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A Novel Spider Monkey Optimized Fuzzy C-Means Algorithm (SMOFCM) for Energy-Based Cluster-Head Selection in WSNs

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ABSTRACT- AI is getting increasingly complex as a result of its widespread deployment, making energy efficiency in Wireless Sensor Network (WSN)-based Internet of Things (IoT) systems a highly difficult problem to solve. In energy-constrained networks, cluster-based hierarchical routing protocols are a very efficient technique for transferring data between nodes. In this paper, a novel Spider Monkey Optimized Fuzzy C-Means Algorithm (SMOFCM) is proposed to improve the lifetime of the network and less energy consumption. The proposed SMOFCM technique makes use of the Fuzzy C-means clustering framework to build up the cluster formation, and the Spider Monkey Optimization technique to select the Cluster Head (CH). MATLAB was used to model the suggested SMOFCM. The suggested framework's network lifetime, number of alive nodes (NAN), energy consumption, throughput, and residual energy are compared to those of more established frameworks like LEACH, K-MEANS, DRESEP, and SMOTECP. SMOFCM technique improves the network lifetime by 11.95%, 7.59%, 4.97% and 3.83% better than LEACH, K-MEANS, DRESEP, and SMOTECP. According to experimental findings, the proposed SMOFCM technique outperforms the existing model.

Keywords: Spider Monkey Optimization, Fuzzy C-Means, Cluster Head (CH), SMOFCM, Wireless Sensor Network.

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1. INTRODUCTION

AI is becoming more and more popular, and it is used in a variety of real-world applications [1] including smart cities, smart agriculture, security monitoring, smart water, smart environment monitoring, industrial control, and healthcare systems. Due to a number of limitations, including those related to energy, architecture, and protocol protection, the Wireless Sensor Network (WSN) required non-traditional paradigms [3]. A node having sensors, transceivers, computer capabilities, and power is referred to as a wireless sensor [4]. The nodes' processing speed, storage capacity, and communication bandwidth are all limited. They establish wireless connections among themselves and utilise a Sink/Gateway to connect to the internet or an external network [5]. Our homes, workplaces, and other sites are now home to the next generation of WSNs, which also brings new comforts and data [6]. Data is gathered and transferred to the BS, and various sensor nodes are placed strategically throughout the area of interest to identify the system design based on one or more physical parameters [7]. The sensor, also known as a transducer, is the wireless node front end, receiving physical input from the sensor, which is subsequently sent into the microcontroller for processing [8]. Clustering, which lengthens the life of the network, is the most popular technique for sustaining WSN topology [9]. Inter-cluster communication is another option, in which the cluster head node of one cluster communicates with the CH node of another cluster [10].

The following list summarizes the primary contributions of the suggested SMOFCM approach;

(a) The suggested SMOFCM framework sets up the cluster formation using the Fuzzy C-means clustering methodology.
(b) Using the Spider Monkey Optimization method, the Cluster Head is selected (CH).
(c) MATLAB has been used to model the recommended SMOFCM.

The remaining section of the work was organized as follows. In *Section-2* briefly explains the similar works. The suggested SMOFCM were shown in *Section 3*, along with an explanation. The performance outcome and their analysis are provided in *Section 4*. *Section 5* encloses with conclusions.

2. LITERATURE SURVEY

Various studies have been conducted to increases the WSN performance factors such as energy consumption, network lifetime, etc. In this section, the existing representative clustering algorithms are discussed.

In 2019 Lin, D., and Wang, Q., [11] developed an energy-efficient clustering method to improve the energy effectiveness of WSNs by lowering and balancing energy constraints. To control energy usage of the CH, a non-cooperative game method was developed. The outcome of the suggested model shows that the ECGD can successfully increase energy efficiency and improves the lifetime of the network. In 2018 Wang, Q., et al., [12] had developed an energy-efficient clustering based on fuzzy-logic. The total distance and residual energy descriptors are created in the initial step. The cluster head probability was locally determined in the second stage. A thorough evaluation of FLEEC's performance was done after extensive experiments.

