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An Energy Efficient Cluster Head Selection in WSN Based on Enhanced Chicken Swarm Optimization

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Abstract

Clustering of data are ab effective energy saving method for wireless sensor networks (WSN). However, they incur additional costs in data collections from sensor nodes and sending them to base station (BS) after aggregations. Cluster heads (CHs) in hierarchical cluster-based WSNs use more energy. Therefore, choosing a suitable CHs is essential to conserve energy for sensor nodes and prolong the life of the WSN. Provide energy-saving cluster head selection techniques in this work. where enhanced fuzzy means clustering is used to perform the first cluster construction. Enhanced Chick Swarm optimization (ECSO) selects CHs which is evaluated strictly for varying WSN scenarios and counts of CHs and nodes for values of remaining energies of sensor nodes, sink distances, and distances within clusters. To demonstrate that the proposed technique is superior, the results are compared with those of several other currently used algorithms.

Keywords: Clustering, Cluster Heads, Improved Fuzzy C Means Enhanced Whale Optimization, Network Lifetime, Energy Efficiency and Intra-cluster Distance.

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Introduction

WSN consists of distributed, autonomous sensor nodes that collaborate to collect and analyze data from the target area while communicating with the remote BS [1]. Low-cost sensors are now readily available thanks to recent developments in microelectromechanical systems (MEMS) technology, and as a result, WSN has focused a great deal of emphasis on their numerous uses in a variety of industries, such as industry, disaster management, the medical profession, the military, and more [2,3].

Nonetheless, the primary constraint of WSNs are restricted energies of sensor nodes. Battery-powered sensors have limited power because they are often used in hostile, unmonitored environments where batteries are difficult to recharge. The primary barrier to the development of large-scale WSNs is sensor node energy conservation [4]. Energy conservation may be achieved by the most efficient grouping of sensor nodes. The network is split up into several groups, or clusters, during the clustering process with their own CHs [5, 6]. CHs need to collect data from their member sensor nodes in clusters, aggregate and transmit that data [7,8] to BSs linked to a public network, such as the Internet, for data transmission. local data to remote BSs directly or through another CH. The challenge of Selection of CHs is an NP-hard optimisation. As the scale of the network increases, conventional optimisation approaches become inefficient [9, 10].

ECSO is an effective method that draws inspiration from nature. Its ease of implementation, good solution quality, local optimal escape ability set, and quick convergence make it a superior option for NP-hard problems of this kind. This study proposes an energy-efficient cluster head selection strategy. where c-means clustering enhancement is used to guide cluster formation. Enhanced Whale Optimization (EWO) is used for efficient energy utilization by selecting CHs which include parameters like distances between clusters, sinks, and residual energies of sensor nodes.

Related Work

Umbreen et al [2020][11] selected CHs based on their mobility and energy efficiencies to get around these restrictions. The choices of CH's specific factors that have significant impacts on power consumptions of sensors. Every node's weight is determined by taking into account its neighbour density, mobility, remaining energy, and distance are sink. Clusters communicate with each other via a single or multi-hop manner. MATLAB is employed in the simulation process. The outcomes of the suggested EEMCS approach showed that it outperforms current CRPD, LEACH, and MODLEACH algorithms in terms of throughputs, energy exhaustions, load balancing, and network stabilities. Compared to other current protocols, EEMCS has a far higher network lifespan and significantly lower energy usages.

Lee et al [2019] [12] suggested a spider monkey optimisation (SMO) technique that is based on sampling. Clusters head will be chosen among the nodes if the sample population has nodes for that purpose. As a result, the issues brought on by clusters heads' and nodes' various locations have been fixed. Thus, by using spider monkey optimisation based on energy-efficient sampling and cluster head selection, we increase the lifetime and stability of WSN (SSMOECHS). This paper explains sampling in basic SMO and sample-based SMO for cluster head node selection. The experimental findings are contrasted with those of comparable protocols, such as SMO Threshold-Based Energy-Efficient, Delay-Sensitive Routing Protocol (SMOTECP), Particle Ensemble Optimisation Clustering Protocol (PSO-C), and Low Energy Adaptive Hierarchical Clustering (LEACH-C) and outcomes for homogeneous and heterogeneous configurations are provided. SSMOECHS increases average network longevity and stability in these setups by 13.4%, 7.1%, 34.6%, and 1.8%, respectively.

