

A Hybrid Elephant Optimization Algorithm-based Cluster Head Selection to Extend Network Lifetime in Wireless Sensor Networks (WSNs)

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Abstract

Wireless Sensor Networks (WSNs) comprise of a number of sensor nodes that are capable of sensing and aggregating the data from the monitoring environment. However, the process of recharging the limited energy sensor node batteries are highly difficult during adverse situations. This limitation of sensor nodes greatly crumbles the network lifetime to a maximum degree and degrades the level of reliable data dissemination. In this paper, a Novel Individual Updating Strategies-based Hybrid Elephant Herding Optimization Algorithm (NIUS-HEHOA) is planned for facilitating energy balanced cluster head selection for the objective of extending the network lifetime. It included energy-aware optimization process during the clustering schemes, since it is considered as a solution to the significant NP complete optimization problem. It is propounded as a swarm intelligent algorithms are identified to be the most applicable candidate for energy optimization that leads to significant improvement in network lifetime. It is contributed to maintain the deviation between exploitation and exploration such that least potential sensor nodes are prevented from being chosen as cluster heads. The simulation experiments confirmed that the proposed NIUS-HEHOA scheme is better than the benchmarked schemes in terms of alive nodes, dead nodes, residual energy, network lifetime and throughput.

Keywords: Elephant Herding Optimization, Novel Individual Updating Strategies, Cluster Head Selection, Wireless Sensor Networks (WSNs), Network Lifetime.

Received on 08 May 2020, accepted on 19 July 2020, published on 27 July 2020

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doi: 10.4108/eai.1-7-2020.165677

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1. Introduction

The Wireless Sensor Networks (WSNs) are considered to be ubiquitously emerging in the everyday life of human beings due to its suitability and applicability in diversified environments that includes military operation, weather

forecasting, health monitoring, surveillance and other plethora of applications [1]. This WSNs comprises of hundreds and thousands of sensor nodes for facilitating the functionalities of sensing and data aggregation [2]. However, the sensor nodes' size contributes towards the crucial issues of restricted energy, limited memory and computation time and computational ability [3]. In this

situation, the network lifetime totally depends on the amount of resources available in the network. The balancing of network resources in turn depends on the adoption of suitable clustering algorithm used for routing processes [4]. At this juncture, establishing closely situated sensor nodes into groups called clusters for adapting and making it convenient for efficient management of clusters as well as the entire network is the challenging task [5]. The potential of the clustering algorithms depends on the cluster head assortment process incorporated in them [6]. The clustering algorithms also need to be potent in balancing the energy of sensor nodes in the network [7]. In the recent past, most of the clustering algorithms propounded for balancing the energy are either random or probabilistic in nature with its core focus aiming at the improvement of network lifetime [8]. The random cluster head selection schemes are determined to be less potent since the sensor nodes near the base station spend most of its energy at the earliest point of time rather than the nodes lying farthest from the base position [9]. The random cluster head selection schemes are also responsible for the issue of hot spots. The issue of hot spot completely reduces the performance of the network leading to earlier mortality of the sensor nodes [10]. Further, the probabilistic cluster head selection schemes propounded in the recent years considered only the past experience of sensor nodes for rotating the cluster heads [11]. Furthermore, the process of cluster head selection is considered as an NP complete problem. Thus, potential meta-heuristic schemes are considered to be highly potent in cluster head selection that aids in effective elongation of network lifetime [12].

In the cluster head schemes propounded in the literature, a diversified number of approaches based on the Artificial Bee Colony (ABC), Ant Colony Optimization, Particle Swarm Optimization (PSO), Harmony Search Algorithm (HSA), Cuckoo Search Algorithm, Elephant Herd Optimization (EHO) algorithms were propounded. But, the proposed schemes as a standalone algorithm are not significant in providing a superior performance in terms of cluster head selection. Further, a number of modifications incorporated in the standalone EHO algorithms have attracted more attention in utilizing the hybrid and modified EHO algorithms for the objective of cluster head selection techniques. This predominant properties of hybridized and modified EHO motivated the formulation of a new cluster head selection algorithm for extending the lifetime of the network with maximized energy conservation.

In this paper, a Novel Individual Updating Strategies-based Hybrid Elephant Herding Optimization Algorithm (NIUS-HEHOA) is planned for facilitating energy balanced cluster head selection for the objective of extending the network lifetime. This proposed NIUS-HEHOA scheme included six

important updating strategies that aid in improving the elitism for preventing the worst sensor node being selected as significant cluster heads. It also used the advantages of clan and separating operator for achieving the purpose of local and global search in the whole search space of the population. The simulation experiments of the proposed NIUS-HEHOA scheme is conducted using mean packet delivery rate, Mean Residual Energy under half network lifetime, Mean End-to-End Delay and Mean number of hops to sink under the different network size.

The major contributions of the proposed NIUS-HEHOA scheme are listed as follows.

1. It is propounded with phenomenal balance between the rate of exploitation and exploitation during the process of searching and selecting the cluster head that aids in better clustering process leading to enhanced network lifetime.
2. It adopted different exploration strategies included in the elephant herd optimization process for better improvement in energy conservation, thereby leading to significant network performance.
3. It inherited a modified version of the clan and separating operator that plays a phenomenal role in efficient and effective cluster head selection that prevents energy hole in the network
4. It also incorporated a fitness function with maximized factors that are indispensable for the process of predominant cluster head selection that prevents degradation of the network.

