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# A Hybrid Meta-heuristic Algorithm for Energy-Efficient Data Gathering in Heterogeneous Wireless Sensor Networks

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***Abstract*:** The energy utilization of sensor nodes is an essential aspect of Wireless Sensor Networks (WSNs) design. Clustering is a well-known topology management technique to shorten the energy utilization of sensor nodes for upgrading the network's performance. The cluster heads or gateways have to carry an additional workload in clustered WSNs due to their operational responsibilities, such as data collection, fusion, and routing data to the sink. Therefore, balancing the load of gateways and minimizing the energy usage of nodes is a significant challenge for the long-term working of WSNs. This study proposes a hybrid meta-heuristic technique called Dragonfly Algorithm-Simulated Annealing (DA-SA) for energy-efficient data gathering in heterogeneous WSNs. The DA-SA can avoid getting trapped in a local minimum and increase its diversity level while examining the best solution in the solution space. The derived fitness function measures the quality of the generated solutions from the DA-SA. The detailed simulations are executed on the DA-SA to illustrate its performance with existing algorithms. The compared results show that the proposed DA-SA carries out more valuable outcomes than state-of-the-art algorithms regarding the Network Lifetime (NL), energy levels of gateways, and the number of active sensor nodes.

***Keywords*:** Wireless Sensor Networks (WSNs), DA-SA, gateways, clustering, Network Lifetime (NL).

## 1. Introduction

Internet of Things (IoT) is an important and rapidly developing technology for the modern era. It usually impacts modern applications such as smart homes, industrial automation, and healthcare. The Wireless Sensor Networks (WSNs) consist of numerous tiny sensor nodes. It can be considered an essential technological class within IoT that has laid a solid basis for IoT to grow [1]. WSN is a network that cooperates in gathering and mining high-level semantic information from a sensed region. The sensor nodes in WSNs are battery-operated, which are difficult to recharge for various reasons like an installation at remote places and high cost. Therefore, research on adequate energy utilization of sensor nodes has gained a great impetus. The sensor nodes in WSNs are deployed randomly or manually with the battery and sink to maintain the information of the target region. The sink is a device for receiving sensed data from the sensor nodes. It may connect to the application server to access data from a remote location through the internet. The nodes in the network contain restricted processing and battery unit [2]. Therefore, designing an energy-efficient algorithm is a primary objective to prolong the Network Lifetime (NL). In the literature, many researchers developed efficient clustering algorithms for improving the NL of WSNs. In clustered WSNs, the sensor nodes are partitioned into clusters, and each cluster selects a specific node named Cluster Head (CH) or Gateway. Generally, CHs collect the data from the member sensor nodes, aggregate the data and transfer data to the sink since CHs need extra energy to operate the more time in the network. The additional workload of CH may drain its energy rapidly and dissolve that sensor node in initial rounds in a network. In the literature, many researchers have equipped a high battery node as a CH called a gateway [3]. Therefore, designing an energy-efficient clustered network for data gathering is a crucial WSNs design factor. The clustering technique balances the load of the gateways and minimizes the energy utilization of sensor nodes. It enhances the scalability and performance of the network.

Evolutionary computation has played a vital role in many WSN applications such as clustering, routing, coverage, and connectivity [4]. The load balancing of gateways and minimizing the energy utilization of normal sensor nodes are two significant factors in enhancing the network's performance. Therefore, an adequate clustered network can solve the problems mentioned above. The paper proposes a hybrid meta-heuristic algorithm named DA-SA and a novel fitness function to select the best solution to resolve this problem. The remaining paper is planned as follows: Section 2 outlines the few existing clustering techniques to prolong the NL of WSNs. Section 3 describes the prescribed preliminaries in detail. The proposed DA-SA based clustering algorithm is explained in section 4 clearly. In section 5, the simulations and performance analysis are mentioned. Finally, in section 6, the proposed DA-SA is concluded based on simulations and performance analysis.

