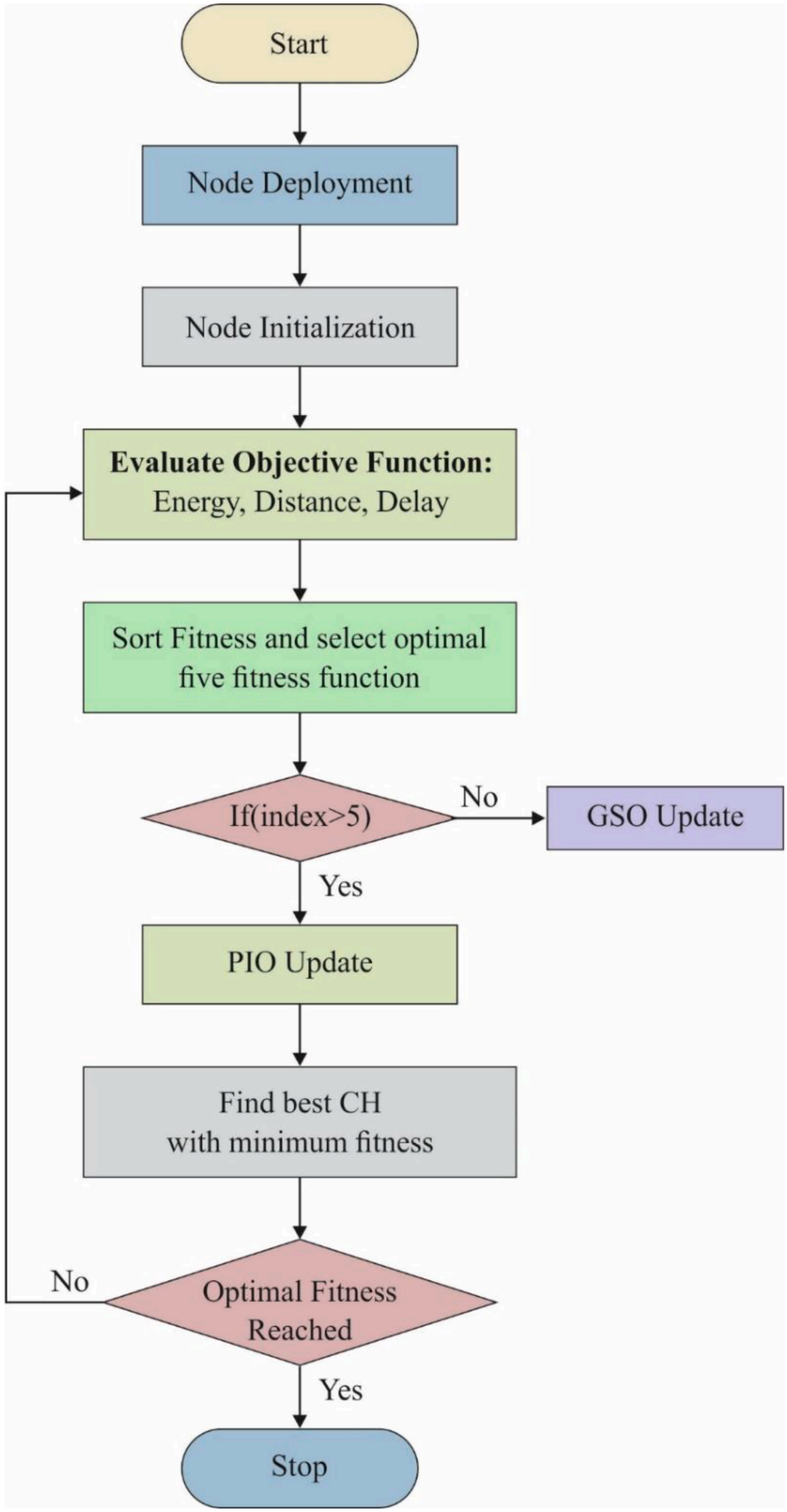

Fig. 2. Flowchart of HPIGSO algorithm.

Table 1
Parameter settings.

