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# Energy-Efficient Grasshopper Optimization Algorithm (EEGOA) Based Cluster Head Election for WSNs

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**Abstract:** The lifespan of a wireless sensor network (WSN) is shortened and energy efficiency declines as a result of unequal energy usage. The goal of clustering approach is to balance energy depletion while minimizing data redundancy in order to increase energy efficiency. Two different types of jobs, the Cluster Head (CH) and the Cluster Member (CM) coexist in each cluster. The Grasshopper Optimization Algorithm (GOA) is used in this article to encourage energy balance throughout the CH election phase. Best of the authors' knowledge, this stays the first occasion that systematic GOA had any influence upon the CH election. In order to achieve this, the Calinski-Harabasz index is used to take the best CH. The CH is calculated using this algorithm in order to maintain energy stability within each cluster. The energy effectiveness of the system was assessed using extensive simulations. Evaluation metrics show it is effective in increasing energy efficiency and extending network time in WSNs as compared to typical clustering strategies.

**Keywords:** Grasshopper Optimization Algorithm (GOA), Wireless Sensor Networks (WSNs), Calinski-Harabasz index, and Clustering.

## 1. Introduction

The word "wireless sensor network" (WSN) refers to a distributed network system made up of many sensor nodes that self-organize. Beyond its initial military applications, wireless sensor network applications have grown in breadth. Due to their inexpensive deployment and maintenance costs, WSNs are used more and more for enemy detection, target tracing, air pollution monitoring, and medical care [1]-[3]. Recent research has focused on extending the network lifetime of WSNs. Since the sensor node not be recharged after deployment, increasing energy efficiency is a practical plan. The best way for improving energy efficiency is clustering, which splits the network into various clusters[4]-[5]. By balancing energy depletion and reducing data redundancy, clustering systems aim to increase energy efficiency. Clustering can be seen as a type of nondeterministic polynomial time (NP)-hard combinatorial optimization problem. Two different types of jobs, the CH and the CM, respectively, coexist in each cluster. The CH and the CM, two different types of functions, coexist in each cluster. As depicted in Figure 1, CM collects the raw data and sends it to relevant CH. After that, a straightforward aggregate process is carried out on the raw data.

As a result, there can be some reduction in data redundancy. In order to reduce energy use for data collisions, overhearing, and other issues, each CH divides its time slots into time division multiple address (TDMA). By using the TDMA mode, each CM alternates among working and resting modes, lowering the liability cycle and energy consumption. It makes sense to alternate the part of CH round each round because each CH has a significantly higher energy load than the CM. Energy consumption reduction and equilibrium can be somewhat simultaneously accomplished by choosing the right CH in each round.

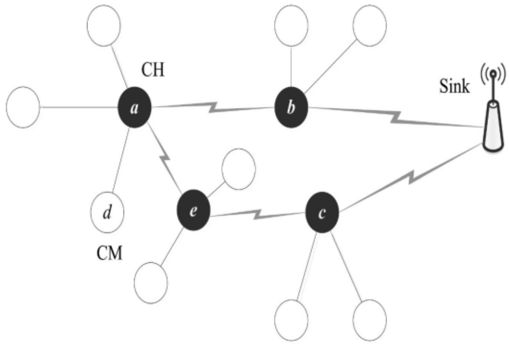


**Fig 1:** WSN Clustering Strategy

It is potential to decrease and regulate energy consumption simultaneously in some cases through CH elections. In contrast to flat networks, structured networks can aggregate data, reduce communication overhead, simplify management, minimize overall control consumption, increase energy efficiency, and extend the sensor network life cycle. Additionally, clustering allows efficient dynamic routing among sensors or to the exact nodes (sink nodes). Clustering within optimization is described along with its formulation. The Grasshopper Optimization Algorithm (GOA) is then introduced briefly, which is the most important component for selecting CH optimally. In GOA, the best person is considered along with the social interaction of agents (grasshoppers). Lastly, it is thoroughly tested in comparison to the most recent smart clustering algorithms and the classic intelligent clustering algorithm in relations of network lifetime and energy efficiency.

