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Memetic Particle Gravitation Optimization Algorithm-based Optimal Cluster Head Selection in Wireless Sensor Networks (WSNs)

Dr. Sengathir Janakiraman[1] and Dr. Rakesh Kumar Godi[2]
[1]Assoc. Professor, CVR College of Engineering/ IT Department, Hyderabad, India
Email: dr.sengathir@cvr.ac.in
[2]Assoc. Professor, CVR College of Engineering/ IT Department , Hyderabad, India
Email: drrakeshkumargodi@cvr.ac.in

Abstract: **Wireless Sensor Networks (WSNs) consist of millions of sensor nodes that operate cooperatively for attaining the objective of sensing and transmitting information to the base station for necessary decision making processes. In WSNs, the problem of hotspot or energy hole is a major issue that arises when the number of sensor nodes in close proximity of the base station decreases rapidly and results in a network partitioning. This issue of energy holes is feasible in the network only when the difference between the energy consumptions of the sensor nodes are quite large and which has the capability of minimizing the network lifespan. This limitation of WSNs needs to be handled through the potential selection of cluster heads with maximized energy efficiency. In this paper, Memetic Particle Gravitation Optimization Algorithm-based Optimal Cluster Head Selection scheme is proposed for handling the issue of the energy hole in order to sustain energy stability and prolonged network lifetime in WSNs. This MPGOA-OCHS scheme facilitates cluster head head selection by integrating the merits of Centralized Particle swarm Optimization (CPSO) and Gravitational search algorithm (GSA) in order to maintain balance between the rate of intensification and diversification in the cluster head selection process. The simulation results proved that the proposed MPGOA-OCHS scheme is predominant in residual energy by 22.21% and prolonged network lifetime by 16.39%, compared to the baseline schemes.**

Index Terms: **Wireless Sensor Networks, Memetic Particle Optimization Algorithm, Gravitational Optimization Algorithm, Energy Hole.**

I. INTRODUCTION

Wireless Sensor Networks (WSNs) include a number of sensor nodes deployed in a wide area to monitor the surroundings. The Internet of Things (IoT) is the prime and vital technology. Much research is done in each area. Initially, WSNs were used only in the defence, but now they finding their applications in various areas like monitoring of healthcare, environment, tracking objects, traffic control, smart homes and cities, etc., This is made possible due to their reduced size, price and sturdiness to withstand the tough conditions and hostile environments. They include a number of sensor nodes to sense the phenomena in a particular region. The device includes several units viz., sensing, computing and communicating unit. The nodes are arbitrarily deployed to collect and process the accumulated data and convey to the Base Station (BS) in a single hop or multiple hops. The BS connects with the administrator through the internet or General Packet Radio Service (GPRS). As sensor nodes are battery powered, they cannot be changed or revitalized. Hence, ensuring energy efficiency is the demand of the hour and needs to be considered while designing a WSN. Energy in a network directly relates to network lifetime. Many techniques are proposed to enhance the lifespan of a network. Designing efficient routing and clustering mechanisms reduce energy consumption and improves network lifetime. Further, as sensors are arbitrarily deployed, there are chances for them to be closely placed thus transmitting redundant data. This can be avoided by aggregating the data collected from the sensors that are in proximity.

Clustering involves data aggregation and concurrently reduces the amount of energy consumed. Cluster Heads (CHs) may be selected based on the residual energy and nodes may be assigned to the CHs. An energy hole or hot spot may be formed in a WSN, wherein the sensor nodes that are close to the BS die soon creating network partitions. The variance in the amount of energy consumed in WSN deals with the reduction of network lifetime. Unequal clustering supports circumventing early node demises and extends the lifespan of the network by reducing the amount of energy consumed. A diversified number of clustering approaches were propounded in the literature over the decades, but each one of the cluster head selection schemes has their own limitations. In this context, metaheuristic algorithms-based clustering schemes are considered to be highly suitable for clustering processes that prolongs the network lifetime.

In this paper, Memetic Particle Gravitation Optimization Algorithm-based Optimal Cluster Head Selection scheme is proposed for resolving the problem of hot-spot for the purpose of prolonging network lifetime and maintaining energy stability in WSNs. This MPGOA-OCHS scheme included the potentialities of the Centralized Particle swarm Optimization (CPSO) and Gravitational search algorithm (GSA) for sustaining the tradeoff between the rate of intensification and diversification involved in the process of cluster head selection. The simulation experiments of the proposed MPGOA-OCHS scheme is conducted using Matlab R2018a with respect to number of alive nodes, the number of dead nodes, throughput and packet delivery rate under the impact of different densities of sensor nodes and number of rounds.

