Improved Energy Efficiency Using Gravitational search Algorithm (GSA) in WSN

Abstract: The most important aspect to enhance in WSN is energy efficiency. Clustering is the most effective method for increasing energy effectiveness. With the use of this method, sensor nodes in the network region are divided into clusters, with this a cluster head (CH) is assigned to each cluster. This CH collects data packets from non-CH members within the cluster as well as forwards them to the base station. Even so, the CH's energy may well be depleted after a number of transmissions. This article introduced a multi optimization scheme based on the GSA for designing energy-efficient WSNs. A QoS requirement is maintained in an energy management situation. It also took into account the selection of suitable cluster heads or the next hop for every cluster head. The CH will route the information to the BS through a neighboring cluster head as well as directly to the base station (if BS can be reached directly). A MATLAB simulation study is used to compute the models. The simulation outcomes demonstrate that our planned method outperforms the existing work in terms of energy consumed, throughput, as well as network lifetime.

Keywords: Wireless sensor Network (WSN), Energy efficiency, Clustering, GSA.

I. INTRODUCTION

WSNs are widely regarded as the great improvements of the twenty-first century [1-2]. Operated by current advancements in wireless communications, small, economical, as well as smart sensors communicated in a physical region as well as networked during remote connections or the Internet offer extraordinary opportunities for a variety of regular citizen and military applications, for example, battle field surveillance, environmental monitoring, and industrial process control [3-4]. WSNs differ from conventional wireless communication networks, for example, cell frameworks and MANET , in that they have a denser level of node arrangement, greater inaccuracy of sensor nodes, as well as significant energy calculation as well as storage requirements [5], which display numerous new upcoming in the development and use of WSNs.

WSNs have received a lot of attention in the last decade in all over the world from both academia and industry. Many experimental studies have been finished in order to assess as well as solving complex design and implementation issues, and important progress has been made in the construction and operation of WSNs. WSNs are expected to be broadly used in diverse civilian and military fields in the future, upsetting the way live, work, as well as interact with the physical world [6].

A WSN is usually made up of a huge amount of low - cost, low - control, and multifunctional sensor nodes which are distributed throughout an area of interest. The SN are smaller in size, but they are fitted with high, radio transceivers, as well as fixed microprocessors, allowing them to sense as well as process data or communicate. They interact over a small distance using a distant medium as well as collaborate to complete a common task, such as industrial processes, battlefield surveillance, or environmental monitoring. Remote sensors have important features over wired sensors [7]. They not only decrease costs and delays in entity, but they can also be attached to any environment, particularly those where conventional wired sensor devices which are hard to implement, such as battlegrounds, inhospitable terrains, outer space, or deep oceans. WSNs were motivated during military applications ranging from large-scale acoustic surveillance technology for ocean surveillance to local applications of unattended ground sensors for ground detection systems [8]. In spite of, the accessibility of low - cost sensors & wireless interaction has ensured the advancement of a large variety of uses in both civilian and military fields.

Clustering is an important method for halting the service life in WSNs. It entails grouping sensor nodes into organizations as well as selecting cluster heads (CHs) for each group [9]. WSN are divided into partitions, each with a facilitator (cluster head) with respect to collecting data from nodes as well as transferring it to the sink (base station) [10]. Sensors are regularly forwarded in a thick layer to meet the scope requirement, allowing definite nodes to access the rest mode and thus allowing critical energy conservations. The cluster heads are randomly selected or in accordance with at least one criterion.

The rest of this paper is structured as follows. Section II elaborates the cluster head selection by using GSA the proposed method. Section III presents the Literature survey. Section IV shows the proposed objectives and methodology in WSNs. Moreover, Section 5 evaluates the experimental results. Finally, Section 6 presents our conclusions.