## 2. Literature Review

The enhancement of energy efficiency in WSNs takes  the focus of many clustering methods in recent years, which are mentioned below.

Kaur et al [6] implemented the usage of natural sensation’s based optimization techniques to solve the problematic of non-clustered nodes. Its goal is to offer effective clustering so that residual nodes can be avoided and dead nodes can be avoided by using mobile nodes. First, use the MATLAB environment to deploy a specific number of mobile nodes. Low Energy Adaptive Clustering Hierarchy (LEACH) protocol is used to cluster these nodes. Some nodes remain after clustering with the LEACH Fire Fly Optimization Algorithm based Clustering by securing remaining Nodes in Mobile Wireless Sensor Networks. For effective clustering and the avoidance of residual nodes, use Firefly Optimization. Like clustering, it makes use of factors for distance and light intensity. The Gravitational Search Technique (GSA) algorithm has been utilised to determine the most efficient path for data transfer.

Łukasik et al [7] suggested the potential for producing reliable data grouping usage the Grasshopper Optimization Algorithm (GOA). The Calinski-Harabasz index are recycled as an internal clustering authentication metric to assess the quality of the solutions that were developed. It provides a explanation of the suggested process and includes an experimental analysis of the approach for a number of benchmark cases. Research has shown excellent accuracy in clustering based on GOA.

Lin et al [8] proposed Energy equilibrium is promoted when Cluster Head (CH) elections are being conducted using the Social Welfare theory-based Energy Efficient Cluster Head Election (SWECE). The CH election is being governed by systematic social theory for the first time, as far as the writers are aware. It is necessary to employ Atkinson's Disproportion Measure in order to determine the best CH. Also, predict energy efficiency welfare is a novel way to get energy equilibrium inside every cluster.  It has raised energy efficiency and extends network lifetime, proving its effectiveness.

Sidhu and Pathak [9] adopted the clustering algorithm Particle Swarm Optimization Based LEACH (PSO-LEACH) for WSN. The principle calculation used in the low energy flexible clustering chain of importance algorithm is where each and every hub present within a group throws its information in a particular order to the locality group leader. In this work, the terms "MS" (mobile sink), which reduces energy consumption, and "RN" (Rendezvous Nodes), which serves as a storage location for the mobile sink, are used.

The steering is improved by using a molecule swarm improvement computation, which lengthens the system's life lifetime.

Rathore et al [10] suggested an energy-harvesting wireless sensor network clustering mechanism (EH-WSNs) based on a hybrid whale and grey wolf optimization (WGWO). When evaluating the algorithm, the suggested hybrid WGWO technique has considerably greater exploitation and exploration capabilities than the conventional and different current meta heuristic algorithms. The best outcomes are produced by this mixed strategy. The clustering process that is based on WGWO is suggested comprises of dynamic CH selection and cluster formation. The act of the proposed method is linked to current cutting-edge routing protocols.

Wang et al[11] centered on improved Whale Swarm Optimization (WSO) algorithm; a WSN coverage optimization model was built. To fully cover the relevant region, a mathematical model of node coverage in a WSN is built. To improves the initial supply, the converse learning concept is added to the original WSO method for the model. The global search is sped up and the node search capabilities are improved using this technique. The experiment demonstrates how this approach can efficiently increase node coverage within a WSN and enhance network efficiency.

Wang et al [12] investigated a double cluster head, better energy optimization routing algorithm for clustering WSNs. The method for the energy overhead is offered to change the sensor node joint a temporary cluster with minimal energy consumption during the cluster setup stage in direction to balance the nodes' energy. Relay nodes then use a hybrid of single-hop and multi-hop technology to transmit sensory data to the sink during the routing selection. Through simulation tests and comparisons with certain current methods, the enhanced protocol is assessed. The results show that the proposed scheme performs better energy usage efficiency than the pertinent procedures. Particularly, the network lifetime is extends because the CH uses less energy.