Parameters	Values
Network Size	100×100 m^2, 500×500 m^2
No. of Nodes (N)	100, 300, 500
No. of BS	1
Initial energy (E_0)	0.5
Energy fraction of intermediate nodes (ϕ) and advanced nodes (ω)	1, 2
No. of intermediate nodes (m) and advanced nodes fraction (m_0)	$M = 0.1$, $m_0 = 0.2$
Energy need to transmit and receive E_{elec}	50 nJ/bit
Threshold distance (d_0)	80 m
Amplification power required smaller distance $d \leq d_0$ (E_{efs})	10 pJ/bit/m^2
Amplification power required smaller distance $d \leq d_0$ (E_{mp})	0.0013 pJ/bit/m^4
Energy utilization incurred while data aggregation (E_{da})	5 nJ/bit/signal
Data packet Size	2000 bits
Population size (P)	100
Selection Method	Rank Selection Method
No. of generation	30
No. of runs	20

with lower number of dead nodes. Consequently, the presented HPIGSO approach has showcased good outcome by obtaining lower count of dead nodes. For sample, with the execution round of 1000, the HPIGSO model has reached minimum count of 171 dead nodes while the maximum of 171, 187, 132, 219, 260 and 292 dead nodes are reached by QOGSO, PIOA-DS, ALO, GOA and FFOA models. Similarly, with the execution round of 2000, the HPIGSO scheme has depicted lower number of 275 dead nodes and the highest of 275, 278, 282, 300, 300 and 300 dead nodes is accomplished by QOGSO, PIOA-DS, ALO, GOA and FFOA algorithms.

Fig. 8 demonstrates the results analysis of HPIGSO scheme with respect to count of dead nodes under the node count of 500. The figure implemented that the FFOA technology has provided to a higher count of dead nodes than the traditional models. Likewise, the GOA and ALO methodologies resulted in minimum and closer number of dead nodes. Similarly, PIOA-DS technology has invoked to showcases better network duration with moderate count of dead nodes. At the same time, the QOGSO technology has attempted to depict closer and nearby results with lower count of dead nodes. Finally, the newly developed HPIGSO model has illustrated gradual result by showcasing lower count of dead nodes. For illustration, with the execution round of 1000, the HPIGSO model has reached minimum number of 280 dead nodes while the maximum of 309, 332, 419, 460, and 492 dead nodes are reached by QOGSO, PIOA-DS, ALO, GOA and FFOA models. Along with that, with the execution round of 2000, the HPIGSO scheme has exhibited minimum number of 427 dead nodes while the maximum of 443, 488, 500, 500 and 500 dead nodes are achieved by QOGSO, PIOA-DS, ALO, GOA and FFOA methodologies.

3.3. *Network lifetime analysis of HPIGSO algorithm on varying node count*

Table 2 showcased the competing analysis of the HPIGSO method with respect to stability duration, HND and network lifespan. The figure illustrated that the HPIGSO model has achieved good network stability than the related technologies. Followed by, the HPIGSO technology has delayed the HND to a higher extent than previous models. Here, the HPIGSO scheme has demonstrated a maximum network lifetime. By seeking into the reached results, it is assured that the HPIGSO model has accomplished supreme function than alternate models.

The above-mentioned figures indicated that the HPIGSO algorithm has achieved maximum network lifetime denoting the network stability, and stability period.