II. Cluster head selection using Gravitational Search Algorithm

The Gravitational Search System's performance is determined by the gravity law. Objects (candidate solutions) are regarded as agents in GSA (masses). The agents in the country generate one another due to the force of gravity. Therefore, the agents with larger masses generate the agents with smaller masses. So, masses aid in the assistance of a direct form of communication through gravitational force. Agents with heavy masses (those associated with optimal solutions) begin to move more slowly than smaller objects. A solution to this issue explains the agent's or mass's position. A fitness function is used to calculate inertial and gravitational masses. In the query arena, the remedy with heavy mass is regarded as the most favorable solution. The location of the CHs to be chosen is an answer to this algorithm [16]. Let us now consider a system with ith agents (masses), i.e.,

$$A_i=[X_{i,1}\ (t)\ ,\ X_{i,2}\ (t)\ldots\ldots\ldots\ldots,\ X_{i,D}\ (t)] \quad (1)$$

Where Xi, d(t) represents the position of the i th agent or CHs in the d th dimension. This is also represented as,

$$X_{i,d}\ (t) = (X_{i,d}\ (t),\ Y_{d,,i}(t)), 1\leq i\leq N_p,\ 1\leq d\leq D \quad (2)$$

the fitness value is measured through the proposed parameters. the fitness value is derived as,

$$Fit_i\ (t)=o_1 \times \beta + O_2 \times (1-\beta),\ 0< \beta<1 \quad (3)$$

The agent with the lowest fitness value has more mass as well as a improved position, i.e., the stronger the cluster head selection. Best (t) & worst (t) values are well-defined as

$$Best\ (t) = min_{j\in(1,\ldots.N)} Fit_j\ (t) \quad (4)$$

$$Worst\ (t) = max_{j\in(1,\ldots.N)}\ Fit_j\ (t) \quad (5)$$

The force on the i th mass from the j th mass at a time t is well-defined.

$$F_{ij}^{t}\ (t) = G\ (t) \times \frac{Mass\ PGi\ (t)\times MassAGi\ (t)}{Rij\ (t)+\epsilon} \times (X_i^d\ (t)- X_j^d(t)) \quad (6)$$

here MassAGj (t) signifies the active gravitational mass linked with the j th agent at time t. MassPGi (t) indicates the passive gravitational mass linked with i th agent at time t.ε and G(t) signify a small constant and gravitational constant in the same way. Rij(t) denotes the Euclidian distance between the agents i and j. G(t) is well-defined as follows.

$$G(t) = G_0 \times \exp(-\gamma \times iter / maxiter) \quad (7)$$

$$F_i^d = \sum_{j\in Kbest, J\neq 1} randj\ F_{ij}^d\ (t) \quad (8)$$

$$Mass_i(t) = \frac{Fiti\ (t) - worst(t)}{best(t) - worst(t)} \quad (9)$$

$$Mass_{in},(t) = \frac{mass(t)}{\sum_{j=1}^{N} mj(t)} \quad (10)$$

As a result, the acceleration of the ith agent at time t is measured using eqs. (6) And (9).ad i ð Þt calculated as.

$$a_i^d = \frac{Fid(t)}{Massi(t)} \quad (11)$$

Velocity & position of an agent are measured using below eqs. (12) and (13) respectively

$$V_i^d\ (t+1) = ran_i \times V_i^d\ (t) + a_i^d\ (t) \quad (12)$$

$$X_i^d\ (t+1) == X_i^d\ (t) + V_i^d\ (t+1) \quad (13)$$

III. LITERATURE SURVEY

Behera et al.,(2019) focuses on an well-organized cluster head election strategy that rotates the cluster head position between many nodes that are quicker than others. The method computes remaining energy, power consumption, as well as an average value of cluster heads to pick the next group of cluster heads for the network that is suitable for IoT applications such as environmental monitoring, smart cities, as well as systems. According to simulation outcomes, the customized view surpasses the LEACH method by increasing throughput by 60%, lifetime by 66%, and residual energy by 64%.

Mehta et al. (2020) introduced a Multi Based Clustering (MOBC) as well as Sailfish Optimizer (SFO) guided routing approach for sustaining energy effectiveness in WSNs. It selects the Cluster Head (CH) relying on an efficient fitness function that is constructed from multiple objectives. It aids in reducing energy consumption as well as the set of dead sensor nodes. Following CH selection, SFO is utilized to determine the best path to the sink node for transmitting data. The system architecture is critically evaluated, as well as the values are presented to similar current solutions in conditions of energy efficiency, throughput, packet delivery ratio, as well as network lifetime, GWO, GA, ALO, as well as PSO. When compared to GWO, the simulation experiments demonstrated that the suggested approach performed 21.9 percent as well as 24.4 percent effectively in terms of energy consumption as well as number of alive sensor nodes, in both. Furthermore, it outperformed other optimization-based methods.