The remaining sections of the paper are structured as follows. Section 2 depicts the comprehensive of the most significant swarm intelligent cluster head selection approaches propounded in the recent years. Section 3 presents the complete view of the proposed NIUS-HEHOA scheme methodology with suitable justifications. Section 4 highlights the results and discussion of the proposed NIUS-HEHOA scheme with the reasons behind its predominant performance. Section 5 concludes the paper with significant contributions of the proposed work with the future scope of enhancement.

2. Related Work

In this section, the important contributions of the literature that formed the basis and motivation behind the formulation of the proposed scheme are reviewed with their pros and cons.

Lee et al. [13] proposed a Sampling-based Spider Monkey Optimization-based Clustering Scheme (SSMO-CS) for portraying how a sampling method can be used for choosing an optimal cluster head. It prevented multiple selection of

sensor nodes as cluster heads between different clusters based on the principle of sampling. It facilitated optimal results based on the best samples as the process of sampling is constrained to searching process. The simulation experiments of SSMO-CS proved its predominance in terms of energy efficiency identified over time. Then, Saranraj et al. [14] planned a clustering scheme founded on finite state machine (FSM). This FSM-based cluster head selection scheme used Marko model for estimating the selection of cluster head in the successive state. It focused on the selection of optimal cluster head based on the estimation of distance factor and present energy consumptions of the sensor nodes of the network. It proved that this cluster head selection process based on node scheduling is vital enough in improving its lifetime by 1.35 times and throughput 1.12 times superior to LEACH and C-LEACH schemes.

Further, Sirdeshpanden and Udipi [15] propounded a cluster head selection scheme using Fractional Lion Algorithm (CHSS-FLA). It used the Fractional Lion Algorithm for effective construction of routing path to energy efficiency. It improved the lifetime and energy by rapid selection of cluster heads. CHSS-FLA used fitness function formulated based on the parameters of the energy associated with cluster head, cluster sensor node members energy, delay, intra and inter-cluster distances between sensor nodes and base station. The simulation experiments of CHSS-FLA proved its prevalence in terms of network lifetime, residual energy identified over time. Cai et al [16] proposed an integrated LEACH and Improved Bat Algorithm (LEACH-IBA) for cluster head selection was proposed for improving the network lifetime. This LEACH-IBA used the curve strategy for enhancing the degree of capabilities related to global and local search. It combined the merits of LEACH and bat algorithm for sustaining the energy involved in the clustering process. LEACH-IBA is proven to improve the network lifetime by 2.38 times and throughput by 2.12 times excellent over ABC-based clustering schemes.

Furthermore, Dattatraya and Rao [17] planned a hybrid cluster head selection approach based on FruitFly and Glowworm Swarm Algorithm (HCSA-FGSA). The energy and alive node investigation were considered to be superior and the cost function is identified to be highly minimized on par with the existing clustering schemes. Then, Janakiraman et al. [18] contributed an integrated ABC and ACO (IABC-ACO-OCHS) for eliminating multiple selection and frequent selection of cluster heads that increases the overhead in energy stability under routing process. The mean delay and residual energy facilitated by IABC-ACO-

OCHS scheme is determined to be highly maintained independent of the network size in an adaptive manner.

In addition, Rambabu et al. [19] propounded an integrated ABC and MBO-based clustering scheme that is vital in prolonging the lifetime by balancing the tradeoffs existing between local and global search. The rate of local and global search was determined to be suitably managed by the used of Butterfly adjustment factor, which acts as the primary factor of search process convergence. A Krill Herd Algorithm-based optimal cluster head selection (KHA-OCHS) technique was proposed in [20] to resolve deviation between the exploitation and exploration. The mean delay and residual energy of the KHA - OCHS scheme are also determined to be highly maintained independent to the network size in a flexible way.

3. Novel Individual Updating Strategies-based Hybrid Elephant Herding Optimization Algorithm (NIUS-HEHOA) for cluster head selection

The proposed Novel Individual Updating Strategies-based Hybrid Elephant Herding Optimization Algorithm (NIUS-HEHOA) used for cluster head selection is described by the simplified rules as specified as follows:

- i) The sensor nodes (elephants) fitting to different clusters (clans) live together lead by a single cluster head (matriarch).
- ii) The cluster (clan) is considered to contain of a fixed number of sensor nodes (elephants). In this proposed scheme, it is assumed that each cluster (clan) is comprised of equal and constant number of sensor nodes.
- iii) The updating action of the sensor node position in the cluster is attained based on its association with the matriarch. This behavioral association is modeled based on an updating operator
- iv) It is expected that a fixed number of sensor nodes leave a cluster after each and every individual generation, as analogous to the mature elephants (impotent sensor nodes (worst fitness sensor nodes) that are strong-minded insignificant based on the evaluation of fitness function) that leave the family for leading an independent life. This updating process is modeled in EHO based on a separating operator.
- v) The cluster head (Matriarch elephant) in each cluster is the highest potential sensor node

(potent sensor nodes (best fitness sensor nodes) that are determined significant based on the evaluation of fitness function).