## 2. Literature Survey

The clustering requirement comes from various challenges such as minimizing energy utilization of sensor nodes, packet transferring, and load balancing of CHs. Under restricted energy and processing unit conditions, many authors have implemented efficient clustering algorithms to enhance the network's performance. The main discerning properties of picked extensive clustering algorithms are shortly reviewed in this section.

In [5], authors have designed a Genetic Algorithm (GA) based clustering technique for balancing gateways load and a fitness function to determine the best cluster network solution. The chromosome with the highest fitness value among all the solutions is the optimal solution for the clustering problem. AtaulBari et al. [6] have enforced GA for transmitting data packets to the sink, either directly or through intermediate nodes, and they considered relay nodes' energy utilization for measuring NL. Kuila et al. [7] have proposed Differential Evolution (DE) based clustering approach for WSNs to enhance the NL. In this algorithm, authors have considered short lifetime CHs and energy utilization of sensor nodes. Zhou et al. [8] have developed an improved PSO-based clustering protocol taking care of both transmission distance and energy efficiency of nodes. The relay nodes are set up to mitigate the increased energy utilization of CHs. In [9], the authors have developed Shuffled Complex Evolution (SCE) based load balancing technique to enhance the NL of the network. The proposed fitness function acknowledges the load of the gateways to find the best solution. In [10], the authors have implemented the Grey Wolf Optimization-Genetic Algorithm (GWO-GA) technique to balance or distribute the load of the gateways. It ignores the energy utilization of normal sensor nodes.

## 3. Preliminaries

### 3.1 Outline of Dragonfly Algorithm (DA)

The static and dynamic swarming behaviour of dragonflies has inspired the Dragonfly Algorithm (DA) [11]. The three essential principles that govern population or swarm behaviour are as follows. Separation: Avoiding static collisions between individuals in the neighbourhood; Alignment: The matching of an individual's velocity to that of others in the vicinity; Cohesion: Individual's inclination to move near the neighbourhood's centre of mass. The swarm is drawn to food and kept away from enemies in order to survive. The position is updated based on the five elements, which include the three principles indicated above as well as the two survival methods. These variables are theoretically modelled as follows. The $i^{th}$ individual's separation $S_i$ is given in Eq. (1), where $P$ represents the current location, $T$ represents the total neighbouring individuals, and $P_j$ represents the position of the $j^{th}$ individual.

$$S_i = -\sum_{j=1}^{T} P - P_j \tag{1}$$

Alignment $U_i$ , of $i^{th}$ individual is shown in Eq. (2):

$$U_i = \frac{\sum_{j=1}^{T} V_j}{T} \tag{2}$$

where $V_j$ denotes velocity of $j^{th}$ individual. $W_i$ is the cohesion and is calculated as given in Eq. (3).

$$W_i = \frac{\sum_{j=1}^{T} P_j}{T} - P \tag{3}$$

$L_i$ represents attraction for the best solution or food source and is calculated as given in Eq. (4), where $P^F$ indicates the position of the food source. Distraction $M_i$, is evaluated based on the position of the enemy or worst solution $P^E$ as presented in Eq. (5).

$$L_i = P^F - P \tag{4}$$

$$M_i = P^E + P \tag{5}$$

The position value is updated using a step vector $\Delta P_k$. $\Delta P_k$ is determined as given in Eq. (6); where $s, u, w, f$, and $e$ are weights and $\delta$ is the inertia weight.

$$\Delta P_{k+1} = sS_i + uU_i + wW_i + fL_i + eM_i + \delta \Delta P_k \tag{6}$$

The positions are computed as Eq. (7) after the step vector has been determined

$$P_{k+1} = P_k + \Delta P_{k+1} \tag{7}$$

The individuals or dragonflies must navigate the search space utilising a random walk (Lévy flight) L(d) when there are no neighbouring solutions in order to advance their randomness, stochastic behaviour, and exploration. Lévy flight computation is performed in a similar approach as given in [11]. The positions are updated using Lévy flight is shown in Eq. (8).