Proposed Methodology

The suggested model is covered in detail in this section. The suggested approach uses improved fuzzy means clustering to create clusters and an ECSO to choose cluster heads in the best possible way. Figure 1 depicts the general architecture of the suggested model.

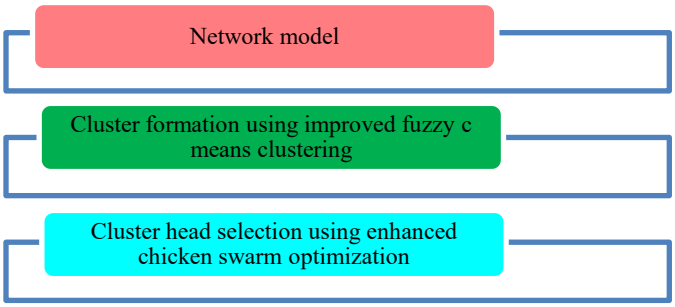


Fig. 1: The Proposed Schema's Overall Architecture

Network Model

This document contains the following WSN scenario features. Sensors are scattered throughout the detection area and depending on the received signal strengths, nodes can compute distances from other nodes without GPS. Sensor nodes are considered stationary on deployments and use clustered modes with CHs. Each node continuously has data to forward to its CH and performs regular discovery. There are more sensors than CH on the planet. Though nodes have similar processing and communication capabilities, they consume varying levels of power in data transmissions to BSs or CHs. The detection and communication distance are a circular field. When two nodes are within communication range of each other, a symmetric wireless communication link will be formed.

Cluster creation and Selection of CHs are the two stages of this effort. By adopting an enhanced fuzzy means clustering approach, it is believed that a sensor node would create a cluster around itself depending on the communication range. CHs are selected from the BSs using improved cluster formation using the fuzzy method. The selections of CHs of ECSO are based on distances and residual energies which announce their locations and remaining energies to BSs to for evaluating their energies (Threshold values) before qualifying as CHs. The first part deals with improved cluster generation based on fuzzy averaging and ECSO-based CH selection.

Cluster Formation Using Improved Fuzzy C Means Clustering

In this study, cluster formation based on contact range is achieved through applying advanced fuzzy C-means clustering. Due to its superior clustering performance and ease of implementation, fuzzy c-means clustering is one of the widely used unsupervised clustering methods in image processing and computer vision [13].

Fuzzy c-means splits datasets X = $\{x_1,\ldots, x_i,\ldots x_n\}$ $(1\leq i\leq n)$ into c clusters based membership degree matrices $U=(u_{ti})c*n$ when objective functions J reach min. values. x_i and with being p dimensional; u_{ti} implies degrees of membership for samples x_i belonging to cluster centers v_t. which are elements of $V=\{v_1,\ldots v_t,\ldots v_c\}$ $1\leq t\leq c$ set arbitrarily. These degree u_{ti} computations are based on [14,15]:

$$u_{ti} = \frac{1}{\sum_{z=1}^{c}(d_{ti}/d_{zi})^{2/(m-1)}} \quad (1)$$

Where d_{ti} implies Euclidean distances amidst samples x_i to cluster centers v_t, m represents power exponents. Cluster centre computations during iterations are as follows [16,17]:

$$v_t=\frac{\sum_{i=1}^{n} u_{ti}^{m} d_{ti}}{\sum_{i=1}^{n} u_{ti}^{m}} \quad (2)$$

Objective functions J are specified as:

$$J=\sum_{i=1}^{n}\sum_{t=1}^{c} u_{ti}^{m}\, d_{ti}^{\,2} \quad (3)$$

The main drawbacks of FCM algorithms are

The best solution is infeasible because the FCM algorithm quickly resolves the local extremum or saddle point.