- vi) The proposed scheme represents the fitness function as a vital indicator of survivability and thus it is determined for each individual sensor nodes based on four parameters such as residual energy, number of cluster heads, cumulative distance between the cluster head and the base station and cumulative intra-cluster distance of communication.
- vii) The fitness function considered that the higher the cumulative intra-cluster distance of communication and lesser the cumulative distance between the cluster head and the base station, leads to lesser number of cluster heads.
- viii) The energy model used for cluster head selection is similar to the model used in [19]

3.1. The clan updating operator considered in the proposed NIUS-HEHOA-OCHS

This proposed NIUS-HEHOA-OCHS scheme follows the updating strategy presented by the authors of [21]. In this context, the number of clusters (clans) is represented as C_k .

The successive location of any sensor node (elephant), l , in the cluster (clan) is determined based on Equation (1)

$$P_{EW,Ck,l} = P_{Ck,l} + \alpha(P_{BEST,Ck} - P_{Ck,l}) \times r_{v(k)} \quad (1)$$

Where, $P_{NEW,Ck,l}$ and $P_{Ck,l}$ presents the updated and preceding position of the sensor in the cluster C_k . Further,

$P_{BEST,Ck,l}$ highlights the matriarch elephant pertaining to the cluster C_k and that sensor node is considered the fittest sensor node in the entire clusters. The value of scaling factor (α) ranges between 0 and 1 and it is determined to investigate the impact of the matriarch sensor node of cluster on $P_{Ck,l}$. Moreover, the value of $r_{v(k)}$ also lies between 0 and 1 which refers to the stochastic distribution that can facilitate significant enhancements in order to sustain the population diversity in the successive search space. In this proposed scheme, the uniform distribution is particularly used.

At this juncture, it is identified that $P_{Ck,l} = P_{BEST,Ck,l}$, which infers that the potential sensor nodes in the cluster cannot be updated based on Equation (1). In order to prevent this situation, the fittest sensor node is updated based on Equation (2).

$$P_{NEW,Ck,l} = \beta \times P_{CENTER,Ck,l} \quad (2)$$

Where, $\beta \in [0,1]$ is the factor of regularization that determines the impact of $P_{CENTER,Ck,l}$ over $P_{NEW,Ck,l}$.

Further, new set of sensor nodes that are possibly designated as cluster heads are determined from the information determined from the complete set of sensor nodes associated with each clan. Furthermore, the determination of cluster center based on dimension D is determined based on Equation (3)

$$P_{CENTER,Ck,l} = \frac{1}{N_{Ck}} \sum_{l=1}^{N_{Ck}} P_{Ck,l} \quad (3)$$

At this point, $1 \leq d \leq D$ depicts the measurement with N_{Ck} as the total number of sensor nodes in the network (population)

3.2 The separating operator considered in the proposed NIUS-HEHOA-OCHS

In this proposed scheme, the worst fitness sensor nodes are separated from the clusters as analogous to the male elephants that leave the family and live independently after reaching the level of puberty. Further, separating operator of EHO is used under the process of handling the optimization that aids in preventing impotent sensor nodes being selected as cluster heads in the network. Moreover, it is considered that the individual sensor nodes with worst fitness is responsible for the implementation of the separating operator for each successive iteration based on Equation (4)

$$P_{WORST,Ck,l} = P_{MIN} + (P_{MAX} - P_{MIN} + 1) \times rand \quad (4)$$

The inclusion of separating operation based on Equation (4) plays an anchor role in enhancing the exploration ability of the EHO method. Here, pertains to the lower and upper bound representing the individual sensor nodes with the uniformly distributed random variable $rand[0,1]$ lying in the range between 0 and 1.

Similar to the existing meta-heuristic cluster head selection algorithms, this proposed scheme also used elitism strategy for the objective of preventing the best sensor nodes from existence ruined by the separating and clan updating operator from the optimal selection process. In the starting, the best sensor nodes are saved, and the worst sensor nodes are replaced by the stores best fitness sensor nodes at the end of the exploration process. This process of elitism is responsible for ensuring the condition in which the successively identified sensor nodes is not worse than the estimated sensor nodes determined in the previous iteration. As mentioned before, the primitive EHO algorithm is not capable enough in guiding the present and successive searches as they do not consider the best existing

information derived from individual sensor nodes. However, under the event of large scale and complex optimization such as cluster head selections, this can lead to slower convergence. Thus, some specific potential amount of information is derived from the sensor nodes from each iteration is always reused for the purpose of enhancing the searching ability in the exploitation and exploration level.

3.3 Novel Individual Updating Strategies-based EHO improvement

In this proposed scheme, six versions of EHO are constructed based on the strategies of individual updating. In general, $u(u \geq 1)$ the sensor nodes determined as cluster heads in the previous iteration can be selected, but when the number of sensor nodes ($u \geq 4$) is selected as cluster heads is selected, the computation of the weights is identified to be more complex.