Dhumane et al.,(2017) In the IoT network model, the FGSA was suggested to extend the lifetime of the node in order to obtain the most favorable cluster head node iteratively. In FGSA, the cluster head node is chosen as well as analyzed by the fitness function with the use of multiple objectives like distance, delay, link lifetime, and energy, which is referred to as multi-objective FGSA (MOFGSA). MATLAB integration is used to evaluate the computation results. The efficiency of the system is contrasted to that of traditional approaches such as the Artificial Bee Colony, the

GSA, and the multi-particle swarm immune cooperative algorithm. As a result, the suggested MOFGSA approach ensures that IoT nodes have a longer lifetime.

Morsy et al., (2018) the issue of choosing CHs in WSN was actually developed as a single-objective optimization issue. The GSA methodology was used to solve this issue with the goal of minimizing energy consumption, increasing established regions, and increasing network life span. The fitness function was designed to account for intra-cluster distance, distance to BS, as well as residual energy for sensor nodes. The issue was fixed utilizing both the GSA as well as PSO algorithms, or the outcomes indicated that the GSA method provided the best fitness value. To test the protocol's efficiency, the suggested approach was designed and tested in a variety of realistic network scenarios. The method was applied in various BS positions, as well as the findings show that the GSA method keeps the scheme stable for a longer period of time and increases throughput more as compared to the PSO and LEACH. The suggested procedure GSA also reduces the network's average energy consumption.

Mittal et al., (2018) To find the best cluster centroids, authors used a novel gravitational search algorithm called the intelligent GSA. The experimental as well as statistical outcomes show that the suggested alternate outperforms existing meta-heuristic methods on 47 benchmark functions from CEC's 2013 unimodal, multimodal, as well as real-parameter single objective optimization issues. The suggested technique's segmentation accuracy is also tested on H&E marked estrogen receptor positive (ER+) breast cancer images.

Tomar et al., (2019) In NS2, presented an energy-efficient GSA and Fuzzy based clustering with Hop count based routing (GSA-FCR). CHs are chosen from the network's accessible sensor nodes using the GSA method. Then, every selected CH formed a cluster by connecting to other sensor nodes within its transmission range. By using Fuzzy Inference System, the super cluster head was chosen from among the chosen CHs. The data collected from the non-CH member was then relayed by the CH via the most efficient route to the chosen SCH. The hop-count of the CHs was used to determine the most efficient route. The suggested GSA-performance FCR's has been assessed with respect to energy efficiency, delivery ratio, delay, drop, as well as throughput, and this has been compared to current systems like GECR and PSOCR. The simulation shows that suggested method's energy efficiency as well as delivery ratio was better to that of the existing work.

(Liu et al., 2020) The enhanced gravitational method with changing various inertia weight as well as pattern factors of speed & position is suggested to enhance the convergence speed as well as enhancement accuracy of gravitational search approach. This type of algorithm with dynamic inertia weight enhances particle mass updating. Furthermore, the mass transformation has a nonlinear decreasing trend, which enhances the system's optimization accuracy & speed of convergence. Simultaneously, the speed trend factor as well as location adaptive factor are presented, which can adaptively restrict the moving step of each generation of particles based on the current population's number of times. As a result, the method is multi-adaptive. The enhanced method is presented as well as evaluated using the classical test function or the CEC2017 benchmark function. The theoretical analysis validates the enhanced algorithm's convergence as well as time complexity.

Alirezanejad et al. (2020) presented a GSA based on learning automata (GSA-LA) for constant problem optimization. The gravitational constant G(t) is an important criterion that is used to modify the search's accuracy. Learning capability is used in this work to pick G(t) predicated on spontaneous reactions. For assessing the effectiveness of the planned method, numerical analysis is performed on a number of well-designed test functions, as well as the outcomes are compared to the initial GSA as well as other evolutionary-based approaches. The simulation outcomes show that the gravitational search approach based on learning automata is more helpful in identifying optimum solutions & outclasses the existing methods.