II. Related Work

An improved Breeding Artificial Fish Swarm Algorithm (IBAFSA)-based cluster head selection scheme was proposed by Sengottuvelan and Prasath [9] for sustaining energy and network lifespan. This IBAFSA scheme was proposed for maintaining the balance between diversification and intensification during the process of cluster head selection. The simulation results of IBAFSA confirmed optimal performance in throughput by 19.31% and network lifespan by 17.28%, compared to the classical LEACH and GA algorithms. A Particle Swarm Optimization (PSO)-based clustering scheme was proposed by Rao et al [10] for attaining better network stability. This PSO approach used an objective function that considered the parameters of residual energy, sink distance, intra-cluster distance for energy efficient cluster head selection process. It utilized the merits of a weight function that aids in the formation of the cluster with the cluster member nodes joining their associated cluster head nodes. The result of this PSO-based clustering approach proved best results in alive nodes by 23.81% and throughput by 18.79%, compared to ACO and ABC-based clustering approaches.

A Fuzzy Logic and Harmony Search (FLHS) algorithm-based cluster head selection scheme was proposed by Agrawal and Pandey [15] for lengthening the network lifetime. This FLHS handled the issue of hotspot through the unequal clustering process independent of the network settings considered for implementation. The results of FLHS were confirmed to improve the network lifetime and energy stability with different sensor nodes by 19.32% and 21.78%, respectively.

III. Proposed Memetic Particle Gravitation Optimization Algorithm-Based Optimal Cluster Head Selection (MPGOA-OCHS)

The proposed Memetic Particle Gravitation Optimization Algorithm-based Optimal Cluster Head Selection (MPGOA-OCHS) was proposed by integrating the benefits of Particle Swarm Optimization (PSO) and Gravitational search algorithm (GSA). This proposed MPGOA-OCHS scheme mutually handles the limitations of CPSO and GSA for maintaining the tradeoff between the diversification and intensification during the cluster head selection process. This cluster head selection approach enhances the capabilities of individual search with rapid convergence rate. The two core strategies utilized in MPGOA targets on diversity enhancement and hybrid operation for preventing impotent sensor nodes from being selected as cluster heads. GSA included the operator of improvement as similar to the differential evolution crossover operator, while CPSO aims in individual exchange of solutions between the sub-populations for attaining maximized diversity and intensification, respectively. The method of the roulette wheel is utilized for accomplishing solution exchanges between CPAO and GSA.

In this section, the detailed view of CPSO and GSA are presented in order to depict the process of integrating them in the cluster head selection process.

A. Centralized Particle Swarm Optimization

Particle Swarm Optimization (PSO) algorithm is a stochastic-based swarm intelligent algorithm proposed through the inspiration derived from the flocking characteristics of birds. In the PSO algorithm, the randomly initialized potential solutions are determined based on the positions and velocities of ‘K’ particles represented in the space of ‘D’ dimensions. The positions and velocities of ‘K’ particles are presented in ‘d_S’ dimensions in order to facilitate potential solutions that are initialized randomly. The particle solution ‘i’ in iteration ‘t’ is presented in Equation (1)

$$S_{(i)}^{(t)} = \left\{ S_{(i,1)}^{(t)}, S_{(i,2)}^{(t)}, \dots \dots . S_{(i,D_{SP})}^{(t)} \right\} \quad (1)$$

with i=1,2,3,….n

Then, the global and local point of optimality is utilized for updating the current solution of each and every particle is calculated based on Equation (2) and (3)

$$V_{(i,j)}^{(t+1)} = I_w . V_{(i,j)}^{(t)} + C_p . r_{nd(1)} \left(P_{(i,j)}^{(t)} - S_{(i,j)}^{(t)} \right) + S_p \, r_{nd(2)} \left(P_{(Gl-Best)}^{(t)} - S_{(i,j)}^{(t)} \right) \quad (2)$$

$$S_{(i,j)}^{(t+1)} = S_{(i,j)}^{(t)} + V_{(i,j)}^{(t+1)} \quad (3)$$

Where ‘$S_{(i)}^{(t)}$’ and ‘$V_{(i,j)}^{(t)}$’ represents the position and velocity of each ‘i’ particle (search agent) explored in ‘d’ dimension. ‘I_w’ is the inertial weight that impacts the speed of convergence with ‘$P_{Gl-Best}^{(t)}$’ and ‘$P_{(i,j)}^{(t)}$’ depicting the global and local optimum point pertaining to the best and current best position of the search agent among all the search agents at time ‘t’. In addition, the constants ‘S_p’ and ‘C_p’ represent the social and cognitive parameters. In this case, the social and cognitive parameters are initialized to 0.5, respectively. The random variables ‘$r_{nd(1)}$’ and ‘$r_{nd(2)}$’ is considered to range between the value of 0 and 1, respectively.