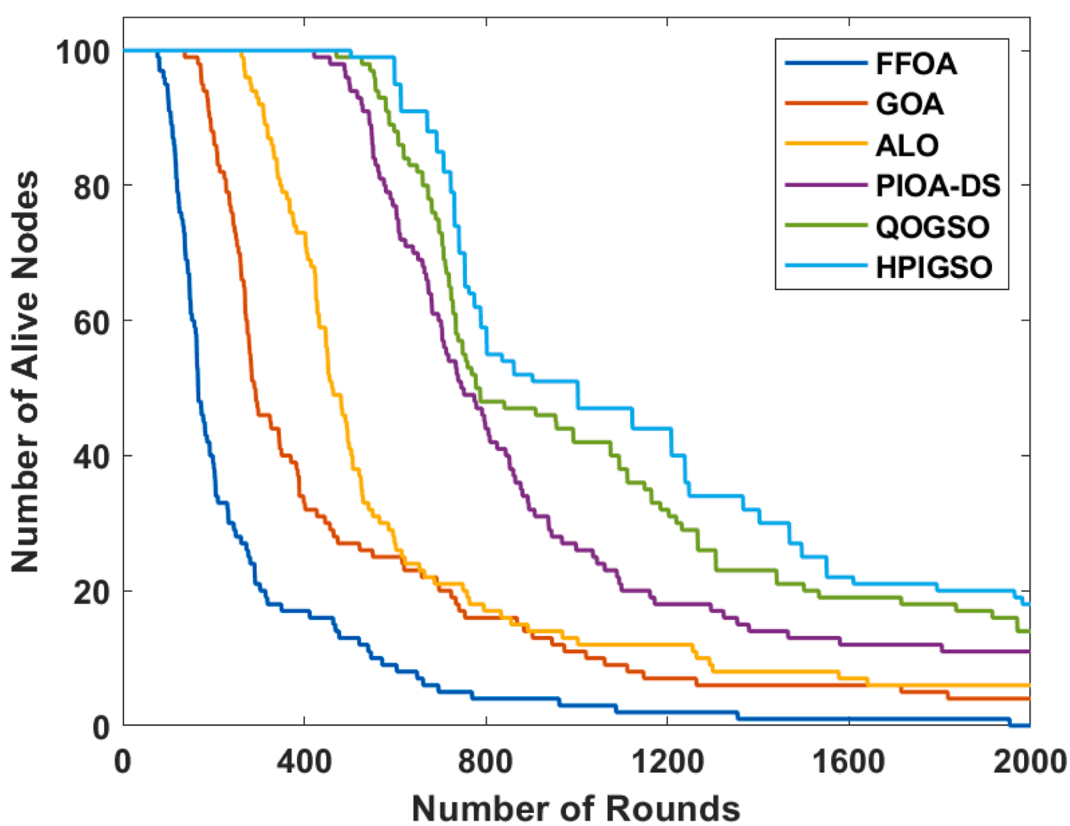

Fig. 3. Alive node analysis of HPIGSO technique under 100 nodes.