In 2020 Augustine, S., and Ananth, J. P., [13] had established a CH selection event based on the Taylor kernel fuzzy C-means method. The proposed technique selects the cluster head based on the acceptableness criteria, which is calculated using the three variables such as trust energy, and distance. In 2019 Jesudurai, S.A., and Senthilkumar, A., [14] had designed an Improved Energy Efficient Cluster Head Selection protocol (IEECHS-WSN) technique. Dual CH are selected in a separate cluster as part of the CH selection technique, and they perform a variety of tasks that can uses less energy in IoT applications and extends the lifetime of the network.

In 2018 Wang, T., et al [15] developed a routing and energy-efficient clustering in WSN utilizing a genetic method. To determine the overall energy constraints, the routing and clustering methods are combined with one chromosome. The preceding hops to the loads on each CH were estimated to ensure model accuracy. To increase energy efficiency, load balance and total energy usage are considered when building the fitness function. In 2018 Lalwani, P.,[16] introduced a harmony search technique for WSN routing and clustering. An HSA-based CH selection technique was initially created for a fitness function with the parameters of node degree energy, and distance. The next step was to derive a possible function for allocating non-CH nodes to CHs. Finally, using the same parameters, an HSA-based routing method is suggested. The outcome demonstrates that the suggested technique outperforms the traditional technique.

In 2021 Dwivedi, A.K. and Sharma, A.K., [17] presented fuzzy logic for WSN using energy enhancement in LEACH. The CH is selected by fuzzy inference using cluster formation in WSN. Two pre-deployed diagrams are used in the suggested model to allow for the relocation of BS. This model balances a network load expressed as equivalent energy dissipation. In 2018 Mittal, N., et al., [18] developed an energy-efficient clustering method based on SMO (SMOTECP), threshold-sensitive to increase network lifetime and network stability. CHs and BSs communicate with each other using dual-hop communication to equalize the load and reduce energy consumption. According to the results, the suggested protocol achieves significantly improved than traditional protocols in terms of usage of energy, lifetime of the system, and stability time.

In 2020 Verma, S., et al., [19] had presented a Cost-effective Cluster-based Routing Protocol (CECRP) to increase the routing in WSN. A routing protocol that provides energy-efficient CH selection using parameters such as remaining energy, node density, total energy of the network, and distance factor. Distance-based Residual Energy-efficient Stable Election Protocol (DRESEP) chose CH based on distance and energy factor. In 2020 EI Khediri, S., et al., [20] had developed a method for producing many node clusters with an upgraded K-means clustering technique. S. Kaviarasan et al.,[26] introduced KM-MWOA strategy by altering the parameters A and B, this method are is able to find in the early stages of the search while also extensively using the search space in the later stages. In intra-cluster communication, single hop communication was used, while in inter-cluster communication, multi-hop communication was used. According to the literature review, node energy consumption and secure routing while sending data packets to their destinations are key problems in WSN. To overcome this challenge, SMOFCM has been proposed.

3. PROPOSED 1D-CNN MODELS

The SMOFCM framework is briefly explained in this section. The setup and steady state phases of each protocol round are separate phases. The CH selection procedure is streamlined during setup. In order to design energy efficient clusters for a certain NAN sensor, network remaining energy, and non-overlapping distance, BS leverages SMO as a tool throughout the setup phase. The CHs gather data from the individuals in their own cluster during the steady-state period and then relay it to a base station (BS).

3.1 Fuzzy C-Means (FCM) Clustering

In FCM the membership function decides the degree to which a data point associate with a cluster. Choosing the cluster centroid plays a vital role in better grouping. Each channel is subtracted from its own centroid to avoid inter channel dependency. A cluster's membership is established by comparing a data point's proximity or dissimilarity from the cluster centroid y_a to f_{da}. The Euclidean formula described in *eq. (1)* is utilized to measure the distances.

$$FCM = \sum_{a=1}^{k} \sum_{d}^{N} x_{da}^{r} f_{da}^{2} \tag{1}$$

Where $\sum_{a=1}^{k} f_{da} = 1$

The objective function's membership degree control was mechanised by the fuzzifier parameter p. *eq. (2) and (3)* were used to express the degree value and membership centroid, respectively.