Case (i): When $u=1$ (only information from one individual solution is considered for updating)

The position of the k^{th} sensor node designated as cluster head can be generated based on Equation (5)

$$P_i^{t+1} = \delta Q_i^{t+1} + \lambda P_i^t \quad (5)$$

Where, P_i^t is the position of the sensor node $l(l \in [1, 2, \dots, N_s])$ as iteration with Fit_i^t as the fitness. Then, δ and λ are considered as weight factors with the condition ($\delta + \lambda = 1$) satisfying as mentioned in Equation (6)

$$\delta = r_{v(1)} \text{ and } \lambda = 1 - r_{v(1)} \quad (6)$$

At this juncture, the best optimal sensor node can be determined through the following ways:

- i) $l = k$;
- ii) $l = r_{v(1)}$

Where, $r_{v(i)}$ is an integer that lies between 1 and N_s which is selected randomly. It is identified that the sensor nodes identified as potent through the second condition have maximum population diversity compared to the sensor nodes determined based on the first condition.

Case (ii): When $u=2$ (information from two individual solution is considered for updating)

In this case, the position of the k^{th} sensor node designated as cluster head can be generated based on Equation (7)

$$P_i^{t+1} = \delta Q_i^{t+1} + \lambda_1 P_{l_1}^t + \lambda_2 P_{l_2}^t \quad (7)$$

Where, $P_{l_1}^t$ and $P_{l_2}^t$ is the position of the sensor node $l(l \in [1, 2, \dots, N_s])$ as iteration with $Fit_{l_1}^{t-1}$ and $Fit_{l_2}^t$ as the fitness. Then, δ , λ_1 and λ_2 are considered as weight factors with the condition ($\delta + \lambda_1 + \lambda_2 = 1$) satisfying as mentioned in Equation (8)

$$\begin{aligned} \delta &= r_{v(1)} \\ \lambda_1 &= (1 - r_{v(1)}) \times \frac{Fit_{l_2}^{t-1}}{Fit_{l_2}^{t-1} + Fit_{l_1}^t} \\ \lambda_2 &= (1 - r_{v(1)}) \times \frac{Fit_{l_2}^t}{Fit_{l_2}^{t-1} + Fit_{l_1}^t} \end{aligned} \quad (8)$$

At this juncture, the best optimal sensor node can be determined through the following ways:

- i) $l_1 = l_2 = k$;
- ii) $l_1 = r_{v(1)}$ and $l_2 = r_{v(2)}$

Where, $r_{v(1)}$ and $r_{v(2)}$ is an integer that lies between 1 and N_s which is selected randomly. Again, It is identified that the sensor nodes identified as potent through the second condition have maximum population diversity compared to the sensor nodes determined based on the first condition.

Case (iii): When $u=2$ (information from three individual solution is considered for updating)

In this case, the position of the k^{th} sensor node designated as cluster head can be generated based on Equation (9)

$$P_i^{t+1} = \delta Q_i^{t+1} + \lambda_1 P_{l_1}^t + \lambda_2 P_{l_2}^{t-1} + \lambda_3 P_{l_3}^{t-2} \quad (9)$$

Where, $P_{l_1}^t$, $P_{l_2}^{t-1}$ and $P_{l_3}^{t-2}$ is the position of the sensor node $l(l \in [1, 2, \dots, N_s])$ as iteration with $Fit_{l_1}^{t-2}$, $Fit_{l_2}^{t-1}$ and $Fit_{l_3}^t$ as the fitness. Then, δ , λ_1 , λ_2 and λ_3 are considered as weight factors with the condition ($\delta + \lambda_1 + \lambda_2 + \lambda_3 = 1$) satisfying as mentioned in Equation (10)

$$\begin{aligned} \delta &= r_{v(1)} \\ \lambda_1 &= \frac{1}{2} \times (1 - r_{v(1)}) \times \frac{Fit_{l_2}^{t-1} + Fit_{l_1}^{t-2}}{Fit_{l_1}^{t-2} + Fit_{l_2}^{t-1} + Fit_{l_3}^t} \end{aligned}$$

$$\lambda_2 = \frac{1}{2} \times (1 - r_{v(1)}) \times \frac{Fit_{l_1}^t + Fit_{l_2}^{t-3}}{Fit_{l_2}^{t-1} + Fit_{l_1}^t}$$

$$\lambda_3 = \frac{1}{2} \times (1 - r_{v(i)}) \times \frac{Fit_{l_2}^t}{Fit_{l_1}^{t-2} + Fit_{l_1}^{t-1} + Fit_{l_3}^t}$$

(10)

At this juncture, the best optimal sensor node can be determined through the following ways:

- iii) $l_1 = l_2 = l_3 = k$;
- iv) $l_1 = r_{v(1)}$, $l_2 = r_{v(2)}$ and $l_3 = r_{v(3)}$

Where, $r_{v(1)}$, $r_{v(2)}$ and $r_{v(3)}$ is an integer that lies between 1 and N_s which is designated randomly. Again, It is identified that the sensor nodes identified as potent through the second condition have maximum population diversity compared to the sensor nodes determined based on the first condition.

The schematic description of the proposed NIUS-HEHOA-OCHS scheme is presented as follows.

Algorithm: Novel Individual Updating Strategies-based Hybrid Elephant Herding Optimization (NIUS-HEHOA)

Begin

Step 1: Population Initialization (the number of sensor nodes with their position is initialized)

Step 1.1: Initialize the Iteration count to $t = 1$.