$$P_{k+1} = P_k + L(d) \times P_k \tag{8}$$

### 3.2 Energy Model

In this study, we have utilized the energy model considering path losses as mentioned in [12]. Free space ($d^2$ path loss) and multi-path fading ($d^4$ path loss) are the energy model's two channels determined by the distance between the transmitter and receiver. If the distance $d$ is less than a threshold value ($d_0$), the free space channel is preferred; otherwise, the multi-path fading channel is utilized. The energy required to transmit a $k$-bit packet across a distance of $d$ is depicted in Eq. (9).

$$E_{TX}(k,d) = \begin{cases} k \times E_{el} + k \times \epsilon_{fs} \times d^2, & d < d_0 \\ k \times E_{el} + k \times \epsilon_{mp} \times d^4, & d \geq d_0 \end{cases} \tag{9}$$

where $E_{TX}$ represents the transmission energy, $d$ is the distance between sender and receiver. $E_{el}$ is an energy usage of the receiver or transmitter. $\epsilon_{fs}$ and $\epsilon_{mp}$ are the energy necessary for transmitter amplifier in free space, multi-path channels, respectively. $d_0$ is a threshold distance calculated as follows, and it is represented in Eq. (10):

$$d_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}} \tag{10}$$

Eq. (11) denotes the energy needed to receive $k$-bit packet in energy model.

$$E_{RX}(k) = k \times E_{el} \tag{11}$$

### 3.3 Network Model

This study considers a WSN composed of randomly equipped sensor nodes and gateways, and both the devices remain fixed after setup. The battery capacity and transmission capacity of the gateways are higher than the sensor nodes. A sensor node is allocated to a gateway only if the gateway is inside the transmission area of that sensor node. Thus, every sensor node has a set of gateways from which it can choose for data transmission. However, at any given point in time, the sensor node can be allowed to only one of the gateways in this set. Communication between the devices is facilitated through wireless links, wherein a link is well-established among two nodes only if both the nodes are inside each other's transmission distance. The data gathering process comprises rounds wherein the sensor nodes gather the local information and transmit it to their equivalent gateway. Upon receipt of this data, the gateways discard uncorrelated and redundant data. Afterwards, these gateways aggregate this data and communicate it to the sink.

## 4. Proposed DA-SA based Clustering Algorithm

The section below describes the proposed DA-SA based clustering algorithm to balance the load of the gateways and minimize the energy utilization of sensor nodes. The construction of the fitness function acknowledges the lifetime of sensor nodes and gateways. In this study, we have combined DA [11] and Simulated Annealing (SA) [13] named DA-SA to improve the convergence speed. The SA is a meta-heuristic based local search algorithm. It can avoid becoming trapped in a local minimum through hill-climbing moves to explore the best solution. DA-SA can avoid becoming trapped in a local minimum and increase its diversity level while examining the best solution in the solution space. Therefore, DA-GA is adopted to find an energy-efficient cluster network to enhance the network's performance. Algorithm 1 represents the pseudo-code of the DA-SA based clustering algorithm. It has the following steps.

**Phase 1: Initialization of population**

Generate a predefined number of dragonflies or random solutions named as population and initialize each dragonfly with a random position and step vectors in dimension $d$. The $d$ value of each dragonfly is equivalent to the count of the sensor nodes present in the network, and all the dragonflies have the same size. The proposed DA-SA follows the encoding technique of solution as used in [3]. Let $P = \{P_1, P_2, P_3, \ldots, P_N\}$ represents the dragonflies in the population. Every solution or dragonfly $P_i$ has a position vector $P_i = \{x_{i1}, x_{i2}, x_{i3}, \ldots, x_{id}\}$, and a step vector $\Delta P_i = \{\Delta x_{i1}, \Delta x_{i2}, \Delta x_{i3}, \ldots, \Delta x_{id}\}$ which is used to show its present state. Eq. (12) represents the $i^{th}$ candidate solution ($P_i$) of the population.

$$P_i = \{x_{i1}, x_{i2}, x_{i3}, \ldots, x_{id}\}, 1 \leq i \leq N \tag{12}$$

where $d$ denotes the size of the candidate solution, $N$ represents the number of dragonflies or candidate solutions in the population, and $x_{i1}$ shows the first component of the $i^{th}$ candidate solution $P_i$. Each dragonfly or candidate solution is encoded into a solution for the clustering problem.