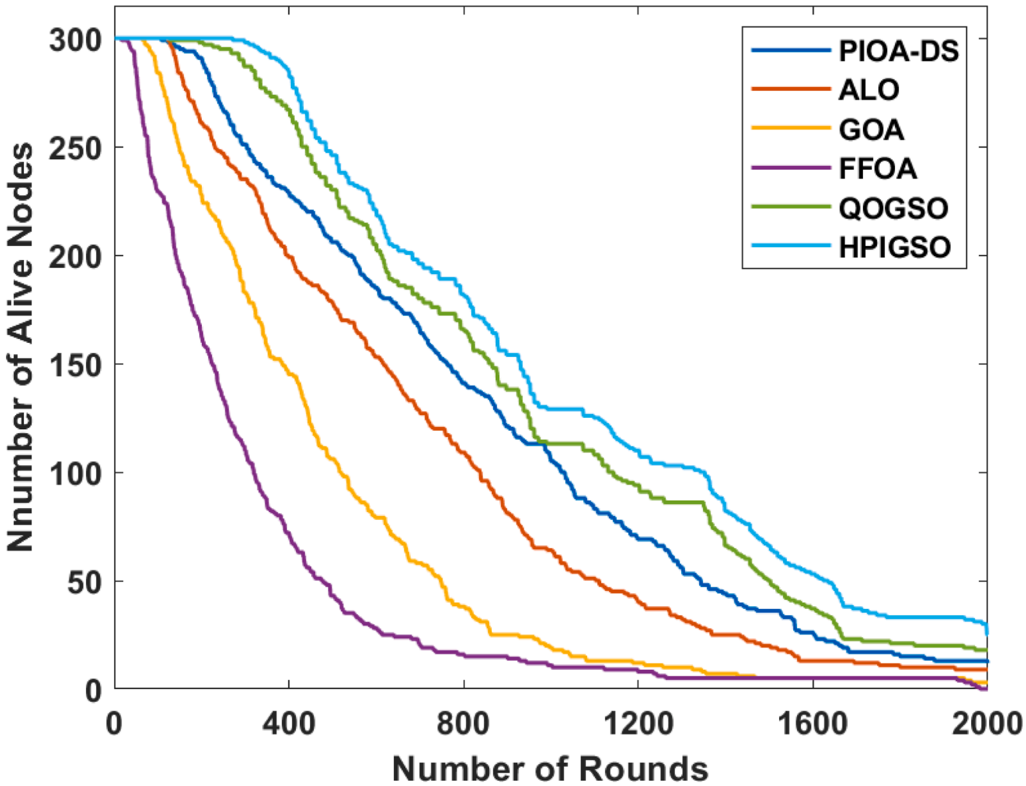

Fig. 4. Alive node analysis of HPIGSO technique under 300 nodes.

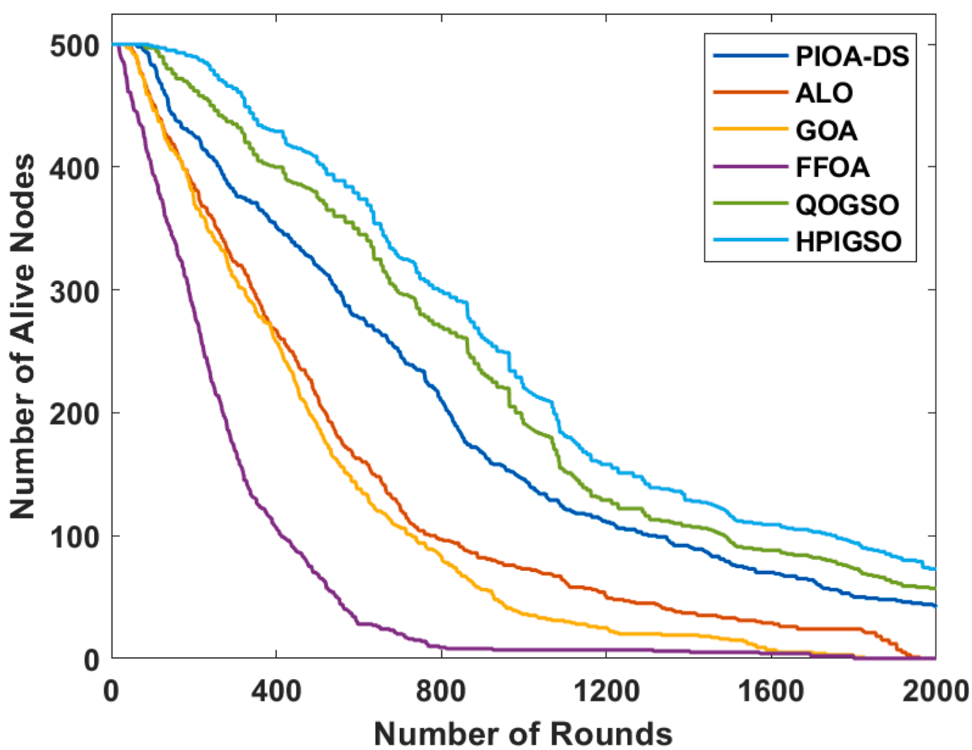

Fig. 5. Alive node analysis of HPIGSO technique under 500 nodes.

4. Conclusion

This paper has developed a new HPIGSO algorithm based clustering technique in WSN, which integrates the characteristics of PIO and GSO algorithms. The proposed algorithm operates on three major stages namely initialization, CH selection and cluster construction. Once the nodes are deployed, initialization process takes place. Followed by, BS executes the HPIGSO algorithm and selects the CHs effectively. Subsequently, nearby nodes join the CH and becomes CMs, thereby cluster construction takes place. Finally, the CMs send the data to CHs which is