Step 1.2: Set the Population (PS) of sensor nodes (NS) in a random way based on a uniform Distribution.

Step 1.3: Set the factor of scaling as α and β .

Step 1.4: Initialize the maximum number of iterations as $Iter_{MAX}$.

Step 1.5: Set the number of cluster, number of sensor nodes in each cluster and cluster

Head before computing Fitness function

Step 2: Evaluation of Fitness

The sensor nodes (elephants) are evaluated based on the formulated Fitness function that considered a number of cluster heads, Residual Energy, Distance of entire intra-cluster message and total distance between cluster heads and Base station for computation

Step 3: Until $t < Iter_{MAX}$ do the following

Step 3.1: Arrange the complete set of sensor nodes based on their evaluated fitness function

Step 3.2: Store the number of potential sensor nodes that can be potentially designated as cluster head.

Step 3.3: Implement clan and separating operator

Step 3.4: Estimate the sensor nodes based on the newly updated positions

Step 3.5: Replace the worst fitness sensor nodes with the already stored potential sensor nodes

Step 3.6: Increment the Iteration count to $t = t + 1$.

Step 4: Implementation of the novel updating strategies

Step 4.1: If When $u=1$ (only information from one individual solution is considered for updating), then apply the weight computation based on equation (5) and (6)

Step 4.2: If When $u=2$ (information from two individual solution is considered for updating), then apply the weight computation based on equation (7) and (8)

Step 4.3: If When $u=3$ (information from three individual solution is considered for updating), then apply the weight computation based on equation (9) and (10)

Step 5: End Until

Step 6: Choice the best optimal sensor node as potential cluster head
End.

4. Simulation Experiments and Discussion

The simulation experiments of the proposed NIUS-HEHOA-OCHS technique and the benchmarked ABC-MBOA-OCHS, ABC-OCHS, EEST-OCHS and KHA-OCHS schemes achieved sing ns-2.35 with the same simulation setup parameters. The simulation environment used for implementing the proposed ABC-MBOA-OCHS technique comprised of 100 * 100 meters terrain area with 1000 sensor nodes deployed randomly in the network. The simulation setup parameters considered for the implementation of the proposed NIUS-HEHOA-OCHS scheme is also presented in Table 1.

The simulation investigation of the proposed NIUS-HEHOA-OCHS approach and the benchmarked ABC-MBOA-OCHS, ABC-OCHS, EEST-OCHS and KHA-OCHS schemes is conducted in four folds. In the chief fold, the performance of the proposed NIUS-HEHOA-OCHS scheme is evaluated using alive nodes percentage, dead node percentage, mean residual energy and mean throughput envisaged under a different number of rounds used for implementation.

Table 1. Simulation step used for implementing the proposed NIUS-HEHOA-OCHS table

Simulation Parameters	The values used for simulation
Simulation Area	400*400 meters
Number of sensor nodes	2000
Initial Energy of sensor nodes	0.5 Joules
Speed	1-10 meters per second
Control packet length	50 bytes
Data packet Length	512 bytes
Mobility Model	Random Way Point
Interface Queue Type	Drop tail
Size of the packets	2000 bits
Distance to the base station	50 meters
Location of the base station	(200,200)
Interval in sensing	0.01 milliseconds
Time of Simulation	600 Seconds
Communication Model	Bidirectional

In the second fold, the performances of the proposed NIUS-HEHOA-OCHS approach is evaluated using average throughput, sustenance in the mean residual energy, improvement in network lifetime and decrease in communication overhead under different network size. In the final fold, the performance of the planned NIUS-HEHOA-OCHS approach is evaluated using mean packet delivery rate, Mean Residual Energy under half network lifetime, Mean End-to-End Delay and Mean number of hops to sink under the different network size.

In the first part of the analysis, the proposed NIUS-HEHOA-OCHS scheme is evaluated using alive nodes percentage, dead node percentage, mean residual energy and mean throughput visualized under a different number of rounds used for implementation. Figure 1 and 2 presents the percentage of alive nodes and percentage of dead nodes realized in the network during the deployment of the proposed NIUS-HEHOA-OCHS scheme under a different number of rounds used for implementation. The percentage of alive nodes in the network facilitated by the proposed NIUS-HEHOA-OCHS scheme is confirmed to be potent over the compared baseline CH schemes. Similarly, the number of alive nodes maintained by the proposed NIUS-HEHOA-OCHS scheme is determined to decrease with an increase in the number of rounds. But, the number of alive

nodes becomes completely zero, only at 2008 rounds, whereas, the benchmarked such as ABC-MBOA-OCHS, ABC-OCHS and KHA-OCHS schemes reach at 1794, 1796 and 1802 rounds, respectively. This significant performance of the proposed NIUS-HEHOA-OCHS scheme is mostly due to the computation of obtainability factor that aids in estimating the significance of the sensor nodes. Similarly, the percentage of dead nodes are confirmed to be minimized by the proposed NIUS-HEHOA-OCHS scheme as it balances the energy consumptions of the network in a predominant way by imposing preventive maintenance strategy. Thus, the percentage of alive nodes in the network facilitated by the planned NIUS-HEHOA-OCHS scheme is proving to be remarkable by 9%, 11%, 14% and 17%, predominant to the benchmarked ABC-MBOA-OCHS, ABC-OCHS and KHA-OCHS schemes.