**Phase 2: Calculation of fitness function**

The fitness function computes the effectiveness of the solutions to find the efficient solution in the solution space. The fitness function's construction to assess the population's solutions is as follows. The main objective is to design a cluster network to enhance the lifetime of sensor nodes and gateways to operate at full network functionality for a more extended period. Considering the lifetime of the sensor nodes and gateways in fitness function construction can achieve the target. Therefore, the proposed DA-SA algorithm acknowledges two objectives to enhance the network's performance. The first objective is to increase the standard deviation of the lifetimes of sensor nodes. The second objective is to focus on the lifetime of gateways in the network, and it considers the standard deviation of lifetimes of all the gateways. The fitness function derivation relies upon the following terminologies.

**1. Lifetime of sensor node**: The lifetime of the sensor node is a significant factor in increasing the network's performance. It depends on the residual energy, the distance between the sensor node and the assigned gateway. The lifetime of sensor node $S_i$ is $LTS(S_i)$, and it is summarized in Eq. (13).

$$LTS(S_i) = \left\lfloor \frac{E_{residual}(S_i)}{E_{round}(S_i)} \right\rfloor \tag{13}$$

where $E_{residual}(S_i)$ denotes the residual energy of sensor node $S_i$, $E_{round}(S_i)$ represents energy consumption of sensor node $S_i$ per round.

The first objective is to decrease the energy utilization of sensor nodes to improve the lifetime. Therefore, the fitness function considers the standard deviation of lifetimes of sensor nodes to achieve the first objective. It is represented in Eq. (14).

$$f_1 = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\mu_1 - LTS(S_i))^2} \tag{14}$$

where $\mu_1 = \frac{1}{n}\sum_{i=1}^{n} LTS(S_i)$ and $n$ is number of sensor nodes. A decrement in the $f_1$ value minimizes the fitness value.

**2. Lifetime of gateways**: The main objective is to enhance the performance of WSNs, which can be attained by increasing the lifetime of the gateways. The necessary convention is that fewer remaining energy gateways should have less energy drain rate in the network than the higher remaining energy gateways. The proper load allotment can increase the lifetime of the gateways. The gateways diminish their energy due to receiving the data from associated sensor nodes, aggregating data, and communicating the aggregated data to the sink.

The notation $E_{gateway}(g_j)$ denotes the total energy utilization of gateway $(g_j)$ per round to gather data from member nodes, aggregate it, and transmit to the sink. The procedure is shown in Eq. (15).

$$E_{gateway}(g_j) = (l \times E_{RX}) + (l \times E_{DA}) + E_{TX}(g_j, sink) \tag{15}$$

where $l$ is the number of packets gateway $(g_j)$ gathering per round from associated sensor nodes. $E_{RX}$, $E_{DA}$ are energy utilization due to receiving, aggregating of data per bit. $E_{TX}$ is the required energy to transmit data over distance $d_{g_j,sink}$. $d_{g_j,sink}$ is Euclidean distance between the gateway $(g_j)$ and sink.