IV. PROPOSED METHODOLOGY

The wireless sensor networks are formed with number of small nodes which are run be smaller batteries. These networks are deployed with the intention of helping in number of applications for military, healthcare sector etc. These nodes have smaller batteries and to improve their lifetime, clustering has been proposed as a solution by various researchers in the past.

Existing work: In clustering, a lot of work has been on selecting the cluster heads optimally based on different parameters of the nodes. Another important point focused in clustering is that the optimization of data transmission technique from cluster heads to base station. The authors in [12] have focused on optimizing the multiple objectives while performing cluster head selection. They have taken parameters such as proximity of the nodes from the other deployed nodes in the network, communication cost, left over energy and coverage of the node as the optimization parameters. In terms of optimizing the data transmission, they have used sail fish optimizer to find a way from cluster head to the base station.

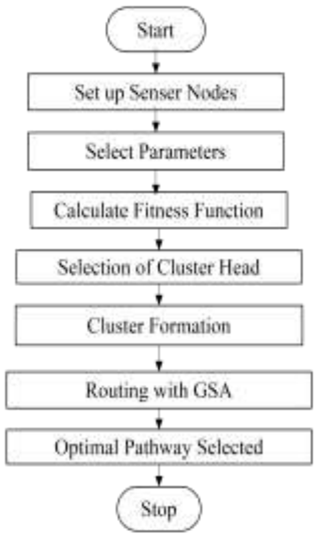
Research Gaps: In [12], the cluster head selection uses the simple weighted average function to compute the fitness value of the nodes. However, some optimization algorithm can be applied here which is better than simple weighted average function to give optimal results. The parameters such as proximity or communication cost are solely on the basis of computing the distance from the neighboring nodes. The distance from the base station is not taken into consideration here which may prove to be important factor in selecting the optimal cluster head.

Another research gap can be identified where the single path is used for data transmission starting from cluster heads to the base station. Even though, the path has been optimized using sail fish optimizer, the path consists of cluster heads only which are already overloaded with other duties such as gathering data from the members. In such case, accumulating the data from other cluster heads and forwarding it to the base station may prove to be more energy consuming task.

- **Objectives**

1. To study various algorithms related to energy efficient clustering in WSN.
2. To proposed the use of gravitational search optimization process for optimal cluster head selection in WSN.
3. To implement the proposed technique and analyze the results in MATLAB.
4. To compare the proposed protocol with other state of the art protocols based on network lifetime, number of alive nodes, and number of dead nodes, energy consumption and throughput of the network.

- **Flow-Diagram**



- **Novelty**

In WSN, the problem of selecting CHs is defined as a single-objective optimization problem. The GSA method was suggested by employed to address this situation with the aim of decreasing costs of energy consumption as well as extending the network's life duration.

This paper presented a multi-strategy optimization to choose the suitable cluster head which is assigned to each Cluster for improving the energy efficiency in WSN based on gravitational search algorithm GSA. The quality of service (QoS) criteria is achieved in an energy-efficient manner.

- **Research Methodology**

The proposed technique will focus on optimal selection of cluster head using gravitational search optimization process instead of using weighted average function as defined in existing protocol [12]. MCH-EOR has used proximity as one parameter in optimizing the cluster head selection process. The proximity was computed from the other deployed nodes in the network. In the proposed gravitational search optimization based protocol, the proximity will be computed from the base station instead of the other nodes. This is because the cluster head has to forward data to the base station in the data transmission stage; therefore it must be situated within a fair distance from it. Another parameter used will be the remaining energy of the node; this will be same as MCH-EOR. Third parameter namely communication cost used in the existing work is computed on the basis of distance of the node from the neighbors, however we will compute it based on the number of neighbor and energy required to communicate with them. These three parameters will be used for multi objective cluster head selection process using gravitational approach.

Once the optimal cluster heads have been selected, they will form the clusters with the nearest neighboring nodes. The elected cluster heads will aggregate data from the cluster members. In the data transmission process of transfer the data to the base station, the MCH-EOR has used sail fish optimizer as the technique to form an optimal path among cluster heads. All the cluster heads will be using the same path only to forward data to the base station. In the proposed protocol, the concept of single path will not be used as it will increase load over the cluster heads forming the path. The cluster heads will forward the data to the base station via neighboring cluster head or directly to the base station (if base station can be reached directly). In other case, where data has to be sent via other cluster head, the relay cluster head will be selected on the basis of least distance toward the base station as well as cluster head and highest remaining energy.

