SSRG International Journal of Computer Science and Engineering
ISSN: 2348 – 8387 / https://doi.org/10.14445/23488387/IJCSE-V9I10P101

Volume 9 Issue 10, 1-8, October 2022


*Original Article*

# Sooty Tern Optimized K-Means Clustering Via Wireless Sensor Network for Energy Consumption

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Received: 13 August 2022 Revised: 18 September 2022 Accepted: 05 October 2022 Published: 20 October 2022

***Abstract*** *- A wireless sensor network (WSN) is a group of specialized transducers with a communications system for observing and documenting conditions in various places. However, large amounts of energy consumption, less network lifetime, malicious attacks, and a limited range of batteries are the critical issues associated with WSN, which results in inappropriate routing, delay in packet arrivals and delivery, imbalanced energy conservation, and so on. Consequently, these issues cannot be resolved reliably. In this research work, a novel Sooty tern-optimized K-means clustering (STO) algorithm was proposed. Initially, the sensor nodes (SN) are initialized to increase the network's lifetime and node density to consume less energy consumption. These sensor nodes are clustered via Fuzzy K-means clustering, and the STO algorithm makes CH selection. Hence, the energy consumption, network lifetime, residual energy, number of alive nodes and throughput are the evaluation metrics used to assess the proposed STO approach. This scheme is simulated by using MATLAB 2019. A comparison is made between the proposed STO and existing algorithms such as SCBRP, MPOTFEM, and GSA in terms of energy consumption, network lifetime, residual energy, and throughput. The proposed STO algorithm enhances energy efficiency by 20.7%, 23.65%, 29.65%, and 42.65% better than the traditional frameworks.*

***Keywords*** *- Wireless Sensor Network, Cluster Head, Sooty Tern Optimization.*

## 1. Introduction

WSN is made up of numerous sensor nodes that communicate wirelessly to collect data and identify certain significant occurrences in physical and environmental circumstances [1,2]. SN in WSN measure different environmental characteristics and sends the information you gather to one or more sinks using hop-by-hop communication [3,4]. A sink processes and transmits sensed data to the users after receiving it. A sensor device with these features can be used for a plethora of appealing applications [5].

WSNs have numerous applications, including smart homes, monitoring, and industrial diagnostics [6]. WSN is being extensively discussed in a variety of research fields. WSNs have been discovered to be the most effective solution in remote areas that have not yet been explored due to their perilous nature and inaccessible locations [7,8]. However, sensor nodes in WSN have limited battery capacity, a limited memory size range, and small-scale computational capabilities. As an outcome, the lifetime of WSN applications is a critical issue that must be addressed before such networks can be used in practice. [9,10].

The most widely used method for maintaining WSN topology is clustering. A clustering method arranges the nodes into a set of groupings known as clusters which improve the network's life [11]. Based on a set of predetermined standards, including network load balancing, Quality of Service (QoS), and resource consumption which increases the network's lifetime [12,13]. Additionally, there is inter-cluster communication between the CH node of one cluster interacting with the CH node of another cluster [14,15].

In order to resolve these shortcomings, this research proposed a novel Sooty tern-optimized K-means clustering (STO) algorithm that reduces the network energy consumption and delay, which boosts up network lifetime and node density. The major contributions of the proposed STO algorithm are given as follows.

- In this research work, a novel Sooty tern-optimized K-means clustering (STO) algorithm was proposed.
- In this STO approach, the Fuzzy K-means clustering algorithm and the STO algorithm are implemented to improve the network lifetime, energy consumption, and node density with longer stability and higher energy level.
- Initially, the sensor nodes are initialized to increase the lifetime of the network and node density and consume less energy consumption. These sensor nodes are clustered via Fuzzy K-means clustering, and the STO algorithm makes CH selection

- Hence, energy consumption, network lifetime, residual energy, and throughput are the evaluation metrics used to assess the proposed STO approach.

The remaining section of the work was organized as follows. Section 2 represents the literature review. Section 3 represents the proposed methodology. Section 4 represents the result and discussion. Section 5 represents the Conclusion.