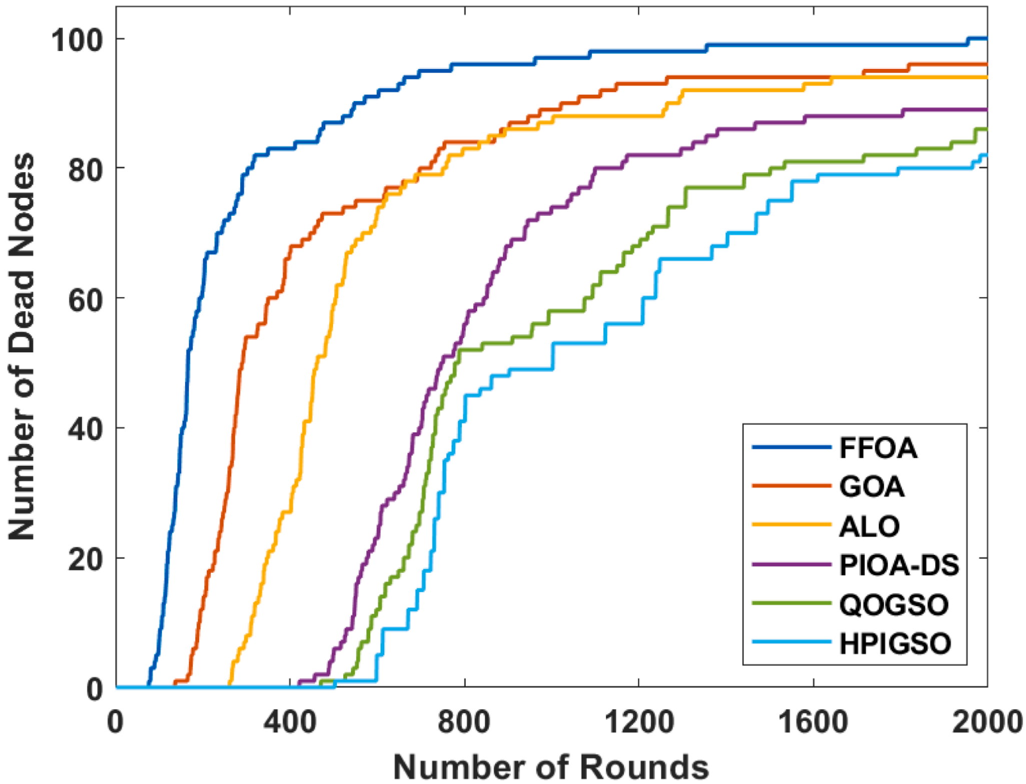

Fig. 6. Dead node analysis of HPIGSO technique under 100 nodes.