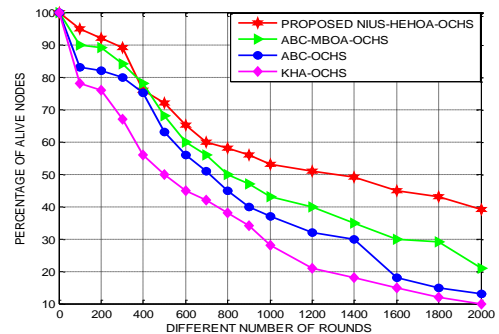


Figure 1. Proposed NIUS-HEHOA-OCHS: Percentage of Alive nodes under different rounds

The number of dead nodes in the network obtained by the proposed NIUS-HEHOA-OCHS scheme is determined to increase with an increase in the number of rounds. But, the number of dead nodes reaches the maximum value of 100, only in the round of 2000. While, the benchmarked such as ABC-MBOA-OCHS, ABC-OCHS and KHA-OCHS schemes reach the same point at 1920, 1950 and 1980 rounds, respectively. Hence, the percentage of dead nodes in the network facilitated by the planned NIUS-HEHOA-OCHS scheme is also proved to be significant by 11%, 14%, 16% and 19%, significant to the benchmarked ABC-MBOA-OCHS, ABC-OCHS and KHA-OCHS schemes.

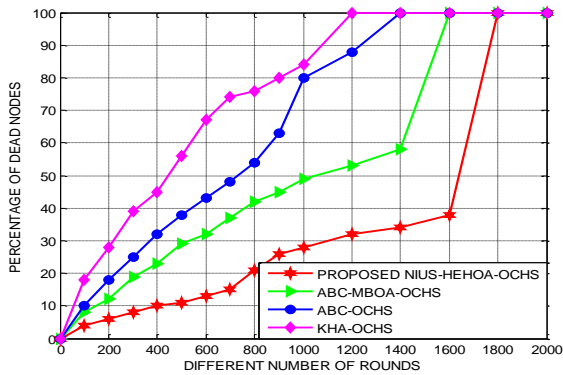


Figure 2. Proposed NIUS-HEHOA-OCHS: Percentage of Dead nodes under different rounds

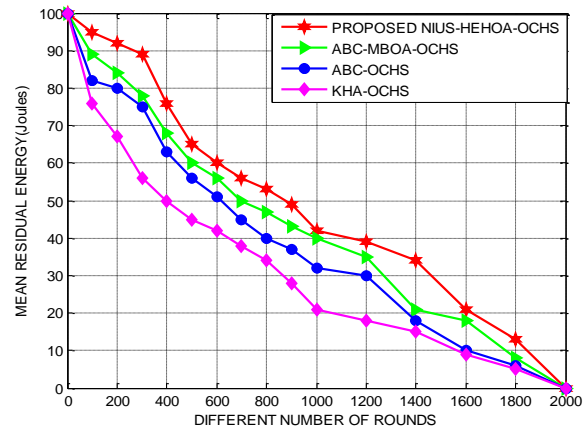


Figure 4. Proposed NIUS-HEHOA-OCHS: Mean Residual Energy under different rounds

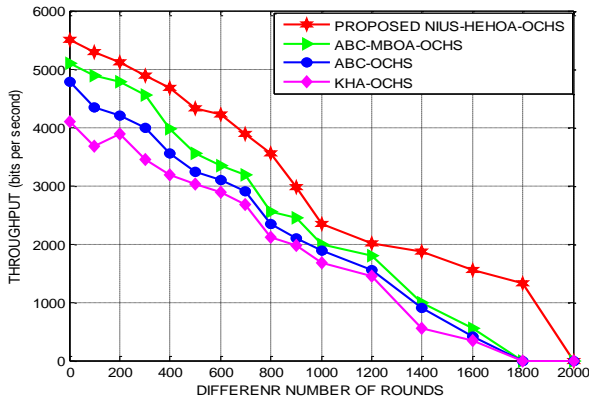


Figure 3. Proposed NIUS-HEHOA-OCHS: Mean Throughput under different rounds

Figure 3 and 4 presents the mean throughput and mean residual energy visualized in the network during the deployment of the proposed NIUS-HEHOA-OCHS scheme under a different number of rounds used for operation. The mean throughput of the proposed NIUS-HEHOA-OCHS scheme is determined to decrease with an increase in the number of rounds. But, the throughput becomes completely zero, only at 2000 rounds, whereas, the benchmarked such as ABC-MBOA-OCHS, ABC-OCHS and KHA-OCHS schemes reach at 1780, 1796 and 1805 rounds, respectively.