## 2. Literature Survey

WSN is a network type of massive node that collect data from sensing fields and send it to a base station. The sensor nodes are mobile and dynamic, and this paper discusses several clustering-based routing protocols because clustering-based routing protocols are important in WSNs.

In 2020, Sankar et al. [1] suggested the Energy Efficient Cluster-based Routing Protocol be used to improve the network's existence throughout its lifetime. This experimental result showed that 5–10% of the network life was increased and 10–20% of end-to-end latency decreased by this technique. This experiment decreases the node-to-sink delays and improves network lifetime by this proposed SOA.

In 2019, PavaniM and Trinatha [2] developed a secure cluster-based routing protocol (SCBRP), which combines adaptive particle swarm optimization (PSO) with the improved Firefly algorithm, as a solution for safe routing in WSN networks that is energy-efficient. The remaining energy, inter- and intra-cluster distances, and distances from base stations are a few of the sensor node parameters employed. In each round, the best cluster centers are selected, going to results in a balanced allocation of energy consumption among sensor nodes.

In 2020 Kumar Shah, I., et al [3] presented the Minimization of Energy Consumption in WSN using DBDDCA Algorithm. The proposed DBDDCA algorithm dynamically distributes the duty cycle depending on the child node from CH, which reduces the energy consumption and increases the network energy utilization, which results in increasing packet delivery and network lifetime. However, the energy required for signal transmission increases with distance.

In 2020 Zhang, J., et al. [4] developed the Energy Consumption for Nodes Cooperation based Optimal Model in WSN. The revenue-sharing mechanism at the node resolves the Nash equilibrium for cooperative games. A confederation of nodes is created in this instance by the interaction of subregional division and depletion. Consequently, the energy-saving effectiveness rises from 12.870% to 38.796% following the increased node count. However, the wireless sensor network node's energy supply is quite limited.

In 2021, Janakiraman, S., et al. [5] suggested Markov Process-base Opportunistic Trust Factor Estimation Mechanism (MPOTFEM) is a reliable method for selecting a suitable cluster head (CH). To assess how effectively the network is being served, this suggested MPOTFEM technique uses the Markov chain and the concept of predictive maintenance (PM). Due to the frequent selection of CHs, malicious nodes are not picked as CHs. The findings indicate that, on average, the suggested method may deliver 9.14% and 10.56% greater PDR and throughput than the current CH election procedures.

In 2020 Kavitha, A., et al. [6] proposed a cluster routing approach to achieve energy efficiency by applying the gravity search algorithm (GSA). GSA was used to assign SN to an appropriate CH in a balanced manner, which reduces energy consumption and thereby increases network lifetime. In terms of power use, network lifetime, and the quantity of packets delivered to the base station, the suggested approach beats conventional clustering algorithms like LEAHC, DEEC, (ACH)2, HCCRFD, and GSA-EC. Moreover, the proposed technique extends the network lifetime by 5.78% compared to GSA-EC.

In 2020 Jain, J.K., [7] suggested a two-layer WSN architecture for coverage gap detection and recovery as well as dynamic clustering-based routing. Cluster creation, cluster head selection (CH), coverage gap detection, recovery, and routing comprise our suggested method's four components. The effectiveness of our suggested solution is then evaluated in terms of power use, network robustness, the number of active nodes, and packet delivery ratio.

From the literature survey, these methods possess some issues, such as large amounts of energy consumption, less network lifetime, malicious attacks, and non-secure routing while sending data packets to their destinations. A novel Sooty tern-optimized K-means clustering (STO) algorithm was proposed to overcome these issues.

## 3. Proposed Methodology

In this research, a novel Sooty tern-optimized K-means clustering (STO) algorithm was proposed to enhance the network lifetime, energy consumption, and node density with longer stability and higher energy level. At first, the sensor nodes are initialized to increase the lifetime of the network and node density and consume less energy consumption. Moreover, these outcomes are achieved by clustering the sensor nodes via Fuzzy K-means clustering, followed by the CH selection by a Sooty algorithm which provides the increased network lifetime and node density and consumes less energy consumption. Figure. 1 depicts the diagram for the Proposed STO Algorithm approach.