The basic fuzzy C-means technique was modified in this study to address such problems. Weighted Euclidean distance is the foundation of feature weight learning. The commonly used Euclidean distance is d_{ij} and the weighted Euclidean distance is shown below with d_{ij}^{w}:

$$d_{ij}^{w} = \sqrt{\sum_{k=1}^{s} w_k\left(x_{jk} - v_{tk}\right)^2} \quad (4)$$

Thus, objective functions *J* specified in Equations (3) become:

$$J^w\ (U, v_1, \ \ldots. v_c; X) = \sum_{i=1}^{C} \sum_{j=1}^{n} u_{ij}^m\ (\ d_{ij}^w)^{\ 2} \qquad (5)$$

Subsequently new u_{ij}, w_k and v_{ik} values are obtained using:

$$u_{ij} = \frac{n(m \sum_{k=1}^{s}\ w_k\left(x_{jk} - v_{tk}\right)^2\ )^{\frac{1}{m-1}}}{\sum_{h=1}^{c}\ \sum_{r=1}^{n}\ \left(m \sum_{k=1}^{s}\left(x_{jk} - v_{tk}\right)^2\right)^{\frac{1}{m-1}}} \qquad (6)$$

$$w_k = \frac{\left(\sum_{t=1}^{c} \sum_{j=1}^{n}\ u_{ij}^m (x_{jk} - v_{tk})^2\right)^{-1}}{\sum_{h=1}^{s}\left(\sum_{t=1}^{c} \sum_{j=1}^{n} (x_{jk} - v_{tk})^2\right)^{-1}} \qquad (7)$$

$$v_{ik} = \frac{\sum_{j=1}^{n} u_{ij}^m x_{jk}}{\sum_{j=1}^{n} u_{ij}^m} \qquad (8)$$

The resultant M-FCM algorithm can be summarized as:

Step 1: Set the threshold value and the maximum counts of clusters (c). Let m be an appropriate constant.
Step 2: Establish centers and members according to FCM.
Step 3: Use the equation (7) to calculate wk
Step 4: Take (6) as the basis for calculating u_{ij}. Update v_{ik} using the new u_{ij} calculated by equation (8).
Step 5: Use (5) to calculate objectives and when values converge or differences amidst adjacent objective function values and when *J w* lesser than specified thresholds stop executions else execute from step 3.

Cluster Head Selection Using ECSO

Improved flock optimizations are used after selecting group leaders. The fitness functions are determined by average distances within clusters, average sink distances, and energies. The idea is to reduce the importance of exercise. When the fitness value is low, the seed placement or CH selection will be larger.

Chicken Swarm Optimization (CSO)

CSO is a meta heuristic optimisation technique inspired by biology [18, 19]. This program simulates the movements of individual chickens as well as the hierarchical structure of the flock. The hierarchical structures of hen flocks are divided into several groups with a rooster and many hens and chicks [20] Many types of chickens have different movement rules. The social lives of hens are strongly influenced by hierarchical organizations. The strongest chickens in flocks dominate and submissive hens and roosters are placed at flock edges, while dominant hens are placed near roosters [21, 22].

Local optimum features are an easy pitfall for traditional CSO to slip into. This work utilizes the mutation operator in CSO to get around this issue. In this work, flip bit mutation was applied. The pieces of the CHsosen genome are inverted by this mutation operator. (i.e. genomic bits are changed from 1 to 0 and vice versa if they are 1).