## 3. Proposed Methodology

Grasshopper Optimization Algorithm (GOA) is used in this research to encourage energy equilibrium during the CH election process. GOA takes into account both the appeal of the best person as well as social interaction between common agents (*grasshoppers).*

### 3.1.Energy Consumption Model

**1) *Energy Consumption Model*:** The first-order radio model is used in this article to describe how much energy is used to transmit data. Specifically, the energy required for a sensor node to convey a message of one bit over a distance of d is equal to

$$e_{tx} = E_{elec} + \varepsilon_{amp} . d^{\alpha} \tag{1}$$

A transmitter circuit consumes a certain amount of energy is denoted as $E_{elec}$,$\varepsilon_{amp}$ is the transmitter amplifier, and $\alpha(2 \leq \alpha \leq 4)$ indicated by the propagation loss exponent. Message bits are displayed as expressions of energy dissipation for the receiver.

$$e_{rx} = E_{elec} \tag{2}$$

***2) Network Topology*:** Lets see the rectangular network that is partitioned into m2 grids in this article. In order to minimise the energy overhead for transmission as much as feasible, each grid's length of side must satisfy the following requirement in order to make equal 2:

$$\sqrt{2}a \leq d_{thre} \& d_{thre} = 87 \tag{3}$$

where $d_{thre}$ is the distance threshold designed for free-space model. Nodes in adjacent grids are connected via one-hop transmission according to equation (3). Energy overhead for one-hop transmission is predicted to stay low by the first-order model. Using one-hop transmission, each node of the grid holding the sink can immediately transmit data to the sink. For suitability, it is called the central grid (CG).

### 3.2. Energy Equality Evaluation

In terms of energy remaining in the nodes, the energy equality index (E2I) assesses network equality. Likewise, it is consistent with Atkinson's social welfare function. Following is a mathematical expression of the E2I for round k, based on Atkinson's inequality measure.

$$E2I(k) = 1 - I_E(k, \varepsilon) \tag{4}$$

$$I_E(k, \varepsilon) = 1 - \left[\frac{1}{n}\sum_{i=1}^{n}\left(\frac{E_{re}^{sn_i}(k)}{E(k)}\right)^{1-\varepsilon}\right]^{\frac{1}{1-\varepsilon}} \tag{5}$$

where $I_E(k, \varepsilon)$ denotes the energy inequality index,rotation round is indicated by k, and ε indicates inequality aversion [13], which penalized the energy imbalance. After k rounds, E(k) is the regular residual energy. Because of this, inequality is to be disciplined. From equation (5), it can be easily deduced that WSNs have evenly distributed residual energy if E2I(k) equals 1.

### 3.3. Clustering

Let us to denote Y as a node matrix of M × N dimensionality. The goal of clustering is to assign nodes $\mathcal{Y}_1, \ldots, \mathcal{Y}_M$ to clusters $CL_1, CL_2, \ldots, CL_C$ [15]. This technique is represented by the Calinski-Harabasz index. The following can be written as it:

$$I_{CH} = \frac{N-C}{C-1}\frac{\sum_{i=1}^{C} d(u_i, U)}{\sum_{i=1}^{C}\sum_{x_j \in CL_i} d(x_j, u_i)} \tag{6}$$

whereas $u_i \in R^N$ for non-empty cluster $CL_i$ cluster center according to equation (7),

$$u_i = \frac{1}{M_i}\sum_{y_j \in CL_i} y_j, i = 1, \ldots, c \tag{7}$$

with $M_i$ being cardinality of cluster $i$ and $U$ corresponds to WSN center of gravity,

$$U = \frac{1}{M}\sum_{j=1}^{M} y_j \tag{8}$$

Clustering result explains the dataset structure will effect in elevated value of $I_{CH}$ index.