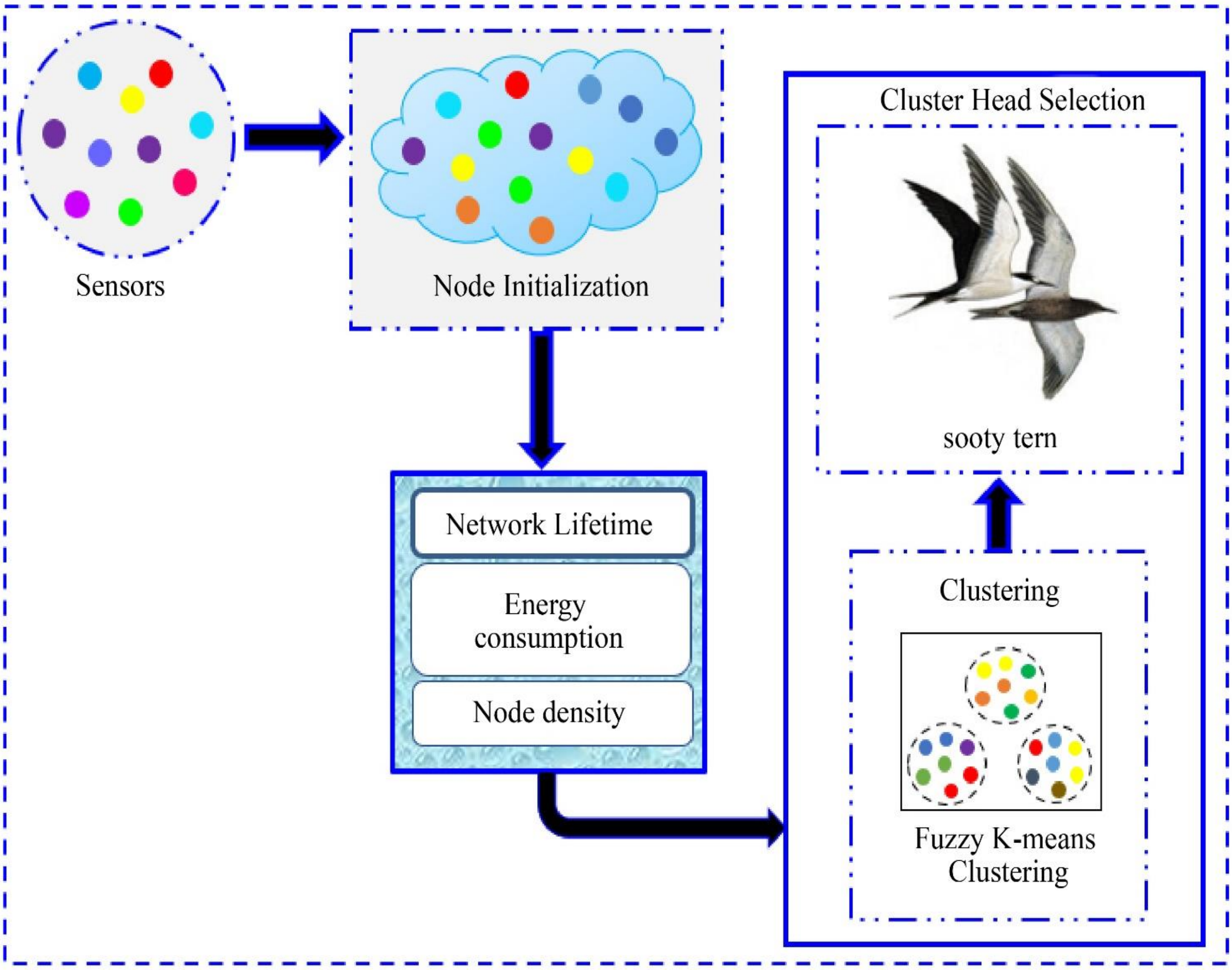


**Fig. 1 Architecture of STO**

### *3.1. Cluster Head Selection via Sooty Tern Optimization*

In the proposed STO, the clustering is done by sooty tern optimization to find out the clusters of users based on their similarity measures, such as word frequency, the strength of words between user profiles, word count between user profiles, and total word count. The STO algorithm is motivated by the natural behavior of sea birds and their lifestyle, which is used as a clustering algorithm to find out the clusters of users. Based on similarity measures, the STO algorithm selects the relevant communities. In this STO algorithm, the number of sooty terns is represented as the similarity from the similarity measure phase; the similarity measures are defined with the best fitness levels, and the irrelevant features indicate the worst fitness value of the STO. The two major steps in the STO algorithm are Migrating behavior and Attacking behavior. STO travel in groups during their journey. STO used a variety of starting positions to prevent collisions or conflicts. Even with lower fitness levels, sooty terns in a group can still cover the same distance as the fittest individuals. An STO with low fitness (irrelevant features) can update its initial position based on an STO with high fitness (relevant features).

#### *3.1.1. Migrating Behavior*

A sooty tern has to satisfy the following three criteria to successfully migrate: *Collision avoidance:* A new search agent (SA) position is computed to prevent conflict between its nearby SA (e.g., sooty terns).

$$a_{ij} = N_{ik} \times m_{ij}(p) \tag{1}$$

where $a_{ij}$ is the position of SA that avoids colliding with other SA, $m_{ij}$ indicates the current position of the search agent, $p$ defines the actual iteration, and $N_{ik}$ signifies the moment of SA in a given search space.

*Converge in the Direction of Best Neighbor*