ECSO

The instructions below summarize the behavior of CHsicken, which is the basis for the Mutant Chicken Optimization (ECSO) mathematical model described in

1) Chicken flocks are divided into several groups with one dominant rooster followed by hens and chicks.
2) The material value of chickens determines the hierarchy of the flock; The roosters with the highest fitness values are the leaders, while the chicks with the lowest fitness values are the individual birds. The chickens will be among them.
3) Within a group, mother-infant relationships, dominance dynamics, and herd hierarchies will not change. Only a few (G) times steps elapse between updates of these states.
4) The N virtual chickens that make up the flock are divided inare following groups:
RN, HN, CN and MN, representing the counts of roosters, hens, chicks and mother chickens, respectively.
The position of each person in D-dimensional space is represented by:

$$x_{i,j\ (\ i \in [i,\ldots\ldots N], j \in [1,\ldots,D])}, \qquad (9)$$

Rooster Movement: Roosters havinh higher fitnesses search for foods in wider ranges of place while worst fitness values of movements are depicted in equations (10) and (11).

$$x_{i,j}^{t+1} = x_{i,j}^{t} * \left(1 + Randn(0, \sigma^2)\right) \qquad (10)$$

$$\sigma^2 = \begin{cases} 1, & if\ f_i \le f_k\ , \mid \\ exp\left(\frac{f_k - f_i}{|f_i| + \in}\right) & otherwise \end{cases} \quad k \in [1, N], k \ne i, \qquad (11)$$

where $x_{i;j}$ represents selected roosters with indices i, Rand $n(0, \sigma^2)$ represents Gaussian distributions having means of 0 and standard deviations σ^2 , $\in$ implies minimal constant values used to avoid errors caused by zero-divisions, k represents randomly chosen rooster indices from groups, f_i represent roosters x_i 's fitness values.

Hen movement: The hens in the flock follow the roosters to find food. Additionally, when chased by other chickens, they will randomly grab any delicious food they come across. Bolder chickens will have an advantage over more hesitant birds in the fight for food. These events can be described mathematically in the form of equations (13) and (14).

$$x_{i,j}^{t+1} = x_{i,j}^{t} + S1 * rRand * \left(x_{r_{1,j}}^{t} - x_{i,j}^{t}\right) + S2 * Rand * \left(x_{r_{2,j}}^{t} - x_{i,j}^{t}\right) \quad (12)$$

$$S1 = exp\left((f_i - f_{r1})/abs(f_i) + \in\right) \quad (13)$$

$$S1 = exp\left(\left(f_{r_2} - f_i\right)\right) \quad (14)$$

Where Rand represents uniform values in the range [0, 1]. $r_1 \in [1,\ldots., N]$ represents rooster indices, which are i^{th} hens' group-mates, while $r_2 \in [1,\ldots., N,]$ represents indices of randomly selected chickens (roosters or hens).

Chick movement: CHsicks move around their mother to search for food. This is formulated as in equation (15).

$$x_{i,j}^{t+1} = x_{i,j}^{t} + FL * \left(x_{m,j}^{t} - x_{i,j}^{t}\right) \quad (15)$$

Where $x_{m,j}^{t}$ is the position of the i^{th} chick's mother such that $m \in [1;N]$, FL is parameter that represent how much speed a chick would follow its mother, to consider the differences between each chick FL is chosen randomly in the range [0, 2].

Since the range of dimensions are between 0 and 1 and representation of features in feature spaces in terms of individual dimensions are very large, intelligent searches are required to determine optimal locations in search spaces to maximize appropriate functions. Equation (16) illustrates CSO's fitness functions aiming to reduce selected features while maximizing classification performance in validation sets based on training data.

$$f_\theta = \omega * E + (1 - \omega)\frac{\sum_i \theta_i}{N} \quad (16)$$

Where f_θ implies itness functions for vectors θ with 0/1 elements representing unselected / selected features, N represents features, E represents error rates and ω signify constant values for classification performance controls of features.

The variables used are feature counts which are limited to ranges [0, 1] and when values of features approach 1, they are candidates for classifications. The variable in the calculation of individual fitness is the threshold that determines the exact attributes to test, as shown in equation (17).

$$f_{i,j} = \begin{cases} 1 \; if \; X_{i,j} > 0.5 \\ 0 \; otherwise, \end{cases} \quad (17)$$

Where X_{ij} represents dimensional values of agents i at dimensions j. While updating positions of fireflies certain dimensions of updated values can violate specified limitations [0, 1], hence truncations are enforced to ensure the values fall within the limits.