## 4. ENERGY-EFFICIENT GRASSHOPPER OPTIMIZATION ALGORITHM (EEGOA)

The aim of the GOA is to find arguments (solutions) that minimize the cost function of CH selection $f: S \to R$. It can be formally written as follows [14,15],

$$x^* = \underset{x \in S}{\operatorname{argmin}} f(x) \tag{9}$$

$S \subset R^D$, population based heuristic algorithms solve equation (9) using a swarm of $P$ individual agents, in iteration $k$ of the algorithm represented by a set $\{x_p\}_{p=1}^{P}$, with $x_p = [x_{p1}, x_{p2}, \ldots x_{pD}]$. Euclidean distance $dist(x_{p1}, x_{p2})$ is also an important concept for the construction of this class of procedures. Best CH selected so for k-iterations is represented as $x^*(k)$ within search space $S$. Their lower bound $LB_1, LB_2, \ldots, LB_D$ and upper bound $UB_1, UB_2, \ldots, UB_D$. Effectively it means that by equation (10) [16,17],

$$LB_D \leq x_{pd}(k) \leq UB_d \tag{10}$$

for all $k = 1,2,\ldots,p = 1,2,\ldots,P$ and $d = 1,2,\ldots,D$. GOA asserts that it was influenced by the interpersonal interactions of grasshoppers, an Orthoptera order insect. A single insect makes up each member of the swarm, which is contained in search space S and travelling in accordance with equation (9). The first is grasshopper interaction, which is displayed through both slow and fast motion. The second is consistent with the propensity to migrate in the direction of the food supply [18,19]. The following equation can be used to represent the movement of individual p in iteration k was left out to make the equation (11) easier to read),

$$x_{pd} = c\left(\sum_{q=1,q\neq p}^{p} c\frac{UB_d - LB_c}{2} s\left(\left|x_{qd} - x_{pd}\right|\right)\frac{x_{qd} - x_{pd}}{dist(x_q, x_p)}\right) + x_d^* \tag{11}$$

with $d = 1,2,\ldots,D$. Parameter $c$ is decreased according to the equation(12),

$$c = c_{max} - k\frac{c_{max} - c_{min}}{K} \tag{12}$$

Maximum and minimum values $- C_{max}, C_{min}$ and $K$ is denoted as the determined amount of iterations for GOA. As a result of $c$, grasshoppers are less likely to move around the CH during the first aftermath, which balances both exploration and exploitation by equation (11).Component $c = \frac{UB_d - LB_d}{2}$ sequentially reduces the space that the grasshoppers should travel and movement [20]. Finally, function s, which was constructed by the algorithm's designers, defines the strength of social pressures as follows:

$$s(r) = fe^{\frac{-r}{l}} - e^{-r} \tag{13}$$

with $l = 1.5$ and $f = 0.5$. Selecting the appropriate solution representation is necessary when using any heuristic optimization [20] procedure. It is natural to express the answer in the clustering scenario as a vector of cluster centres. $x_p = [u_1, u_2, \ldots, u_C]$.

**Algorithm 1. Grasshopper Optimization Algorithm**

1. $k \leftarrow 1, f(x*(0)) \leftarrow \infty$ {initialization}
2. for $p = 1$ toPdo
   $x_p(k) \leftarrow$ Generate_Solution(LB, UB)
3. end for
4. for $p = 1$ to P do
   $f(x_p(k)) \leftarrow$ Evaluate_quality$(x_p(k))$
5. if $f(x_p(k)) < f(x^*(k-1))$ then
   $x^*(k) \leftarrow x_p(k)$
6. else
   $x^*(k) \leftarrow x^*(k-1)$
7. end if
8. end for
9. repeat
   $c \leftarrow$ Update_c$(c_{max}, c_{max}, k, K_{max})$
10. for p = 1 to P do
   $x_p(k) \leftarrow$ Move_Grasshopper$(c, UB, LB, x^*(k))$
   $x_p(k) \leftarrow Correct_{Solution}(x_p(k)\ UB, LB)$