To avoid collisions, the search agents move in the direction of their best neighbor.

$$b_{ij} = X * (Y_{best}(P) - m_{ij}(p)) \tag{2}$$

Where $b_{ij}$ defines the various positions of search agents, $m_{ij}$ towards the best fittest search agent (relevant features), $X$ is a random variable that represents the better exploration. $X$ is derived as follows:

$$X = 0.5 \times R_{and} \quad (3)$$

Where $R_{and}$ is a random number that lies between the ranges from [0, 1].

$$C_{ij} = S_{ij} + T_{ij} \quad (4)$$

where $C_{ij}$ defines the gap between the search agent and the best fittest search agent with a high fitness value.

*3.1.2. Attacking Behaviour*

The sooty tern can change its speed as well as angle of attack during migration. The wings of these birds help them reach higher altitudes. In the air, sooty terns exhibit spherical behavior when attacking prey. This behavior is mathematically derived as,

$$l = S_{radius} \times sin(i) \quad (5)$$

$$m = S_{radius} \times cos(i) \quad (6)$$

$$n = S_{radius} \times j \quad (7)$$

$$D = a \times e^{kb} \quad (8)$$

where $S_{radius}$ stands for the radius of each spiral round, $i$ indicates that the variable within an interval of $\{0 \leq k \leq 2\pi\}$. $a$ and $b$ are constant variables to denote the spiral form, and $e$ is the base of the natural logarithm. Therefore, the updated position of SA when the constant values of $a$ and $b$ as 1 and is derived as,

$$V_{ij}(p) = (C_{ij} \times (l + m + n)) \times Y_{best}(P) \quad (9)$$

Afterwards, the inputs are multiplied by the feature vectors; the randomly selected clusters are summed. Finally, the STO algorithm is evolved based on the clusters gathered from migrating and attacking operations, and it can be fed into a fully connected (FC) layer for further clustering. As the result of the previous layer, the FC layer uses selected clusters of the STO algorithm to group the relevant user.