Furthermore, the primitive PSO is improved into a centralized PSO approach by adding an individual solution ($S_{(Center,i)}^{(t+1)}$) with maximized centrality into the original population presented in Equation (4).

$$S_{(Center,j)}^{(t+1)} = \frac{\sum_{i=1}^{n-1} S_{(i,j)}^{(t)}}{n-1} \quad (4)$$

B. Gravitational Search Algorithm (GSA)

Gravitational search algorithm (GSA) is a population-based meta-heuristic approach developed based on the inspiration developed from mass interactions and laws of gravity. The search agent in the GSA systems is the mass aggregates that are utilized attaining mutual cooperation based on laws of motion and Newtonian gravity. The search agents used for identifying the cluster heads are randomly generated by GSA with the solution consisting of position and velocity possessed by them. In the process of cluster head selection, GSA calculates the fitness values and updates the position and velocity of every search agent based on the existing population present in the search space. In this scenario, the search agent (representing the significant solution for the complete set of 'n' agents) position in an iteration 't' is defined based on Equation (5).

$$S_{(i)}^{(t)} = \left\{S_{(i,1)}^{(t)}, S_{(i,2)}^{(t)}, \dots \dots S_{(i,D_{SP})}^{(t)}\right\} \quad (5)$$

with i=1,2,3,….n

The aforementioned equation depicts the position of the search agent determined through the dimensions with as the maximum dimensions used

The coefficient of gravitation in an iteration is calculated based on Equation (6).

$$G_{Coeff}^{(t)} = G_{Coeff\,(0)}^{(t)} + \exp\left(-\alpha \frac{t}{t_{max}}\right) \quad (6)$$

Where 'α' is the constant of shrinking.

Then, the individual masses (possible solutions) and the overall mean mass (average mean solutions) are computed using the worst agent ($Worst_{Fit\,(t)}$) and best agent ($Best_{Fit\,(t)}$) based on Equation (7) and (8), respectively.

$$a_{(t)}^{(i)} = \frac{Fit_{(t)}^{(i)} - Worst_{Fit(t)}}{Best_{Fit(t)} - Worst_{Fit(t)}} \quad (7)$$

$$OA_{Mean\,(t)}^{(i)} = \frac{m_{(t)}^{(i)}}{\sum_{i=1}^{n} m_{(t)}^{(i)}} \quad (8)$$

Further, the complete force imposed on each agent, by all the other agents is randomly weighted and its influence is determined based on Equation (9).

$$T_{Force\,(i,j)}^{(t)} = \sum r_{nd(j)} * \frac{\left(OA_{Mean(i)-ip}^{(t)} * OA_{Mean(i)-op}^{(t)}\right)}{ED_{(i,r)}^{(t)} + \xi_{DE}} \left(S_{(Center,j)}^{(t)} - S_{(i,j)}^{(t)}\right) \quad (9)$$

Where, '$ED_{(i,j)}^{(t)}$' represents the Euclidean distance between an agent 'i' and the other agents 'op' influencing its selection with 'ξ_{DE}' as the constant used for preventing division by zero exception.

Finally, the acceleration towards which the cluster head selection is attained at iteration 't' is computed based on Equations (10) and (11).

$$ACC_{(i,j)}^{(t)} = \frac{T_{Force\,(i,j)}^{(t)}}{OA_{Mean(t)}^{(i)}} \quad (10)$$

$$T_{Force(i,j)}^{(t)} = \sum_{K-Best(sa)} r_{nd\,(j)} * \frac{\left(OA_{Mean(i)-ip}^{(t)} * OA_{Mean(i)-op}^{(t)}\right)}{ED_{(i,r)}^{(t)} + \xi_{DE}} \quad (11)$$

In this scenario, the agent 'K-Best(sa)' is the agent which possesses the greatest mass (solutions containing sensor nodes with maximized energy and has the possibility of being selected as cluster head) is presented in Equation (12).

$$K - Best(sa) = \left(\beta + \left(1 - \frac{t}{t_{max}}\right)(1 - \beta n)\right) \quad (12)$$