$f(x_p(k)) \leftarrow$ Evaluate_quality$(x_p(k))$

11. $if\, f(x_p(k)) < f(x^*(k)\ then$

    $x^*(k) \leftarrow x_p((k)), f(x^*k) \leftarrow f(x_p((k))$
12. end if
13. end for
14. for p = 1 to P do

    $f(x_p(k+1)) \leftarrow f(x_p k), x_p(k+1) \leftarrow x_p(k)$
15. end for

    $f(x^*(k+1)) \leftarrow f(x^*k), x^*(k+1) \leftarrow x^*(k)$
16. $k \leftarrow k + 1$
17. until $k < K$
18. return $f(x^*(k)), x^*(k)$

The solution $x_p$ (representing those centres) is assessed in accordance with the equation after each data element $y_i$ has been assigned to the closest cluster centre (14),

$$f(x_p) = \frac{1}{I_{CH,p}} + \#CL_{i,p} = \emptyset, i = 1, \dots, c \tag{14}$$

$\#CL_{i,p} = \emptyset, i = 1, \dots, c,$ appending the second component is intended to penalise solutions that do not contain the ideal number of clusters.

## 5. Results And Discussion

In this unit, the experimentation locations are labeled. Afterwards, key metrics are presented. At the end, analysis and results are described.

### 5.1 Experiments Settings

EEGOA is a type of clustering strategy that uses Atkinson's variation measure to encourage energy equilibrium throughout the CH election process. The CH election is being governed by systematic social theory for the first time, as far as the writers are aware. As a result, SWECE and EEGOA, two standard clustering algorithms that concentrate on cluster formation, were used as the baseline in the experiment. Proposed system is compared with three intelligent clustering techniques such as LEACH, T2FL, and EIRNG. Through the use of the simulator NS2, the energy performance of several strategies was assessed in these units. All of the device modes in the simulation are arranged in ma × ma square region at random. Let m range from 3 to 11 with step 2, and let an equal 30. To thoroughly assess the energy efficiency, the trials were divided into five sets, and in each set, extensive simulations were run. Additionally, a 2J starting energy assumption was made for each sensor node.

### 5.2 Metrics Utilized in the Experimentations

Some associated metrics must first be specified in order to analyze SWECE and EEGOA's energy efficiency in detail.

***1) First Node Dies (FND):***This indicates quantum of period when the first node takes used up all of their remaining energy. Data reliability is typically strictly required for requests with strict reliability requirements, such as tracking endangered animals and military monitoring. As a result, the coverage rate is crucial for ensuring the accuracy of the data. By way of a outcome, throughout the comparison procedure, the FND measure are assessed.

***2) Half of the Nodes Die (HND):*** A timer indicates when half of the sensor nodes are finished. It represents energy depletion in the network.

***3) Last Node Dies (LND):*** This show how long until the sensors run out of power. Other metrics such as network execution and energy efficiency are accepted in addition to the lifespan indicator.

***4) Total Throughput of the Sink*:** This represents the entire quantity of data the sink established during the simulation. It is essential to consider throughput when assessing energy efficiency, since WSNs are directly proportional to how much accurate data they can collect. Furthermore, network performance can be evaluated using this statistic.