***3.4. Fuzzy K-means Clustering Algorithm***

The water bodies in the images are segmented and extracted using the FKM clustering algorithm. A data point, however, can be a member of more than one cluster when using fuzzy clustering. The standard FKM is a well-known and used clustering algorithm. This method is an iterative, unsupervised clustering algorithm that can be applied to image segmentation. Fuzzy K-Means (FKM) develops soft clusters compared to the hard clusters determined by the k-Means clustering algorithm, where a point might belong to more than one cluster under consideration. When using FKM, the functions include dividing data points to translate a given collection of representative vectors into an enhanced model. The method ensures that no two clusters have the same cluster representative and begins with a set of initial cluster centres before repeatedly performing the mapping process until a stopping condition is satisfied. If two cluster centres agree, one should be disturbed to avoid agreement during the iterative phase. The FKM algorithm aims to be optimized, similar to the FCM algorithm.

$$K = \sum_{j=1}^{k} \sum_{k=1}^{m} (v_{jk})^n (g_{jk})^2 \quad (10)$$

Where g denotes the Euclidean distance between data samples, $v_{jk}$ is the membership that indicates the level of each data sample's centre-wide affiliation. On the other hand, n controls as fuzzy the algorithm; when n=1, the Fuzzy k-means algorithm is replaced by the Hard Clustering algorithm. An instance of aerial image segmentation is looked at to determine the reasons behind the objective.

## 4. Result and Discussion

A comparison of the suggested STO Performance with SCBRP, MPOTFEM, and GSA is made. In terms of network energy usage, remaining energy, network's lifetime, and throughput, MAT LAB 2019 is utilized to run the simulation. The network consists of one sink and 100 sensors. The 100m x 100m network's sensor nodes are strewn about at random. The suggested STO is evaluated using performance measures such as energy consumption, latency, and packet reception rate. Table 1 contains a list of the simulation parameters.

**Algorithm: Fuzzy k-means Clustering algorithm**

1. **Input:** The Dataset L and the quantity of K clusters
2. **Output:** The Effective original centroids for K clusters
3. Process K-means
4. All m characteristics b1, b2, b3……bn of L to be a number. Convert any characteristics that are not numeric to a number value.
5. The entire dataset into K equal sections using percentiles based on the initial component.
6. Calculate each characteristic's estimated value for the divided datasets.
7. Take the mean of each dataset as the initial cluster centroids, D = d1, d2..., dk, where d1, d2, ..., dk are the initial centroids for 1,2…., k clusters successively.
8. Allocate the centroids to the fuzzy k-means clustering algorithm.

**Table 1. Parameters and Simulation**

| Simulation | Parameters |
|---|---|
| Nodes | 100 |
| Location of BS | (50m, 50m) |
| Initial Energy | 50 J |
| Simulation area | 100m X100m |
| Packet Size | 4000 bits |
| Number of CH | 10 |
| Simulation Time | 400s |