In the subsequent iteration, the agents' solution space gets updated based on Equation (13) and (14).

$$V_{(i,j)}^{(t)} = r_{nd\,(i)} * V_{(i,j)}^{(t)} + ACC_{(i,j)}^{(t)} \quad (13)$$

$$S_{(i,j)}^{(t+1)} = S_{(i,j)}^{(t)} + V_{(i,j)}^{(t)} \quad (14)$$

C. Integration Of CPSO And GSA For Cluster Head Selection

Finally, the integration of CPSO and GSA is achieved by initializing the solution of each individual system randomly. Then, CPSO is utilized for estimating the center agent and particle of the center. Further, GSA and CPSO are run simultaneously for attaining global optimality for enhancing the potentialities of exploration and exploitation for determining better solutions. Further, the diversity is improved through the use of crossover attributed by Differential Evolution algorithm. In addition, roulette wheel selection is included for selecting the individuals from the GSA and CPSO for better cluster head selection process.

IV. Simulation Results and Discussion

The simulation experiments of the proposed MPGOA-OCHS scheme and the baseline FLHS-OCHS, HEOA-OCHS and BAFSA schemes are conducted using Matlab R18a. These simulation experiments are conducted for evaluating the potential of the proposed MPGOA-OCHS scheme based on percentage improvement in throughput, percentage sustenance in energy stability, the percentage improvement in network lifetime and percentage improvement in resisting energy holes with different number of sensor nodes.

Figure 1 and 2 presents the percentage improvement in throughput and energy stability with the number of sensor nodes changed in the environment. The percentage improvement in throughput and energy stability facilitated by the proposed MPGOA-OCHS scheme is confirmed to be improved with a systematic increase in sensor nodes, since the dynamic searching ability of CPSO aided in sustaining the tradeoff between intensification and diversification process. The percentage improvement in throughput enabled by the proposed MPGOA-OCHS scheme is improved by 8.42%, 10.54% and 12.96%, compared to the benchmarked FLHS-OCHS, HEOA-OCHS and BAFSA schemes. The percentage improvement in energy stability enabled by the proposed MPGOA-OCHS scheme is improved by 7.12%, 9.64% and 11.88%, compared to the benchmarked FLHS-OCHS, HEOA-OCHS and BAFSA schemes.

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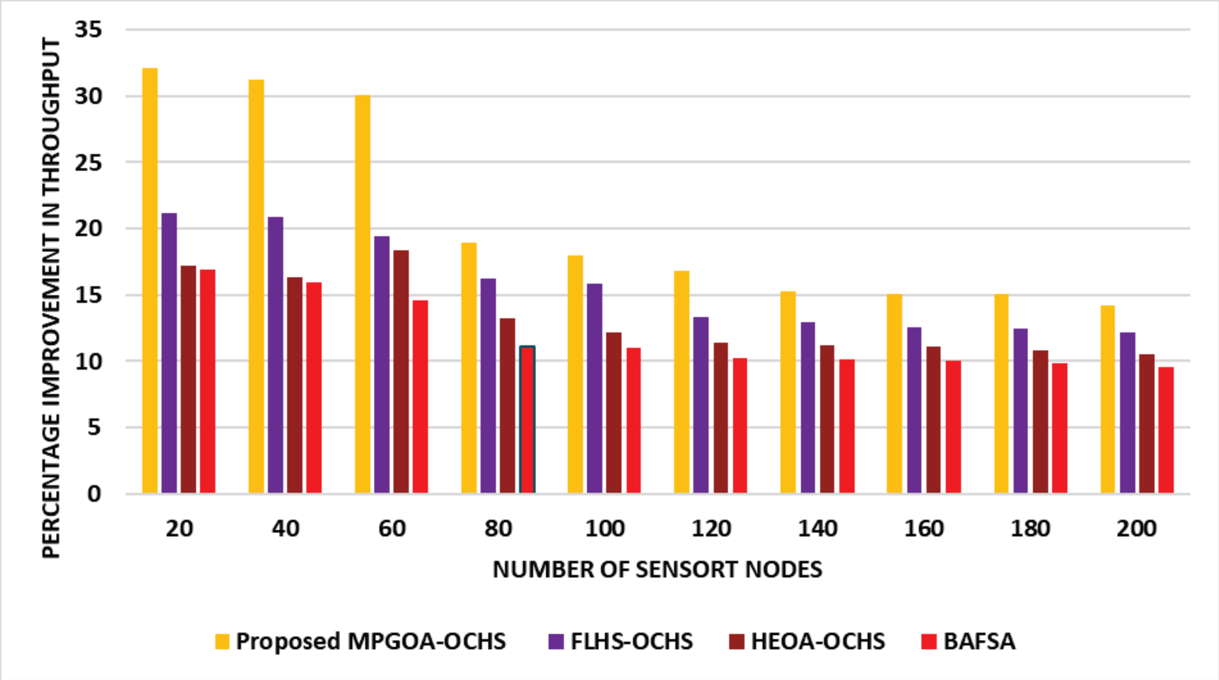