1. Set initial values folr RN, HN, CN, MN, G;
2. Initialize chickens in swarms randomly
3. X_i (i = 1,2,……;N).;
4. Initialize max. iterations T_{max};
5. while $T < T_{max}$ do for each iteration
6. if T % G equals 0 then
7. Assess performances of CHs create herd's orders.
8. Divide flocks into groups and determine relationship between hens and mother in groups;
9. end
10. for chickens Xi in swarms do
11. if Xi are rosters then
12. Use Equation (11) to update Xi's locations
13. end
14. if Xi are hens then
15. Use Equation (13) to update Xi's locations;
16. end

17. if Xi are chicks then
18. Use Equation (16) to update Xi's locations
19. end
20. Use Equastion (17) for solution evaluations;
21. If new solutions are better than prior ones update them;
22. end
23. end
24. Apply flip bit mutations as updated solutions
25. Evaluate new solution using equation (17)
26. end

Results and Discussion

This section displays evaluated experimental results of ECSO implemented in Matlab for values of packet delivery speeds, energy consumptions, end-to-end latencies, throughputs, and network lifetime and contrasted with existing EEMCS and SMO.

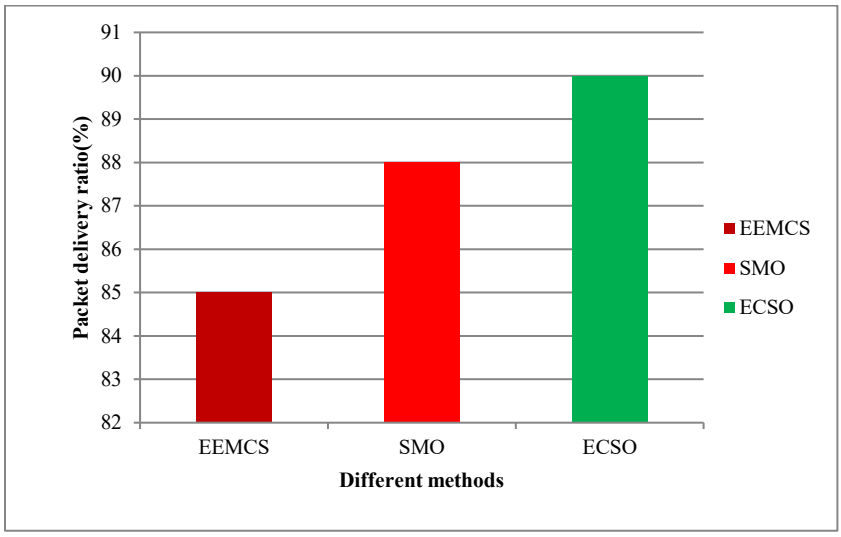


Fig. 2: Packet Delivery Ratio Results

In terms of packet delivery speed, Figure 2 compares the performance of the suggested ECSO approach with current EEMCS and SMO systems. Based on the data, it can be said that whereas current EEMCS and SMO approaches only yield 85% and 88% packet delivery rates, the suggested ECSO model produces outcomes that are greater than 90%.