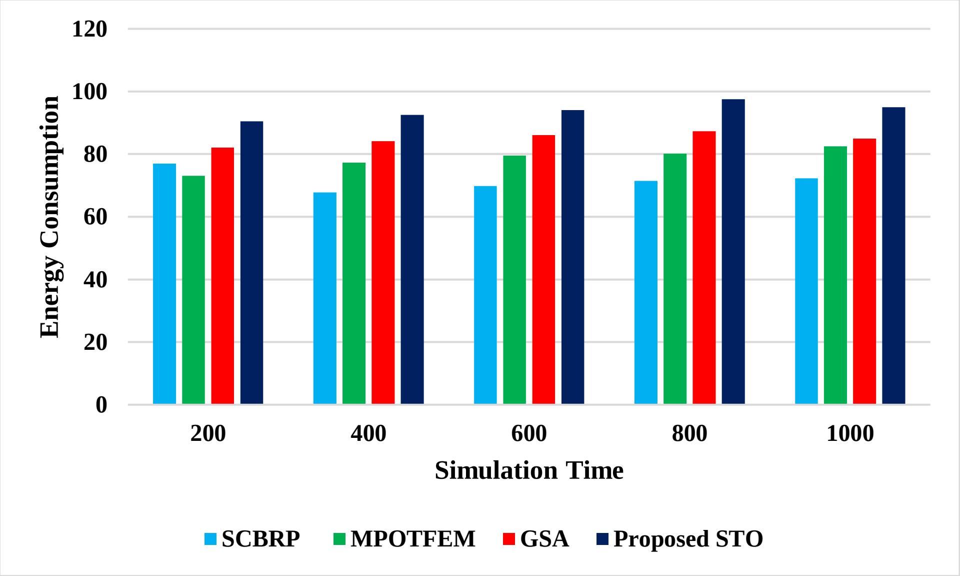


**Fig. 2 Energy consumption and the existing method**

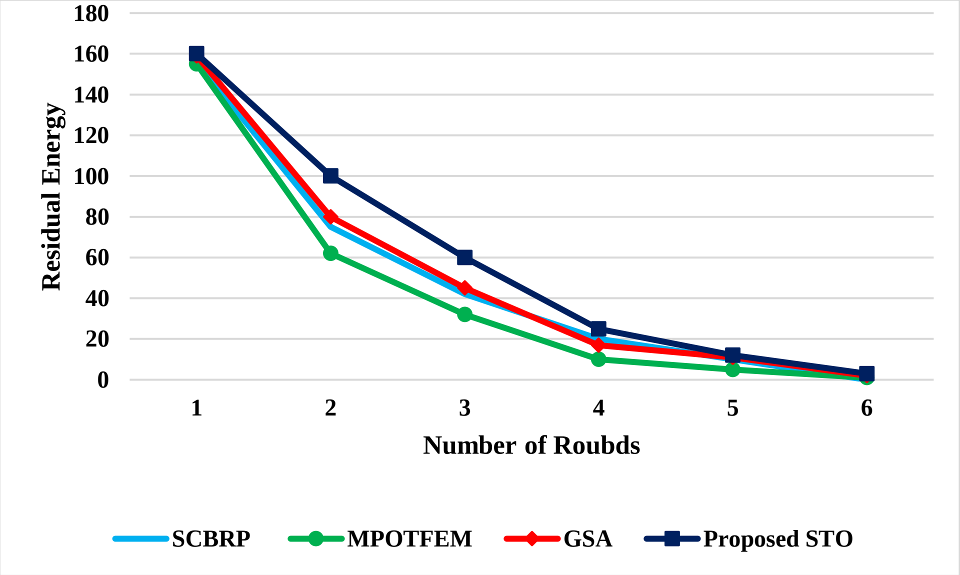


**Fig. 3 Comparison of residual energy**

Figure 3 illustrates the Energy Consumption for the proposed STO with the existing system such as SCBRP, MPOTFEM and GSA. From Fig. 2, it has been discovered that the suggested strategy offers a longer network lifetime. The time comes under 200, 400, 600, 800 and 1000 in the simulation.

Figure 3 depicts the residual energy comparative analysis. The proposed STO algorithm's average node is higher than the traditional technique. As a result, the proposed STO algorithm has a greater average node residual energy efficiency.