Figure 1. Proposed MPGOA-OCHS-Percentage improvement in throughput with different sensor nodes

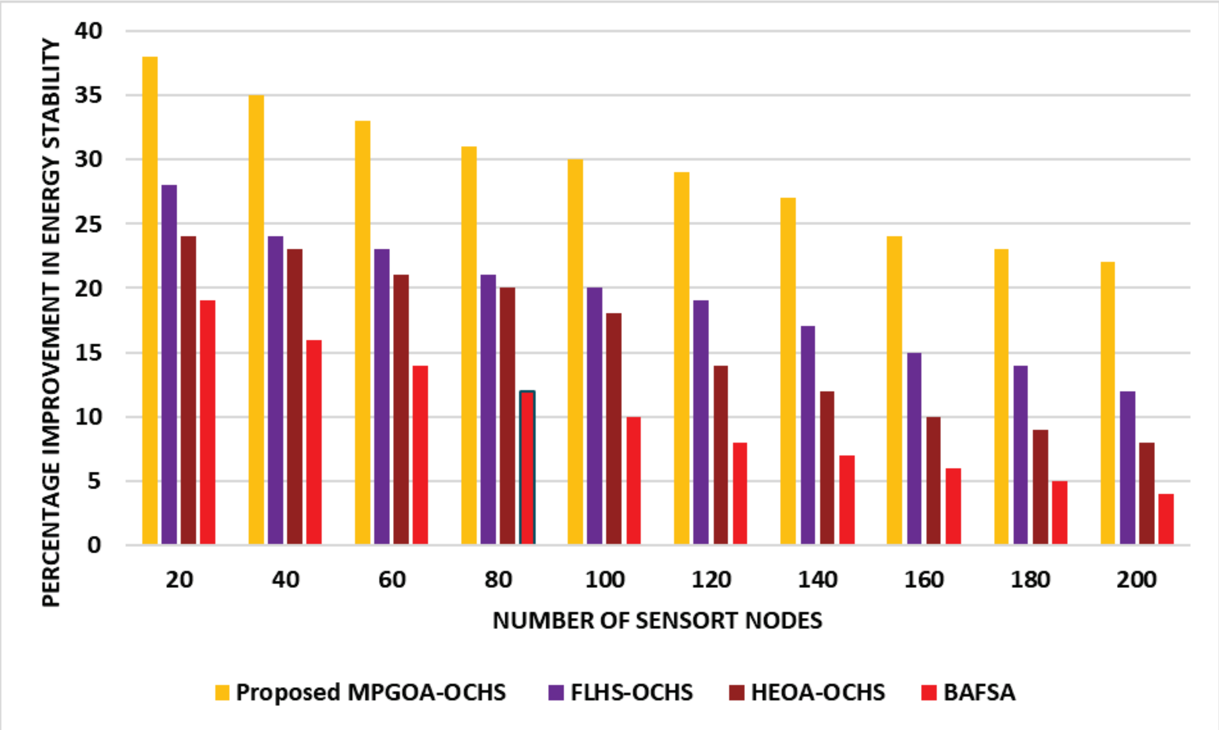

Figure 2. Proposed MPGOA-OCHS-Percentage improvement in energy stability with different sensor nodes