$$x_{da} = \frac{1}{\sum_{n=1}^{k} (f_{da}^{2}/f_{dn}^{2})} \tag{2}$$

$$y_{a} = \frac{\sum_{d=1}^{N} x_{da}^{r} i_{d}}{\sum_{d=1}^{N} x_{da}^{r}} \tag{3}$$

The membership of the object also indicates the level of contribution made by each data object to the new cluster center

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under adjustment in the clustering center update. The created membership may not be available in the application of a typical representative because it is a relative number. Consequently, the cluster center determined by these memberships may not be the real cluster center. It can later lead to an unexpected cluster outcome.

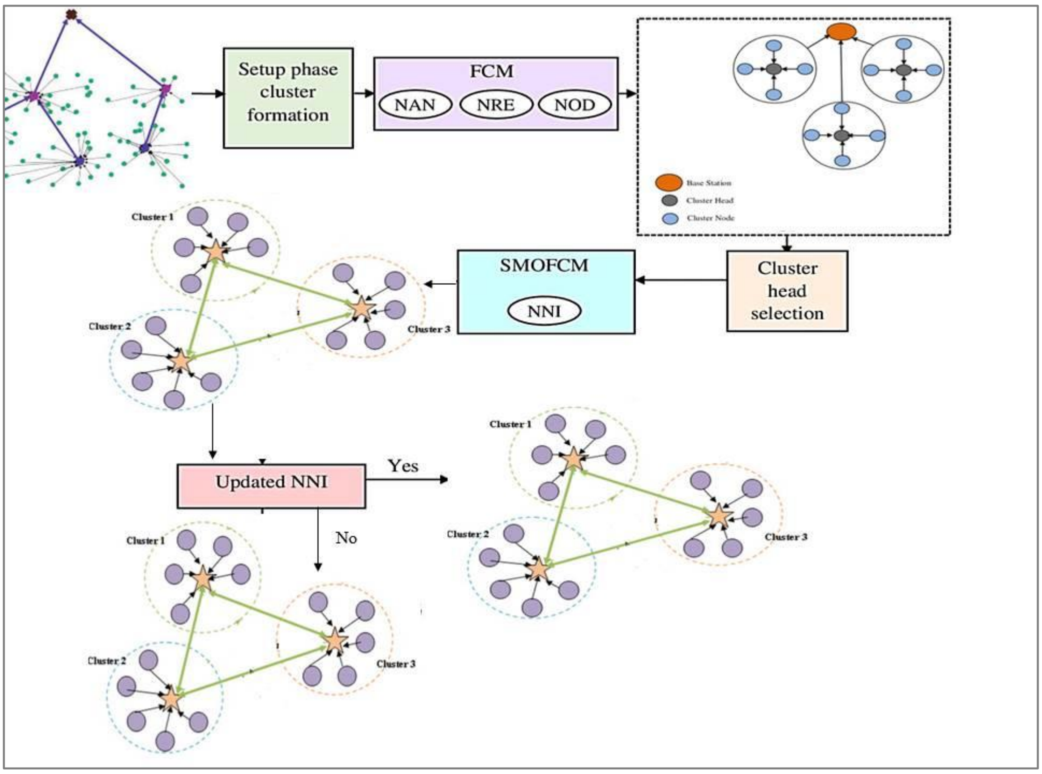

Figure 1: Block diagram of the proposed SMOFCM model

3.2 Cluster Head Selection

The network lifetime is optimised using SMO technique. Work with nearby nodes to replace any damaged nodes if they are unable to transmit data due to damage. The Cluster head SMO version described in this work improves the performance of the previous SMO by using node replacement. The Spider Monkey approach was developed primarily because of the difficulty of maintaining them inside a limited area. Eq. provides the arithmetic model for SMO (4)

$$T_y^x = \begin{cases} ET_y + q_1[(VC_y - NC_y)q_2 + NC_y]q_3 \geq 0 \\ ET_y - q_1[(VC_y - NC_y)q_2 + VC_y]q_3 < 0 \end{cases} \quad (4)$$

where, T_y^x is the First cluster head position in yth dimension, ET_y is Food Source's position in yth dimension, VC_y is upper bound in yth dimension NC_y is lower bound in y^{th} dimension and q_1, q_2 is random numbers based on the interval [0,1]. The significant coefficient r1, which is employed in Eq. (5) to balance the processes of food acquisition and consumption, is the most crucial factor.

$$q_1 = 2f^{-\left(\frac{4m}{M}\right)^2} \quad (5)$$

The number L denotes the recent round, and M is the extreme number of rounds, where q 1 is a significant coefficient of SSA.