Let $LTG(g_j)$ denotes the lifetime of gateway $(g_j)$ and $E_{residual}(g_j)$ is residual energy gateway $(g_j)$. The $LTG(g_j)$ of $g_j$ is as given in Eq. (16).

$$LTG(g_j) = \left\lfloor \frac{E_{residual}(g_j)}{E_{gateway}(g_j)} \right\rfloor \tag{16}$$

The second objective is to balance the gateways' load to enhance the network's performance. Therefore, the fitness function considers the standard deviation of the lifetimes of gateways to achieve the second objective. The gateways use their energy to handle the additional workload from their associated sensor nodes, and the lifetime of gateways is necessary for the long-haul working of WSNs. To judge the well-balanced lifetime of the gateways, we calculate the SD of the gateway's lifetime. Eq. (17) shows the SD of the lifetime of gateways.

$$f2 = \sqrt{\frac{1}{m}\sum_{j=1}^{m}(\mu_2 - LTG(g_j))^2} \tag{17}$$

where $\mu_2$= $\frac{1}{m}\sum_{j=1}^{m} LTG(g_j)$ and $m$ denotes number of gateways. A Decrement in the $f_2$ value decreases the fitness value.

Finally, the fitness function $(F)$ is derived from Eq. (14), Eq. (17), and it is represented in Eq. (18):

$$F = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\mu_1 - LTS(S_i))^2} \times \sqrt{\frac{1}{m}\sum_{j=1}^{m}(\mu_2 - LTG(g_j))^2} \tag{18}$$

The main objective is to achieve a lower fitness value. A lower fitness value gives a better position to the candidate solution.

**Phase 3: Apply SA algorithm to best candidate solution**

Here, the approach begins with a solution in a solution space $(S_p)$ of a specific dragonfly with an updated solution $P_i'$. The $P_i'$ is generated from $P_i$. The fitness function $F(P_i)$, which denotes the fitness value of $P_i$. The relative change in fitness function $\Delta F$ between $P_i$ and $P_i'$ is expressed as $\Delta F = \frac{F(P_i') - F(P_i)}{F(P_i)}$. Therefore, this approach starts with the solution generated from the population, and it accepts only the solution that provides a better cost value than the previous solution, i.e., $F(P_i') < F(P_i)$. However, the following probability function decides the acceptance or rejection of a newly generated solution with a higher fitness function for $P_i'$, and it shown in Eq. (19).

$$P(\Delta F, T) = \begin{cases} e^{\frac{-\Delta F}{KT}}, & \Delta F > 0 \\ 1, & \Delta F \le 0 \end{cases} \tag{19}$$

where $K$ represents the Boltzmann constant, $T$ denotes the temperature.

The probability function $P(\Delta F, T)$ is more important for minimum values of $\Delta F$. It states that the newly generated solution $P_i'$ is only marginally higher cost than the present position $P_i$. If the $P_i'$ is a much higher cost than the present solution $P_i$ means that $P_i$ is higher chance to be preferred than the newly generated solution $P_i'$. The temperature value $T$ is a significant control parameter. Its value proportionally reduces in each iteration with $P(\Delta F, T)$. Thus, if the temperature value $T$ minimizes, the probability of selecting an inefficient solution also minimizes. Eq. (20) illustrates the minimizing the parameter $T$ in each iteration.

$$T_{new} = C_f \times T_{old} \tag{20}$$

where $C_f$ is a temperature reduction factor or cooling coefficient, a random constant number from $(0, 1)$.

**Phase 4: Update the candidate solution**

Find the best source and worst solutions from the population to update the present position of dragonflies. Update the dragonflies or candidate solutions using Eq. (6), Eq. (7), and Eq. (8).

**Algorithm 1** The Pseudo-code of proposed DA-SA based clustering

**Initialization**: DA-SA parameter values
**for** Each dragonfly i **do**
  **for** Each Dimension d **do**
    Initialize position $x_{id}$ value randomly
  **end for**
**end for**
Initialize the step vector $\Delta P_i, (i = 1, 2, 3, \ldots, N)$
Calculate the fitness function of all dragonflies using Eq. (18)
Store the best and worst dragonflies
Apply SA algorithm on best solution and update it.
**while** (Maximum iterations reached) **do**
  Update $s, u, w, f, e$, and $\delta$
  Compute $S, U, W, L$, and $M$ using Eq. (1)- Eq. (5)
  Update neighbouring radius
  **for** Each dragonfly $(P_i)$ **do**
    **if** $P_i$ has minimum one neighbouring solution **then**
      Update the velocities by using Eq. (6)
      Update the positions by using Eq. (7)
    **else**
      Update position values by using Eq. (8)
    **end if**
  **end for**
  Modify the position values if it goes out of bound
**end while**
**return** global best candidate solution