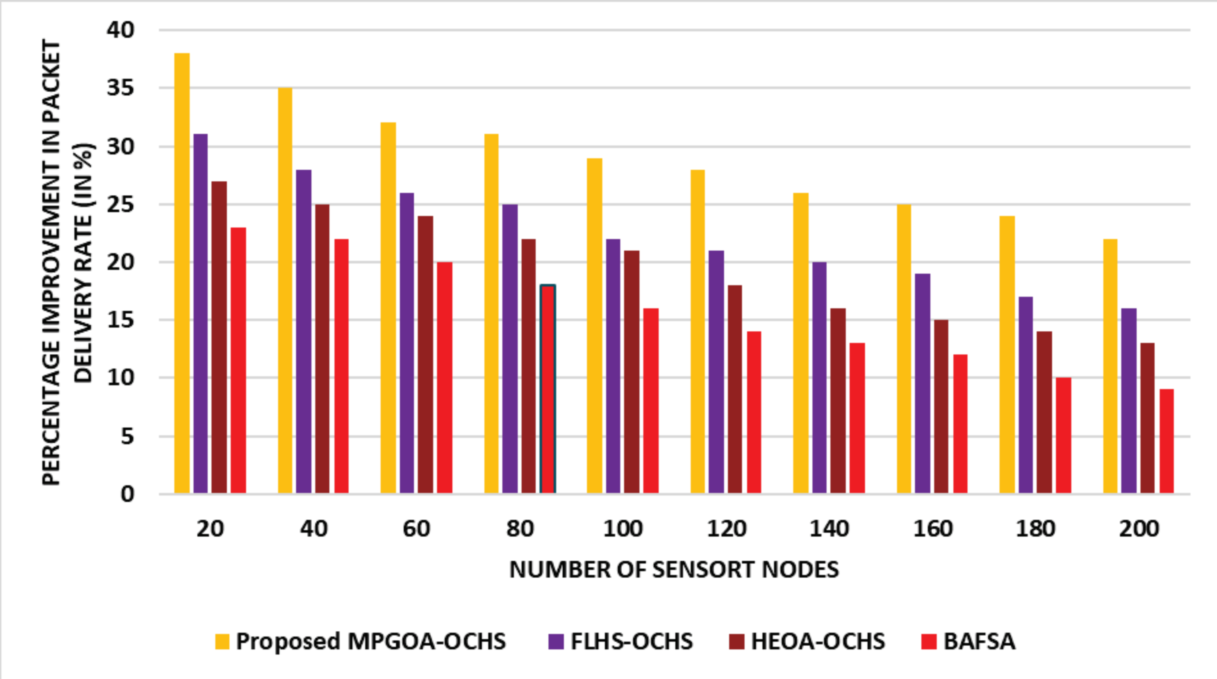

Figure 3. Proposed MPGOA-OCHS-Percentage improvement in packet delivery rate with different sensor nodes

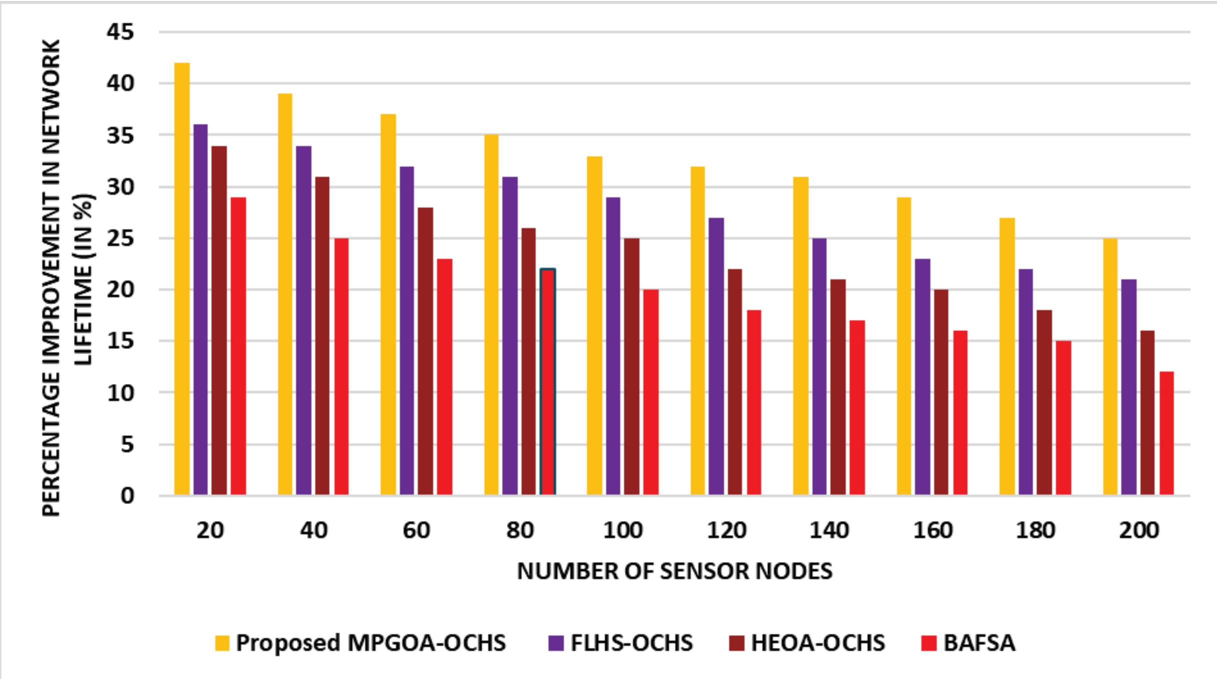

Figure 4. Proposed MPGOA-OCHS-Percentage improvement in network lifetime with different sensor nodes