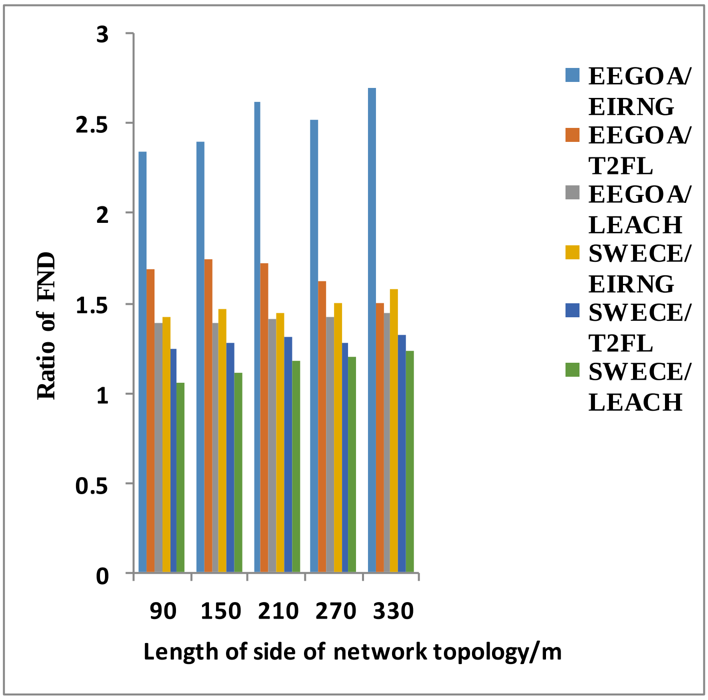


**Fig 2:** Ratio Of FND Comparison between Various strategies

Comparisons of the ratios of various methods in FND and HND are shown in Figures 2 and 3, respectively. Percentages of EEGOA to other techniques in FND and HND are obviously considerably larger when compared to SWECE algorithm, as illustrated in Figure 2. According to LEACH, T2FL, and EIRNG, the suggested EEGOA algorithm yields the maximum FND of 2.695, 1.5, and 1.442 for load 330/m, respectively. The suggested EEGOA algorithm yields the maximum HND of 2.335, 1.902, and 1.806 for load 330/m, respectively, with respect to LEACH, T2FL, and EIRNG.