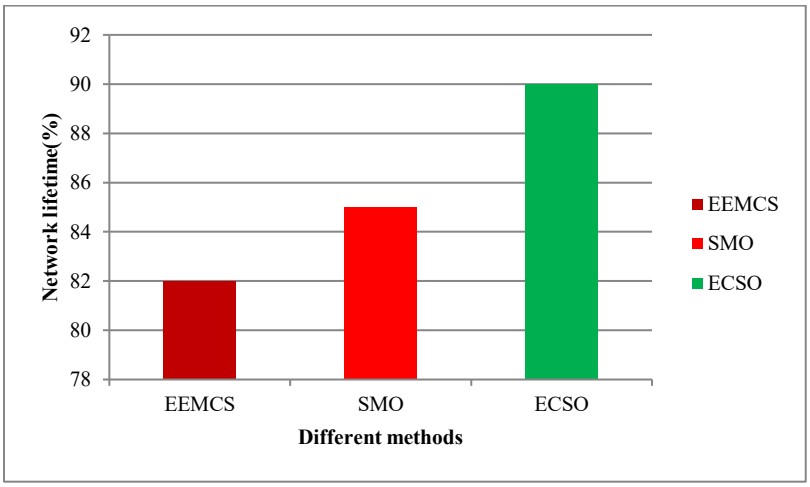


Fig. 3: Network Lifetime

In terms of network longevity, Figure 3 compares the performance of the suggested ECSO approach with current EEMCS and SMO methods. Based on the findings, it can be said that although current EEMCS and SMO approaches only yield 82% and 85% of network lifetime outcomes, the suggested ECSO model delivers results greater than 90%.

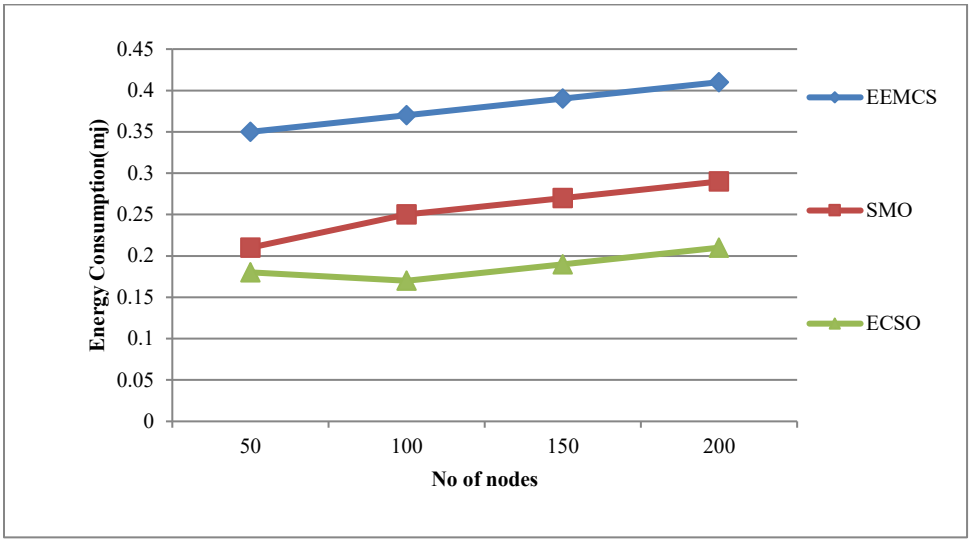


Fig. 4: Energy Consumption (mj)

The results of an energy consumption comparison between the suggested ECSO approach and current EEMCS and SMO methods are displayed in Figure 4. According are results, the suggested ECSO model has a reduced energy consumption result of 0.21 (mj), whereas current EEMCS and SMO techniques have values of 0.41 (mj) and 0.29 (mj), respectively.