Figure 3 and 4 demonstrates the percentage improvement in packet delivery rate and network lifetime with the number of sensor nodes increased in the environment. The percentage improvement in packet delivery rate and network lifetime attained by the proposed MPGOA-OCHS scheme is determined to be minimized with a corresponding increase in the sensor nodes. This predominant performance of the proposed MPGOA-OCHS scheme visualized in terms of packet delivery rate and network lifetime is mainly due to the sustenance attributed between the rate of intensification and diversification during the clustering process. The percentage improvement in packet delivery rate facilitated by the proposed MPGOA-OCHS scheme with varying sensor nodes is improved by 8.21%, 10.82% and 12.34%, compared to the benchmarked FLHS-OCHS, HEOA-OCHS and BAFSA schemes. The percentage improvement in lifetime attained by the proposed MPGOA-OCHS scheme is improved by 9.36%, 10.94% and 12.18%, compared to the benchmarked FLHS-OCHS, HEOA-OCHS and BAFSA schemes.

Further, the proposed MPGOA-OCHS scheme and the benchmarked approaches are explored based on the number of alive and dead sensor nodes visualized with the number of increasing rounds. The number of alive nodes maintained by the proposed MPGOA-OCHS scheme with increasing rounds is identified to be enhanced due to its capability of preventing worst fitness sensor nodes from being selected as cluster heads. The number of sensor nodes is also considerably minimized as the frequency of cluster head selection is completely minimized to the maximum level.