V. RESULTS

Both the proposed GSA clustering procedure as well as the existing technique was simulated using MATLAB. For simulation, five cases were produced from 500 randomly distributed nodes in the network. The base station was not network-connected. The energy consumed, the amount of alive nodes, the amount of dead nodes, as well as the network's throughput were all used to analyze the network's performance.

Network Lifetime: The network life span of the network is defined as the period in which the network can execute the preferred functionality**.**

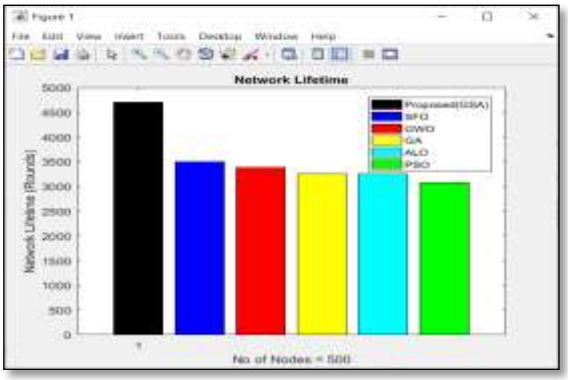


Figure 1: Network Lifetime

Table 1: Comparsion values of Network lifetime

Techniques	**Lifetime**
GSA	4700
SFO	3500
GWO	3380
GA	3255
ALO	3250
PSO	3080

From the table 1 clearly indicates that the proposed GSA algorithm maintains highest lifetime of the network i,e 4700 as compared to existing techniques like SFO,GWO,PSO,GA, ALO.

Energy: Energy is known as the major resource of WSN nodes, and it determines the life span of system.

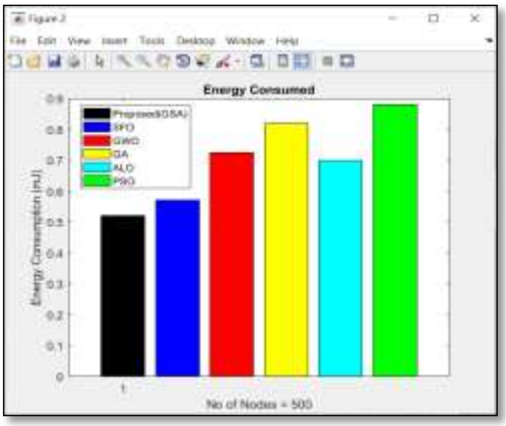


Figure 2: Energy Consumed

Table. 2: Comparsion values of Energy Consumed

Techniques	**Energy consumed (%)**
GSA	0.52
SFO	0.57
GWO	0.725
GA	0.82
ALO	0.7
PSO	0.88

From the table 2 it shows that the proposed GSA algorithm consumed less energy i.e 0.52 as compared to existing techniques like SFO, GWO, PSO, GA, and ALO.

Throughput: The throughput is usually defined as the quantity of success data transmission in the network. In this situation, the following formula is used to calculate the throughput:

$$\textbf{Throughput} = \frac{\text{Total Number of packets successfully transferred}}{\textit{Total Number of packets transferred}}$$

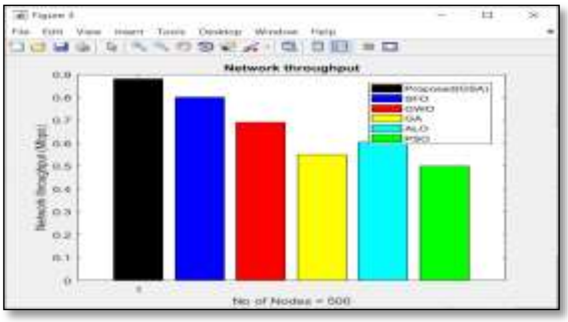


Figure 3: Network Throughput

Table 3: Comparsion values of Throughput

Techniques	Throughput
GSA	0.88
SFO	0.8
GWO	0.69
GA	0.55
ALO	0.605
PSO	0.5

From the table 3 it shows that the proposed GSA algorithm the total Number of packets successfully transferred i.e 0.88 which is more as compared to existing techniques like SFO, GWO,PSO,GA.ALO.