3.2.1 Spider Monkey Optimization

In SMO, a mathematical model based on fission fusion social structure (FFSS) is applied to simulate intelligent behaviour in spider monkeys. The FFSS shows that 100 monkeys move from larger groups to minor groups for searching. The following are the main components of the FFSS:

- All spider monkeys initially remain in a group of 40–50 people. Every group has a head who oversees the investigation of the food resources. It is known as the organization's global leader (GL).
- When there isn't enough food for everyone, the global leader split the larger group into smaller one, each of which has three to eight members who can hunt on their own. A local leader (LL) then takes charge of each group.
- A leader known as the local leader makes the choice to look for food in each sub-group.
- The group members communicate with each other and with the other members of the group using a distinctive sound to keep social relationships and defensive borders.

There are six phases in the scientific model of the searching behaviour of SMO for optimization problems. Initial populations of spider monkeys are generated by SMO at random. Spider monkeys are represented by a D-dimensional

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vector. Let Q_{ab} depicts the b^{th} dimension of a^{th} individual. In spider monkey optimization, each Q_{ab} is initialized as follows,

$$Q_{ab} = Q_{minb} + S(0,1) \times (Q_{maxb} - Q_{minb}) \tag{6}$$

Where Q_{minb} and Q_{maxb} are upper and lower bounds in b^{th} direction for Q_a and $S(0,1)$ indicates a random amount between the range [0,1].

Initialization stage
In initial step of the SMO method, the Bernoulli technique is used to initialize a population of N spider monkeys (SM) at random.

$$SMO_{u,v} = \begin{cases} 1, & a < prob \\ 0, & otherwise \end{cases} \tag{7}$$

where $SMO_{u,v}$ is the v^{th} dimension of u^{th} spider monkey, an evenly spaced random number with a range of [0,1], and prob is probability with a value of 0.5. A randomly produced solution's suitability SMO_u (for the minimization issues) is evaluated as:

$$fitness_u = \begin{cases} 1 + |f_u|, & F_u \le 0, \\ \frac{1}{1+F_u}, & F_u \ge 0 \end{cases} \tag{8}$$

where $fitness_u$ is the issue under consideration's fitness function.

Local leader stage: Stage two involves updating the solution based on the local leader and team members' experiences. Logical OR, AND, and XOR operators have been applied to a binary optimization issue. The following is the position update equation:

$$SMO_{u,v} = \begin{cases} SMO_{u,v} \oplus \left((b \otimes (ll_{k,v} \oplus SMO_{u,v})\right) + \left(b \otimes (gl_v \oplus SMO_{u,v})\right), & rand \ge pr \\ \text{use equation 1}, & otherwise \end{cases} \tag{9}$$

where $SMO_{u,v}$ and $SMOn_{u,v}$ is the past and prior position of u^{th} SMO in the v^{th} dimension, $ll_{k,v}$ indicates the kth groups local head in the v^{th}dimension, d and b are the binary random values in the range [0, 1] and $\otimes$, +, $\oplus$ are logical AND, XOR, and OR operators respectively, and pr indicates the perturbation rate.

Global leader stage
In the third step, each SM updates its location or velocity update equation in accordance with the information known to the group leader and other members. Positions are modified in accordance with a likelihood provided by:

$$p_u = 0.9 \times \frac{fitness_u}{maximum\_fitness} + 0.1 \tag{10}$$

where p_u denotes the probability, $fitness_u$ denotes the fitness of u^{th} SM and maximum_fitness denotes group's level of extreme fitness. For this stage, the position update equation is presented as follows:

$$SMOn_{u,v} = SMO_{u,v} \oplus \left(\left(b \otimes (gl_v \oplus SMO_{u,v})\right) + \left(d \otimes (SMO_{r,v} \oplus SMO_{u,v}v)\right)\right) \tag{11}$$

where gl_v denotes the GL in the v^{th} dimension.