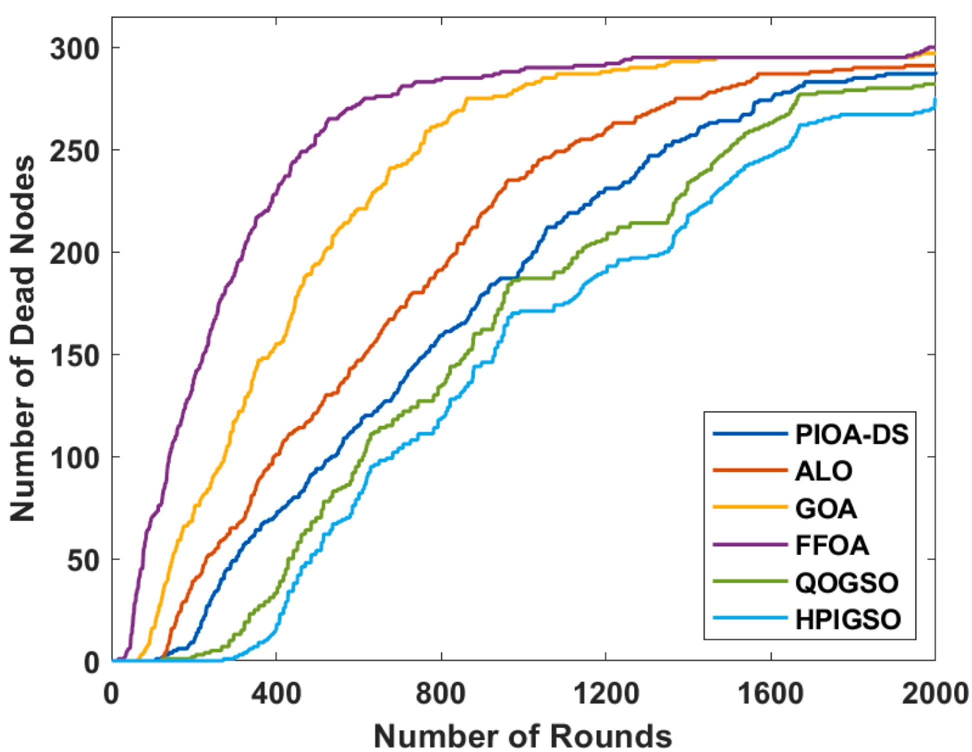

Fig. 7. Dead node analysis of HPIGSO technique under 300 nodes.

then forwarded to BS via inter-cluster communication. The proposed HPIGSO algorithm involves an objective function using residual energy, distance and energy. The proposed method has the ability to select the CHs in an optimal way; thereby network lifetime can be maximized. An elaborate experimental validation takes place and the results ensured that the HPIGSO algorithm has attained maximum network lifetime compared to other methods. The presented HPIGSO model has delayed the HND to 1421 rounds with the overall network lifetime of 2345 rounds. In future, the network lifetime can be further increased by the use of data aggregation mechanisms.

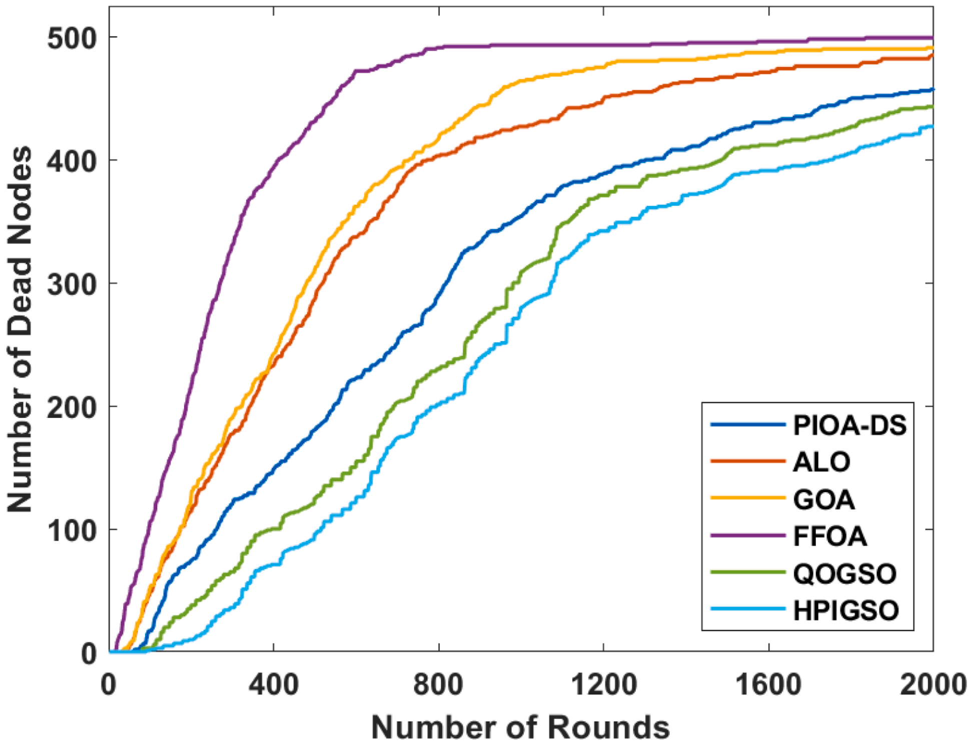

Fig. 8. Dead node analysis of HPIGSO technique under 500 nodes.

Table 2
Network lifetime analysis of the HPIGSO method.

Performance	PIOA-DS	ALO	GOA	FFOA	QOGSO	HPIGSO
Stability Period	602	505	426	350	657	778
HND	1098	965	895	695	1214	1421
Network Lifetime	1986	1889	1826	1650	2121	2345

Declaration of Competing Interest

The authors declare that they have no conflict of interest. The manuscript was written through contributions of all authors. All authors have given approval to the final version of the manuscript.

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