## 5. Results and Discussion

This section describes in-depth the experimental configuration of the network and the work-study of the proposed DA-SA compared to other current approaches.

### 5.1 Experimental setup

The simulations are carried out for randomly set up sensor nodes and gateways in a region of $200 * 200\ m^2$. The BS station is placed in $(100, 100)$ in target region. We run the algorithm for a different number of sensor nodes and gateways. The sensor nodes range from $100 - 250$ with 10 and 15 gateways. Sensor nodes' initial energy measure is considered $2J$, and gateways as $5J$. Table 1 shows the network configuration and typical DA-SA parameter values. The results are taken using MATLAB.

### 5.2 Performance Analysis

Algorithms that perform well can keep the network running for a more extended amount of time. The network performance is measured in terms of NL, the SD of energy levels of gateways in a specific round, and active sensor nodes. The proposed DA-SA compared with existing clustering techniques GWO-GA, SCE, and NGA. The parameters mentioned above are explained in detail.

**Table 1.** List of parameters and their values

| Network configuration | |
|---|---|
| **Parameter** | **Value** |
| Target region | $(200 \times 200)$ m$^2$ |
| Location of BS | $(100, 100)$ |
| Sensor nodes | 100, 150, 200, 250 |
| Gateways | 10, 15 |
| Initial sensor node energy | 2 J |
| Initial gateway energy | 5 J |
| $E_{el}$ | 50 $nJ/bit$ |
| Message size | 200 bits |
| Packet size | 4000 bits |
| Communication range | 100 m |
| $\epsilon_{fs}$ | 10 $pJ/bit/m^2$ |
| $\epsilon_{mp}$ | 0.0013 $pJ/bit/\ m^4$ |
| **DA** | |
| Population size $(N)$ | 50 |
| Maximum number of iterations | $100 - 150$ |
| **SA** | |
| Boltzmann constant $(K)$ | 1 |
| Initial temperature $(T)$ | 1 |
| Temperature reduction factor $(C_f)$ | 0.8 |
| Maximum number of generations | $20 - 40$ |

#### 5.2.1 Network Lifetime (NL)

The NL of WSNs is a vital aspect of the operating functionality of devices long period. As discussed in the above sections, the definition of NL differs depending on network topology and application requirements. Here, we considered NL for the total number of operational rounds the full network functionality. We have run the algorithm for the network scenario by varying sensor nodes from $100 - 250$ with 10 and 15 gateways, respectively. Fig.1 and Fig.2 show the comparison of proposed DA-SA with existing algorithms GWO-GA, SCE, and NGA in terms of NL. The results demonstrate that the proposed DA-SA operates better than GWO-GA, SCE, and NGA. The design of fitness decides the quality of the solution to a problem. The GWO-GA, SCE, and NGA build fitness with the help of a load of gateways, whereas the proposed DA-SA considers the lifetime of sensor nodes and gateways.