Local leader learning stage
Each individual updates their place in the group during this phase, and the best performer is selected to serve as the local authorities. This procedure keeps going unless the local leader gives up providing updates. When a predetermined amount of updates have passed without the LL being updated, the LL number is subsequently raised by 1.

Global leader learning stage
The position of GL is revised to reflect the LL's status as the best among them. When the global leader quits updating, this process is continued. If that the GL is not updated after a certain amount of updates, the GL number is then raised by 1.

Local leader decision stage
If the local leader count surpasses a predetermined threshold, LLL, each group member's status is altered as follows at this point.

$$SMO_{u,v} = \begin{cases} SMO_{u,v} \oplus \left((b \otimes (ll_{k,v} \oplus SMO_{u,v})\right) + \left(b \otimes (gl_v \oplus SMO_{u,v})\right), & rand \ge pr \\ \text{use equation 1}, & otherwise \end{cases} \tag{12}$$

Global leader decision stage
If the number of global leaders exceeds a GLL threshold during the last step of the SMO technique, the larger set is split into a minor group. The GL merges to create a single team once the highest number of groups has been created, and the local leader's status is updated.

4. RESULT

The result of the proposed Spider Monkey Optimized Fuzzy C-Means Algorithm (SMOFCM) is discussed in this section. For implementation, MATLAB was used. The effectiveness of the proposed SMOFCM is examined using a number of limitations such as energy consumption, lifetime of the network, throughput, residual energy and NAN. The suggested framework is compared with traditional techniques LEACH, K-means, DRESEP and SMOTECP.

Table 1: Illustrates the simulation parameters of the proposed SMOFCM framework

Simulation	Parameters
Total no of nodes	100
Size of Network Area	100m X 100m
Location of base station	(50,50)
Packet Size	4000 bits
Number of CH	10
Simulation Time	400s
Initial Energy	50

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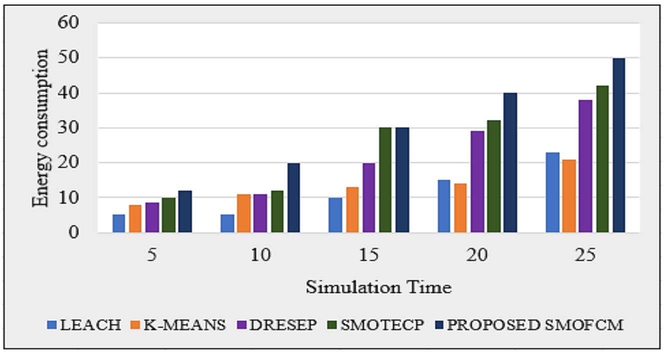
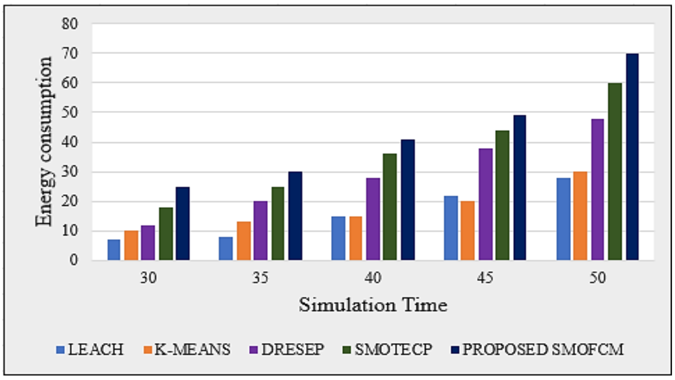
4.1 Energy Consumption