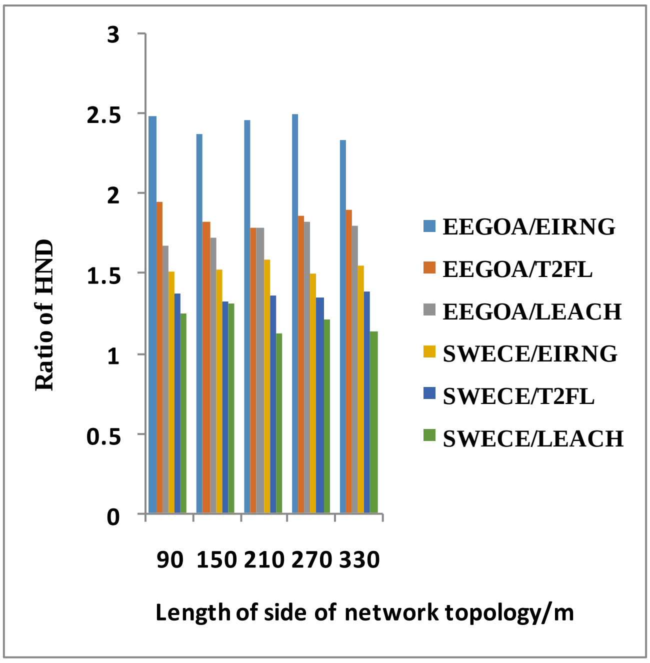


**Fig 3:** Ratio of HND Comparison Between Various Strategies

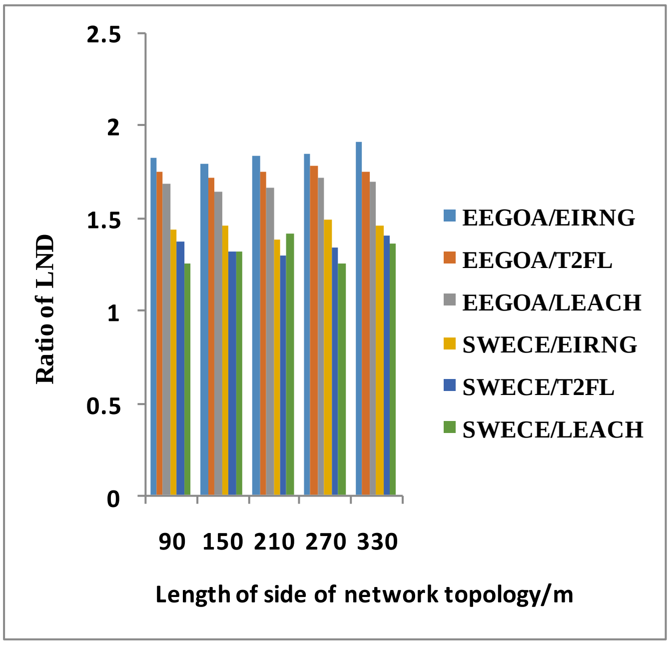


**Fig 4:** Ratio Of LND Comparison Between Various Strategies

Comparisons of the LND ratios for various techniques are shown in Figure 4. Figure 4 makes obvious that when compared to SWECE algorithm, the percentages of EEGOA to another techniques in LND are substantially bigger. According to LEACH, T2FL, and EIRNG, the suggested EEGOA algorithm yields the highest FND values for load 330/m of 1.9205, 1.75, and 1.695, respectively.

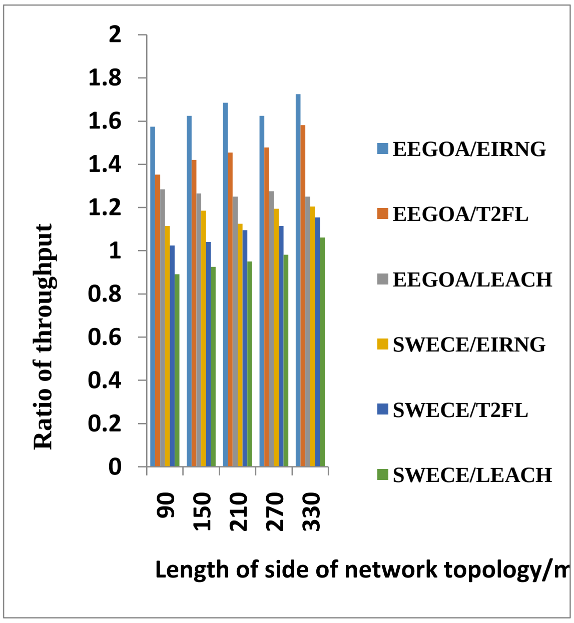


**Fig 5:** Ratio of Throughput comparison Between Various Strategies

The correlation between the throughput ratios and the parameter *m* value is depicted in Figure 5. It displays how EEGOA stacks up against the competition in terms of data volume. Comparing the tactics at the same time, it is clear that EEGOA has the highest throughput. Additionally, it is clear from figure 5 that EEGOA's impact on throughput is greater than that of SWECE/LEACH. In comparison to LEACH, T2FL, and EIRNG, the proposed EEGOA/EIRNG offers the maximum throughput of 1.725, 1.582, and 1.250 at load 330/m.

## 6. Conclusion and Future Work

In this study, a novel Energy-Efficient Grasshopper Optimization Algorithm (EEGOA) basedCluster head Election scheme is introduced to increase the energy usage of WSN throughout procedure of CH election. EEGOA, the idea of GOA is introduced to attain energy equality when CH is elected, and it is used for communication. It is the initial time with the purpose of the CH selection is regulated using the GOA.GOA takes into account together the appeal of the best CH as well as social interaction among usual cluster members (grasshoppers).EEGOA is proposed toward select the CH by attaining energy balance inside each cluster.Through Atkinson's inequality measure, each individual sensor node can be flexible in its behaviour in order to maintain energy stability in a WSN. E2I is a concept that measures network equality based on the remaining energy in the nodes. In Forthcoming work can attention on the proposed scheme has been introduced to the contractive sensing in unsupervised routing towards decrease energy overhead, and enhances network lifetime.

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