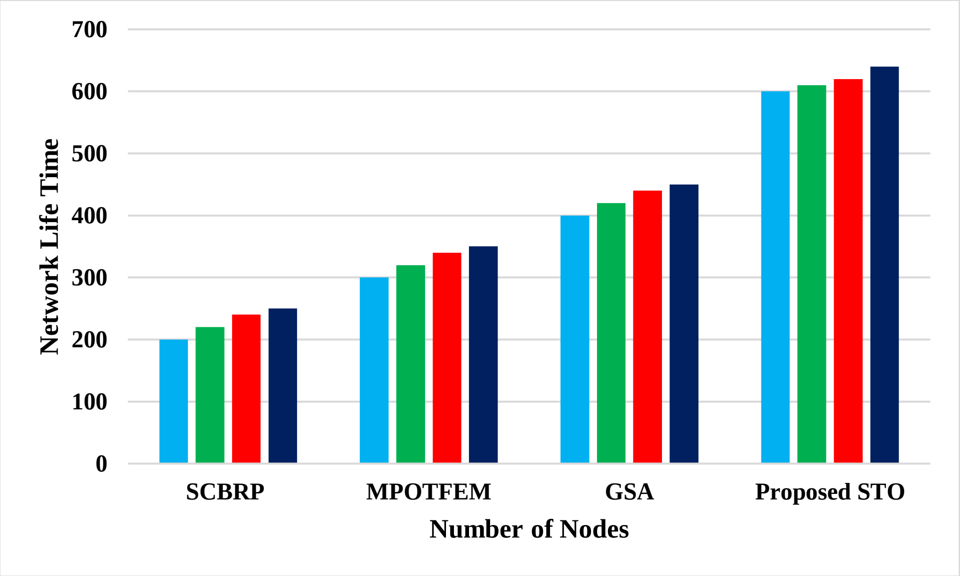


**Fig. 4 The lifetime of the network**

The network lifetime with varying node counts is depicted in Figure 4. The SCBRP method attains the lowest lifetime up to 100 rounds, whereas the proposed STO algorithm technique attains the highest lifetime up to 100 rounds.

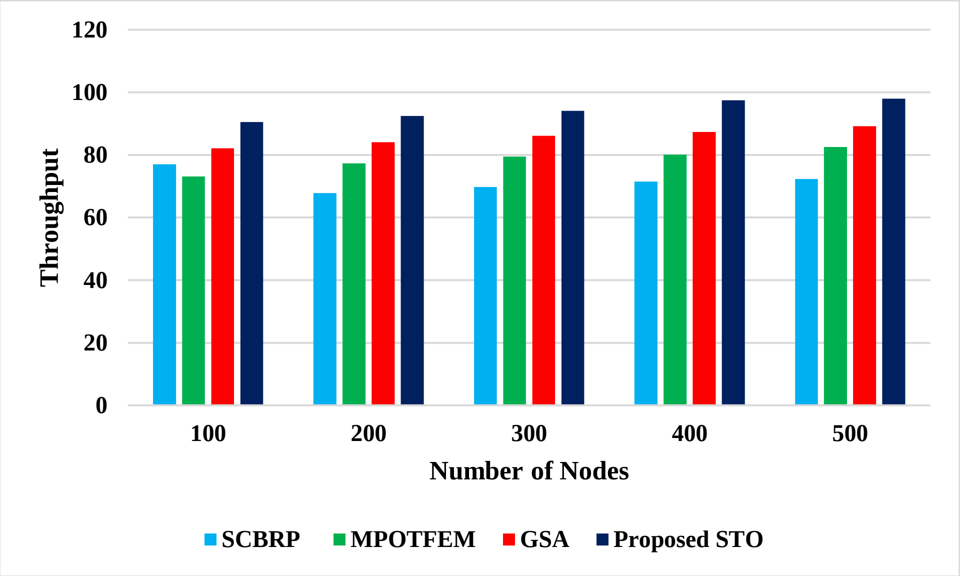


**Fig. 5 Throughput**

The simulation outcomes were compared to the traditional methods are shown in Figure 5. SCBRP received the lowest data packets. Finally, compared to SCBRP, MPOTFEM and GSA, the proposed STO algorithm technique has received a significant amount of data packets at the BS.

## 5. Conclusion

A novel Sooty tern-optimized K-means clustering (STO) algorithm was proposed in this research work. Initially, the SN is initialized to increase the lifetime of the network and node density and consume less energy consumption. These sensor nodes are clustered via Fuzzy K-means clustering, and the STO algorithm makes CH selection. Hence, the evaluation metrics used to assess the proposed STO approach are energy consumption, network lifetime, residual energy, and throughput. This scheme is simulated by using MATLAB 2019. A comparison is made between the proposed STO and existing algorithms such as SCBRP, MPOTFEM, and GSA in terms of energy consumption, network lifetime, residual energy, and throughput. The proposed STO algorithm enhances the network Life Time by 20.7%, 23.65%, 29.65%, and 42.65% better than the traditional frameworks. Future improvements to the routing protocol and the provision of effective, secure routing could be made utilizing a novel trust mechanism.

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