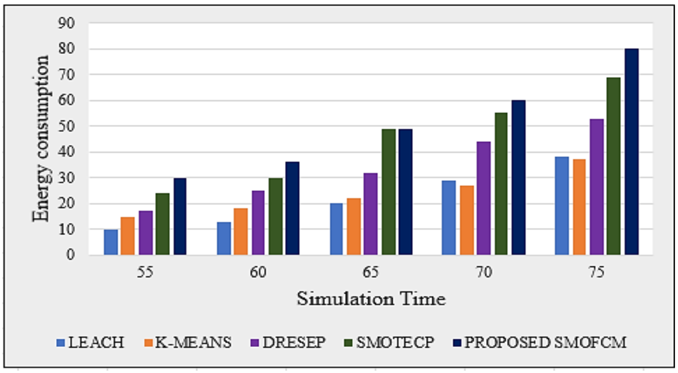
Energy consumption is used to describe the system's overall energy usage while transmitting a data packet



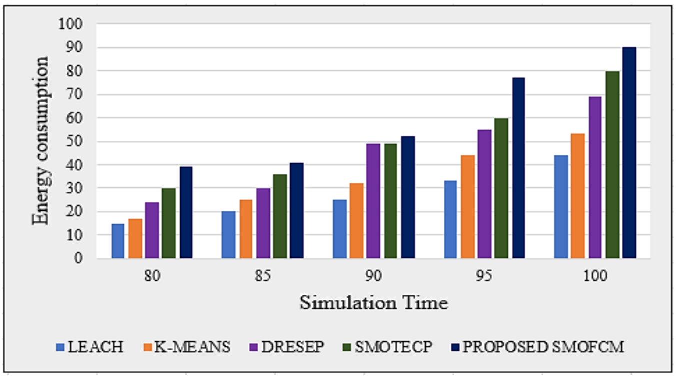
(a)



(b)



(c)



(d)

Figure 2: Energy usage of the suggested and the traditional method

The *figure 2* illustrates the Energy Consumption for the proposed SMOFEM with existing system such as LEACH, K-MEANS, DRESEP, and SMOTECP from *figure 2*, it has been discovered that the suggested strategy offers a longer network lifetime. In the Simulation time comes under 25, 50, 75, and 100.

4.2 Residual Energy

A sensor node lose energy while sending, receiving, and aggregating data in a WSN. After that, remaining energy exists and this energy is called residual energy

Table 2: Comparison of residual energy

Number of rounds	Residual Energy				
	LEACH [12]	K-MEANS [13]	DRESEP [14]	SMOTECP [15]	SMOFCM (proposed)
0	150	150	150	150	150
0.5	9	75	72	83	97
1	8	9	25	38	55
1.5	0	1	4	15	24
2	0	0	0	5	8
2.5	0	0	0	1	3
3	0	0	0	0	1

Figure 3 shows the Residual Energy comparative analysis. The suggested method average node is higher than the traditional technique. As a result, our suggested approach has a greater average node residual energy efficiency.

4.3 Network Life Time

A network's lifetime is the period of time it is fully functional. Route requests are calculated at each node as they are sent through the network. The network lifetime with varying node counts is illustrated in *figure 4*. The LEACH method attains the lowest lifetime up to 100 rounds, whereas the proposed SMOFCM method attains the highest lifetime up to 100 rounds.