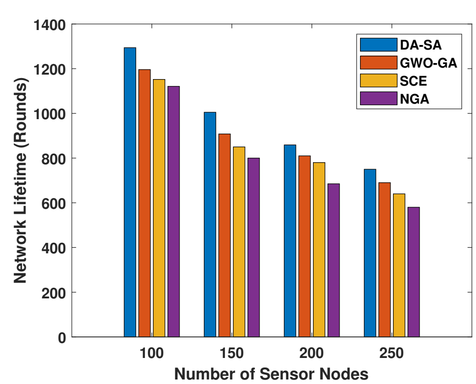


**Figure 1.** Comparison of NL with 10 gateways for diverse number of sensor nodes

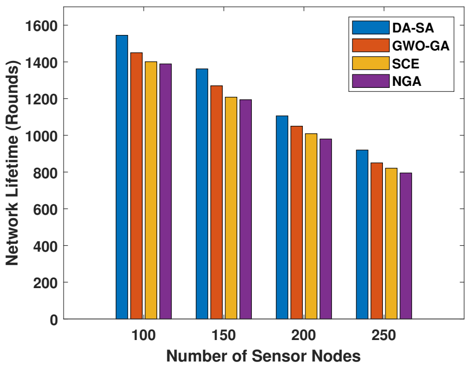


**Figure 2.** Comparison of NL with 15 gateways for diverse number of sensor nodes

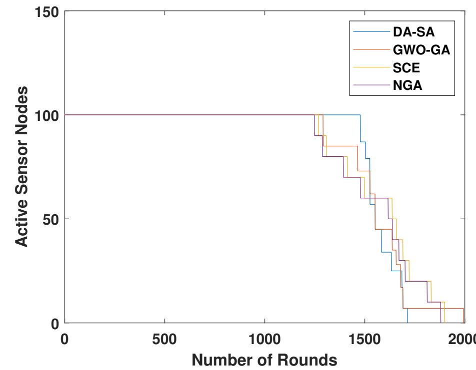


**Figure 3.** Comparison of number of active sensor nodes with 15 gateways

**Table 2.** Results of SD of gateways energy levels in 700 round for 15 gateways.

| Sensor nodes | DA-SA | GWO-GA | SCE | NGA |
|---|---|---|---|---|
| 100 | 0.381 | 0.422 | 0.471 | 0.512 |
| 150 | 0.462 | 0.516 | 0.541 | 0.532 |
| 200 | 0.512 | 0.548 | 0.576 | 0.618 |
| 250 | 0.543 | 0.568 | 0.607 | 0.645 |

### 5.2.2 Energy Levels of Gateways

The energy level of a gateway is a significant parameter in enhancing the performance of the WSN. Here, we assessed the Standard Deviation (SD) of energy levels of gateways in a given round to measure the efficiency of the clustered network. We have run the algorithm for the network scenario by varying sensor nodes from $100 - 250$ with 15 gateways. Table.2 show the comparison of DA-SA with GWO-GA, SCE, and NGA in terms of the SD of the gateway's energy levels at round number 700. The results show that the DA-SA based clustering algorithm performs better compared to GWO-GA, SCE, and NGA. The fitness function of DA-SA acknowledges the SD of the lifetime of gateways. The lower the SD of the gateway's energy levels, the better the load distribution.

### 5.2.3 Active Sensor Nodes

The active sensor nodes define the number of functionally operational nodes in the network, and it evaluates in rounds. The factor lifetime of the sensor node can affect the sensor node energy utilization. We run the algorithms for 100 sensor nodes with ten gateways for the network scenario. Fig.3 shows the observation of DA-SA with GWO-GA, SCE, and NGA in terms of active sensor nodes. The results show that DA-SA performs well as related to other existing methods. The DA-SA considers the lifetime of the sensor nodes to compute the generated solutions.

## 6. Conclusion

In this study, we have proposed DA-SA based clustering technique for energy-efficient data gathering in heterogeneous WSNs. The fitness function acknowledges the lifetime of sensor nodes and gateways to determine the best solution in the solution space. It can help in choosing the energy-efficient clustered network for data gathering. The DA-SA algorithm avoids getting trapped in a local minimum and increases its diversity level while examining the best solution in the solution space. The total amount of time the complete network functionally operates is the measure for NL. Finally, the experiments are analyzed based on network measures such as NL, energy levels of gateways, and the number of active sensor nodes. The proposed DA-SA approach outperformed existing clustering algorithms such as GWO-GA, SCE and NGA.

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