Thus, the mean throughput of proposed NIUS-HEHOA-OCHS scheme is confirmed to be sustained over the compared baseline CH selection schemes. This significant performance of the proposed NIUS-HEHOA-OCHS scheme in terms of mean throughput is mainly due to the high prevention of malicious sensor nodes from being selected as CH nodes. Likewise, the mean residual energy of the network maintained by the proposed NIUS-HEHOA-OCHS scheme is also predominant as it included a preventive maintenance process of rehabilitating sensor nodes. Thus, the mean throughput of the network facilitated by the proposed NIUS-HEHOA-OCHS scheme is proving to be superior by 12%, 14%, 17% and 19%, compared to the benchmarked ABC-MBOA-OCHS, ABC-OCHS and KHA-OCHS schemes. Similarly, the mean residual energy sustained by the proposed NIUS-HEHOA-OCHS scheme is determined to decrease with an increase in the number of rounds. But, the mean residual energy becomes completely zero, only at 2025 rounds, whereas, the benchmarked such as ABC-MBOA-OCHS, ABC-OCHS and KHA-OCHS schemes reach at 1794, 1796 and 1802 rounds, respectively. Thus, the mean residual energy sustained in the network during the enforcement of the proposed NIUS-HEHOA-OCHS scheme is also proved to be significant by 8%, 11%, 14% and 17%, significant to the benchmarked ABC-MBOA-OCHS, ABC-OCHS and KHA-OCHS schemes.

Figure 5 and 6 demonstrates the average throughput and sustenance in the mean residual energy of the proposed NIUS-HEHOA-OCHS scheme and the benchmarked ABC-MBOA-OCHS, ABC-OCHS and KHA-OCHS schemes under different network size. The average throughput of the proposed NIUS-HEHOA-OCHS scheme is enhanced independent of the network size, since the updating strategies are adaptively updated with a diverse

number of nodes in the network. The average throughput of the planned NIUS-HEHOA-OCHS scheme is confirmed to be improved by 11.21%, 12.86% and 14.32%, on par with the compared schemes. The sustenance in the mean residual energy of the planned NIUS-HEHOA-OCHS scheme is determined to be enhanced with respect to the network size, since it prevents worst fitness from been chosen as cluster head in the network. The sustenance in the mean residual energy of the planned NIUS-HEHOA-OCHS scheme is confirmed to be enhanced by 12.32%, 14.21% and 16.58%, on par with the compared schemes.

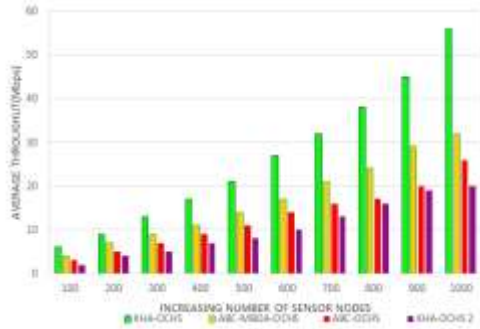


Figure 5. Proposed NIUS-HEHOA-OCHS: Improvement in Mean Throughput under different network size

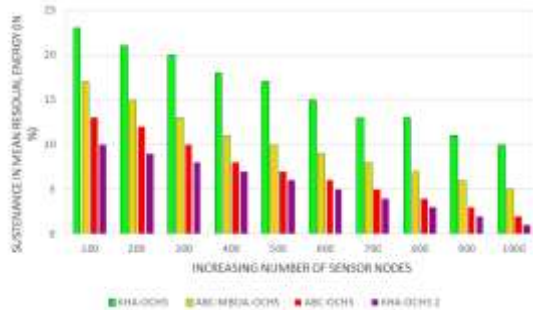


Figure 6. Proposed NIUS-HEHOA-OCHS: Sustenance in Mean Residual Energy under different network size

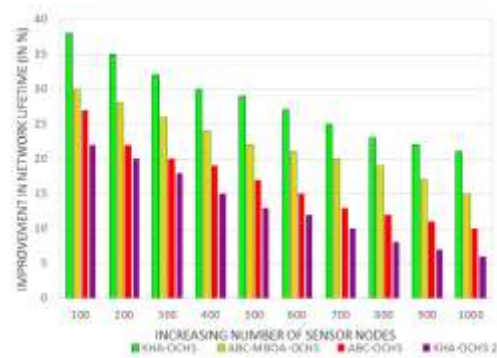


Figure 7. Proposed NIUS-HEHOA-OCHS: Improvement in Network Lifetime under different network size

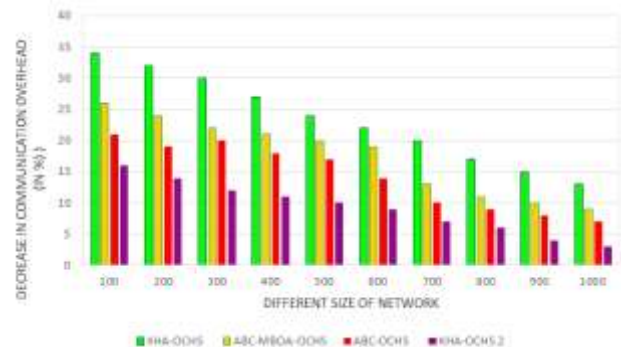


Figure 8. Proposed NIUS-HEHOA-OCHS: Decrease in communication overhead under different network size

Figure 7 and 8 depict the improvement in network lifetime and decrease in communication overhead of the proposed NIUS-HEHOA-OCHS scheme and the benchmarked ABC-MBOA-OCHS, ABC-OCHS and KHA-OCHS schemes under different network size. The network lifetime of the planned NIUS-HEHOA-OCHS scheme is enhanced independent of the network size, since the updating strategies are adaptively updated with different number of nodes in the network. The network lifetime of the proposed NIUS-HEHOA-OCHS scheme is confirmed to be improved by 11.21%, 12.86% and 14.32%, on par with the compared schemes. The communication overhead of the proposed NIUS-HEHOA-OCHS scheme is determined to be minimized with respect to the network size, since it prevents worst fitness from been chosen as cluster head in the

network. The communication overhead of the proposed NIUS-HEHOA-OCHS scheme is confirmed to be minimized by 10.12%, 11.79% and 12.32%, on par with the compared schemes.