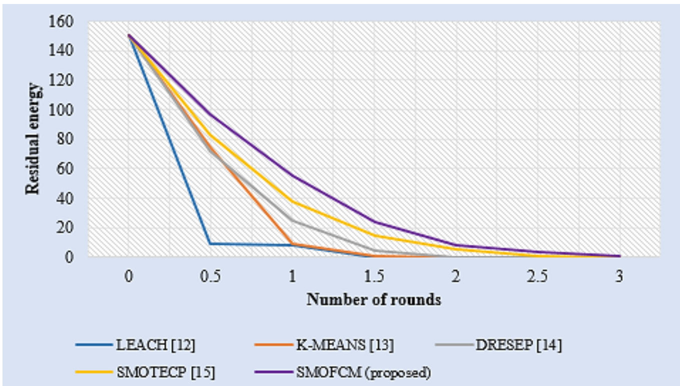


Figure 3: Comparison of residual energy

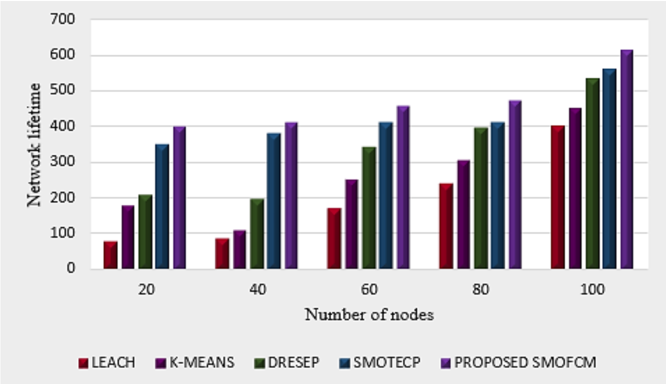


Figure 4: Lifetime of network

4.3 Alive Nodes

A measure of the number of nodes that are still operational after a particular number of data collection rounds. Nodes will perform better if there are more active nodes.

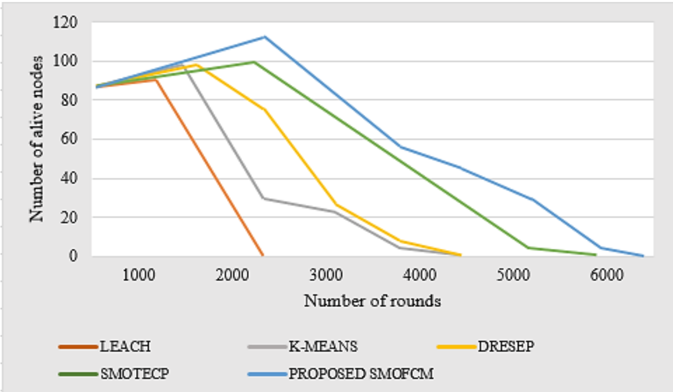


Figure 5: Number of alive nodes

From the *figure 5* it is clear that, though in first rounds the LEACH, K-MEANS, DRESEP and SMOTECP are found to give comparable outcomes but, after around 10–20% nodes are dead. The suggested system functions better since it modifies the cluster heads in accordance with the remaining energy.

4.4 Through-put

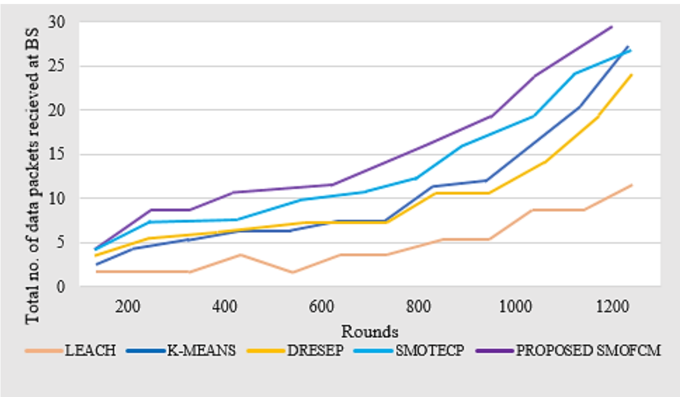


Figure 6: Throughput

Throughput refers to the number of data packets that have reached the BS effectively. The simulation outcomes were compared to the traditional methods are shown in *figure 6*. Lowest data packets were received by LEACH. Finally, comparing to LEACH, K-MEANS, DRESEP, and SMOTECP, our suggested technique has received a significant amount of data packets at the BS.

5. CONCLUSION

In this research, a novel Spider Monkey Optimized Fuzzy C-Means Algorithm (SMOFCM) is proposed to increases the network lifetime and less energy usage. The Fuzzy C-means clustering framework is used in the suggested SMOFCM method to setup the cluster formation, and the Spider Monkey Optimization technique is utilized to choose the CH. The simulation result illustrates that the proposed SMOFCM framework outperforms the traditional techniques such as LEACH, K-MEANS, DRESEP, and SMOTECP. The suggested technique increases the network lifetime by 11.95%, 7.59%, 4.97% and 3.83 % better than LEACH, K-MEANS, DRESEP, and SMOTECP. According to experimental findings, the proposed SMOFCM technique outperforms the existing model.

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