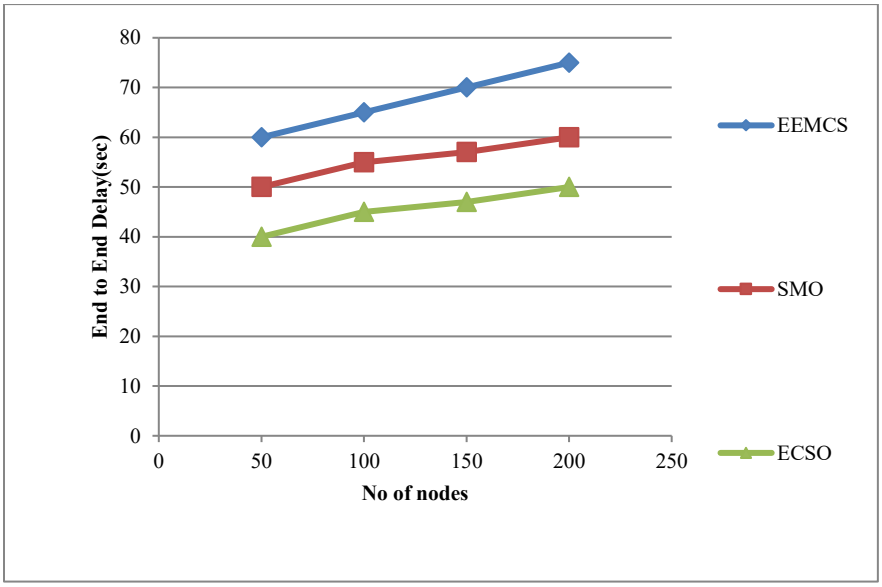


Fig. 5: End to End Delay Results

Regarding the end-to-end latency, Figure 5 presents the performance comparison results between the proposed ECSO method and the existing EEMCS and SMO methods. The results show that, compared to current EEMCS and SMO methods that only give end-to-end latency results of 75 (seconds) and 60 (seconds), the proposed ECSO model gives lower results of 50 (seconds) and 60 (seconds). second).

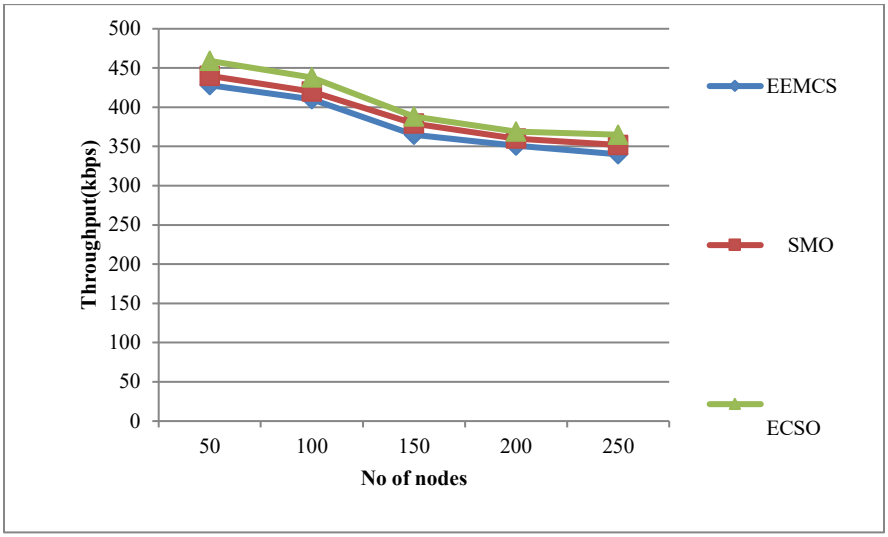


Fig. 6: Throughput (Kbps) Results

The throughput performance comparison findings between the proposed ECSO technique and current EEMCS and SMO methods are displayed in Figure 6. The results show that, in comparison to current EEMCS and SMO approaches, which only provide throughput results of 340 (Kbps) and 352 (kbps), respectively, the suggested ECSO model produces superior throughput results of 365 (Kbps).

Conclusion and Future Work

This work proposes energy efficient selections of CHs called ECSO that uses adaptive function and effective particle representation functions. This work considers residual energies, sink distances, and intra-cluster distances in nodes for optimizations and algorithm's energy efficiency. To create clusters, advanced fuzzy means clustering is employed. displays the simulation results along with a comparison to many current algorithms, including the SMO and EEMCS techniques. The technique has undergone rigorous testing using a variety of WSN situations and scenarios. The suggested method works better than current algorithms, according to experimental results for obtained values of energy consumptions, network lifespan, and data packet counts received at BSs. Nevertheless, the suggested method does not take any routing algorithms into account. Future work aims at creating routing algorithms that employ meta heuristics. This method will take into account a count of factors, including WSN fault tolerance and energy balance. As opposed are suggested approach, which is limited to homogeneous networks, we also plan to build the same for heterogeneous WSNs.

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