In addition, Table 2 and 3 demonstrates the mean packet delivery rate and Mean Residual Energy under half network lifetime achieved by the proposed NIUS-HEHOA-OCHS and the benchmarked ABC-MBOA-OCHS, ABC-OCHS and KHA-OCHS schemes under different network size. The mean packet delivery rate achieved by the proposed NIUS-HEHOA-OCHS is determined to be improved by 10.28%, 11.38% and 12.38% and the benchmarked ABC-MBOA-OCHS, ABC-OCHS and KHA-OCHS schemes under different network size. The Mean Residual Energy under half network lifetime sustained by the proposed NIUS-HEHOA-OCHS is determined to be improved by 11.38%, 12.46% and 14.21% and the benchmarked ABC-MBOA-OCHS, ABC-OCHS and KHA-OCHS schemes under different network size.

Table 2. Mean packet delivery rate for the proposed NIUS-HEHOA-OCHS

Algorithms	Size of the network				
	400	800	1200	1600	2000
Proposed NIUS-HEHOA-OCHS	0.9721	0.9704	0.9624	0.9612	0.9604
ABC-MBOA-OCHS	0.9612	0.9604	0.9558	0.9421	0.9414
ABC-OCHS	0.9533	0.9411	0.9402	0.9354	0.9276
KHA-OCHS	0.9408	0.9218	0.9164	0.9121	0.9048

Table 3. Mean Residual Energy for proposed NIUS-HEHOA-OCHS under half-lifetime

Algorithms	Size of the network				
	400	800	1200	1600	2000
Proposed NIUS-HEHOA-OCHS	0.62	0.59	0.57	0.55	0.52
ABC-MBOA-OCHS	0.54	0.52	0.51	0.48	0.46
ABC-OCHS	0.48	0.45	0.44	0.42	0.38
KHA-OCHS	0.46	0.42	0.40	0.39	0.36

Table 4. Mean End-to-End Delay for the proposed NIUS-HEHOA-OCHS

Algorithms	Size of the network				
	400	800	1200	1600	2000
Proposed NIUS-HEHOA-OCHS	0.00201	0.00204	0.00209	0.00213	0.00218
ABC-MBOA-OCHS	0.00212	0.00218	0.00222	0.00228	0.00234

KHA-OCHS	0.00242	0.00233	0.00239	0.00244	0.00249
ABC-OCHS	0.00248	0.00235	0.00239	0.00244	0.00249

Table 5. Mean number of hops to sink for the proposed NIUS-HEHOA-OCHS

Algorithms	Size of the network				
	400	800	1200	1600	2000
Proposed NIUS-HEHOA-OCHS	8.4	8.9	9.6	10.4	11.8
ABC-MBOA-OCHS	7.2	7.6	8.2	8.6	9.4
ABC-OCHS	5.8	6.2	6.6	7.2	7.6
KHA-OCHS	4.3	4.9	5.3	5.9	6.4

Finally, Table 4 and 5 demonstrates the Mean End-to-End Delay and Mean number of hops to sink attained by the proposed NIUS-HEHOA-OCHS and the benchmarked ABC-MBOA-OCHS, ABC-OCHS and KHA-OCHS schemes under different network size. The Mean End-to-

End Delay attained by the proposed NIUS-HEHOA-OCHS is determined to be minimized by 12.28%, 14.49% and 16.21% and the benchmarked ABC-MBOA-OCHS, ABC-OCHS and KHA-OCHS schemes under different network size. The Mean number of hops to sink attained by the proposed NIUS-HEHOA-OCHS is determined to be improved by 9.34%, 10.94% and 12.68% and the benchmarked ABC-MBOA-OCHS, ABC-OCHS and KHA-OCHS schemes under different network size.

5. Conclusion

The proposed NIUS-HEHOA-OCHS is proposed as an attempt to achieve potential cluster head selection for satisfying the network lifetime enhancement. It included the method of elitism such that each and every iteration is phenomenal in identifying the potential cluster heads in each current iteration compared to the previous iteration considered for analysis. This used of elitism is also improved through the inclusion of six updating strategies that depends on the number of solution considered for determining the fitness of sensor nodes under the process of cluster head selection. The simulation results of the proposed NIUS-HEHOA-OCHS transparently proved that the mean packet delivery rate and mean number of hops to sink is improved, on an average by 12.38% and 11.28% with minimized Mean Residual Energy under half network lifetime and Mean End-to-End Delay by 14.21% and 10.93%, respectively. The simulation results also proved that the throughput of the proposed scheme is enhanced by 13.42%, compared to the benchmarked systems. As the part of the upcoming research, it is decided to express an Emperor Penguin-based optimization and compare its performance with the proposed scheme contributed in this paper.

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