Number of Alive Nodes: The number of alive nodes was measured for each round with respect to find the energy efficiency of the network. For the proposed work the number of rounds consists is [2000, 2400, 2800, 3200, 3500, and 4000].

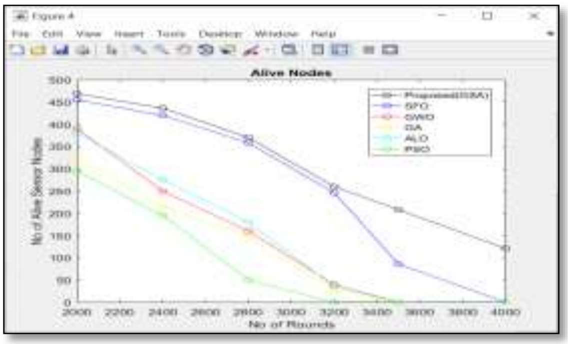


Figure 4: Graphical representation of Alive Nodes

Table 4: Number of Alive nodes

Techniques	Alive nodes
GSA	[469,436,370,260,208,121]
SFO	[455,420,358,246,86,0]
GWO	[390,250,160,40,0,0]
GA	[325,213,148,25,0,0]
ALO	[380,275,180,35,0,0]
PSO	[295,195,50,0,0,0]

Number of Dead Nodes: The no. of dead nodes was measured for each round in order to find the energy efficiency of the network. For the proposed work the number of dead rounds consists is [400, 800,1200,1600,2000,2400,2800, 3200,3500,4000].

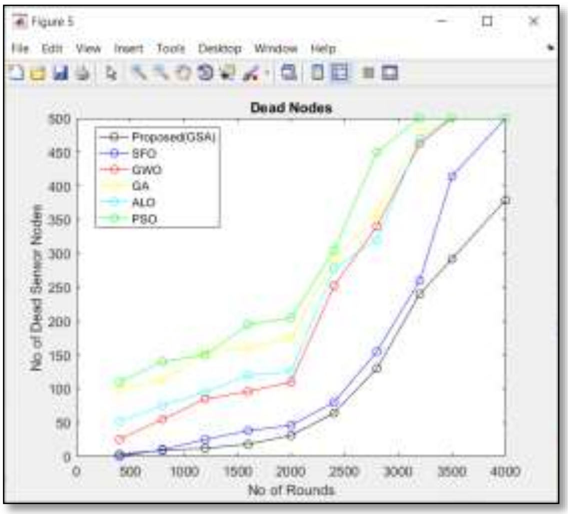


Figure .5: Graphical representation of Dead Nodes

Table 5: Comparsion values for rounds of Dead nodes

Techniques	Dead Nodes
GSA	[3,9,12,18,31,64,130,240,292, 379]
SFO	[0,10,25,38,46,80,155,260,41 4,500]

GWO	[25,55,85,96,110,252,340,462,500,500]
GA	[100,112,155,160,175,290,360,480,500,500]
ALO	[52,75,95,120,125,278,320,470,500,500]
PSO	[110,140,150,195,205,305,450,500,500]

Above mention tables clearly shows that the proposed gravitational search optimization algorithm improves the values for all five parameters like lifetime, energy, throughput, no. of alive nodes and dead nodes because the concept of single path will not be used as it will increase load over the cluster heads forming the path. The cluster heads will forward the data to the base station via neighboring cluster head or directly to the base station (if base station can be reached directly) as compared to existing techniques.

VI. CONCLUSION

From this article, an energy efficient Gravitational search algorithm (GSA) for WSN is described. In addition, suggested method is applied in MATLAB. CHs are chosen from the network's existing sensor nodes using the GSA method. Then, every chosen CH founded a cluster by connecting to other sensor nodes within its coverage area. The suggested GSA approach's performance has been measured in terms of energy consumed, life span, the number of alive and dead nodes, and throughput, and it has been contrasted to that of existing methods such as GA,PSO,ALO. The computation outcomes showed that the suggested method consumed less energy & had a higher throughput than the current work.

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