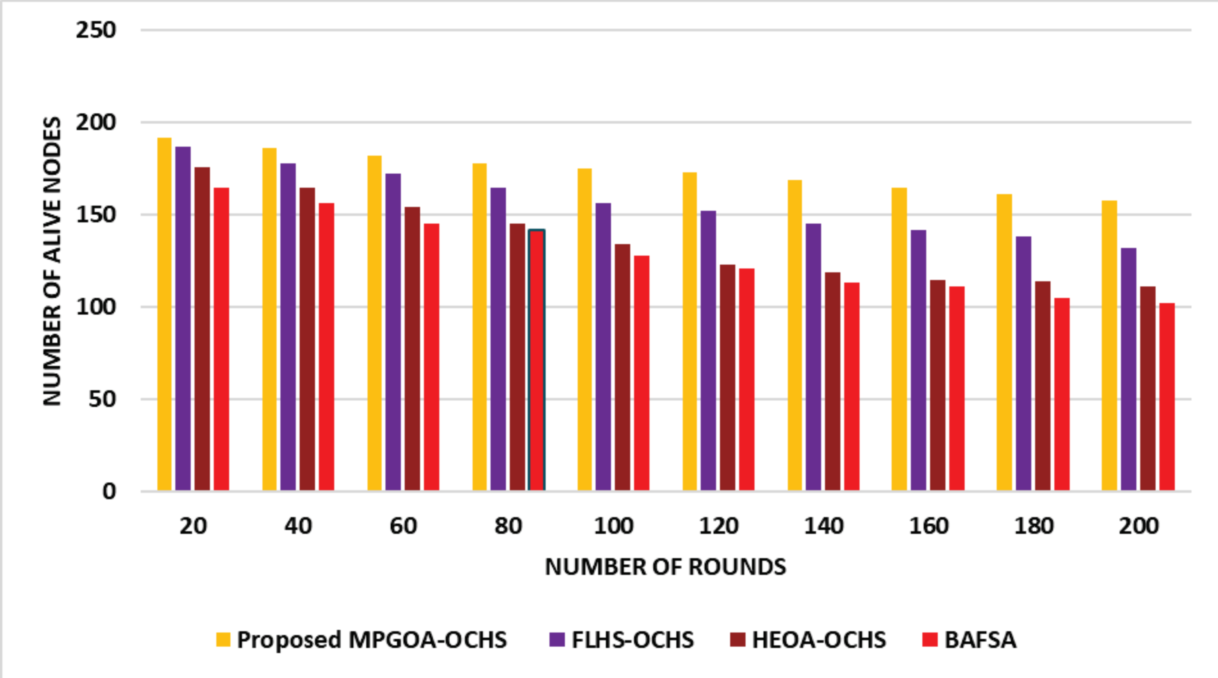

Figure 5. Proposed MPGOA-OCHS-number of alive nodes with different sensor nodes

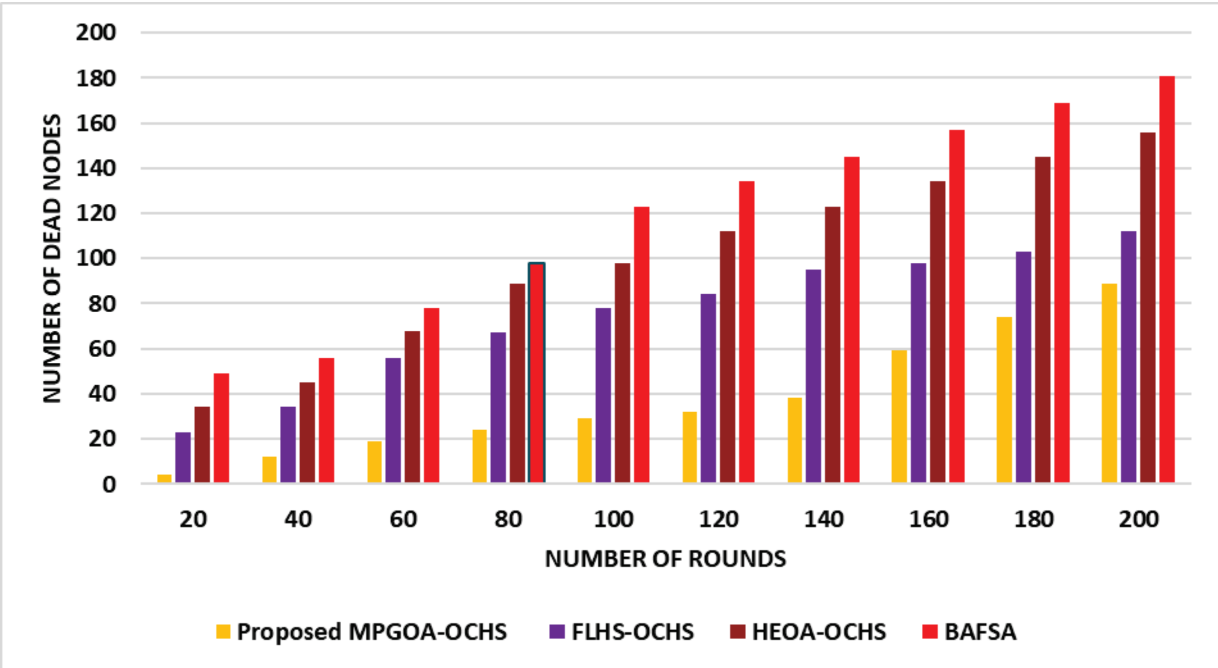

Figure 6. Proposed MPGOA-OCHS-number of dead nodes with different sensor nodes

The number of alive nodes sustained by the proposed MPGOA-OCHS scheme is improved by 9.31%, 11.54% and 13.47%, compared to the benchmarked FLHS-OCHS, HEOA-OCHS and BAFSA schemes. The number of dead nodes prevented from death by the proposed MPGOA-OCHS scheme is improved by 9.32%, 10.41% and 12.74%, compared to the benchmarked FLHS-OCHS, HEOA-OCHS and BAFSA schemes.

V. Conclusions

In this paper, MPGOA-OCHS scheme was proposed for sustaining energy stability and prolonging network lifetime by addressing the issue of energy holes in WSNs. This proposed MPGOA-OCHS scheme attains maximized diversity through the use of crossover attributed by Differential Evolution algorithm. In addition, roulette wheel selection is included for selecting the individuals from the GSA and CPSO for better cluster head selection process. The percentage improvement in throughput enabled by the proposed MPGOA-OCHS scheme is improved by 8.42%, 10.54% and 12.96%, compared to the benchmarked FLHS-OCHS, HEOA-OCHS and BAFSA schemes. The percentage improvement in energy stability enabled by the proposed MPGOA-OCHS scheme is improved by 7.12%, 9.64% and 11.88%, compared to the benchmarked FLHS-OCHS, HEOA-OCHS and BAFSA schemes.

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