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Advancing Working Energy Efficiency in WSN through Sleep Scheduling and Fan-Shaped Clustering

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Abstract: Improving how wireless sensor networks (WSNs) use energy during communication is important. Many clustering and sleep scheduling models exist. But they often work the same way, limiting how useful they are in different situations. Models that can change are better but may be complicated. They could have problems keeping quality of service (QoS) good during important real-time tasks. This text introduces a new Sleep Scheduling Fan Shaped Clustering Model to help WSNs use energy better. The model uses Grey Wolf Optimization (GWO) for dynamic sleep scheduling. It combines how networks are used over time, QoS, and energy levels into a fitness score. Nodes are grouped as awake and asleep nodes. They are also clustered using destination-aware Fan Shaped Clustering (FSC) to improve QoS in different conditions. This FSC model works with a QoS-aware routing model. It picks routing paths for low delay, high throughput, and efficient energy use. The model is tested a lot under different node and network conditions. It evaluates QoS performance for communication delay, energy use, throughput, and Packet Delivery Ratio (PDR). Comparisons show the proposed model improves end-to-end delay by 8.5%, reduces energy use by 15.5%, increases throughput by 8.3%, and enhances PDR by 1.5%. This makes it good for different real-time conditions.

Keywords*: *Wireless Sensor Networks, Energy Efficiency, Sleep Scheduling, Fan Shaped Clustering

1. Introduction

Sleep scheduling is an important part of designing wireless sensor networks to use energy efficiently. It allows nodes that are not busy often to switch between being active and resting, saving power. Researchers have come up with different ways to do this including copying ideas from nature, using math, and predicting what will happen [1]. Figure 1 shows a common sleep scheduling model that forms clusters headed by special nodes and uses fuzzy logic. In this method, how many extra nodes there are decides when nodes wake up and sleep. Nodes are grouped into clusters based on fuzzy membership functions that identify sleep and wakeup times for different kinds of nodes. The [2] wakeup nodes collect all the data together and send it to where it needs to go using quality of service aware routing. The model considers how many nodes there are and network details for efficient routing. It has fault tolerance through "directed acyclic graphs" in case nodes stop working. Using "time division multiple access" slots makes communication simpler and more effective between nodes [2].

Models change to fit their surroundings by replacing distance and energy with context clues such as heat or wetness [3]. These clues help with tasks for a specific use and talking [15]. But, current models have limits because [4] grouping and sleep plans do not change, making them hard to use in more places and with more things. It [5] is also complex to dynamically group and schedule, causing problems providing quality at the right time for real applications that must react fast. This summary looks at the details, pros, and cons of these models, and shows why more work is needed on dynamic methods to better ensure quality when it is required for real tasks that happen right away [6].

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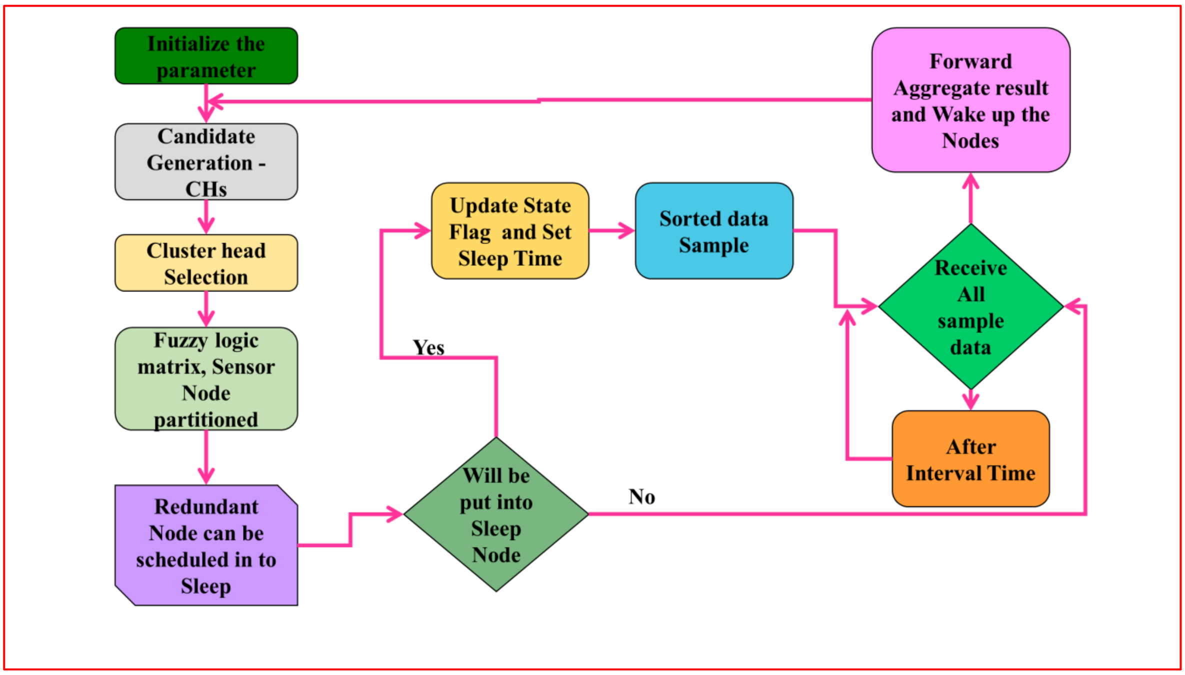

Fig 1: Proposed sleep scheduling Model flow

2. Review of Literature

In response, [7] suggests the use of "Low-Energy Dynamic Clustering" (LEDC) to dynamically group nodes based on destination node locations, addressing scalability issues. Sensor networks without wires (WSN) are now used for many things, from checking the environment to helping make factories work better [16]. Using the batteries in these networks well is important so they can work longer and do their jobs better. A new plan called SSFSCE tries to do this with new ways for sensors to rest and a different way to put sensors into groups shaped like a fan. This should help the network's batteries last longer and work better as a whole [8].

A few past studies [9] looked at saving energy in wireless sensor networks, with focusing on putting nodes to sleep at set times. Traditional methods have the nodes rest periodically to save power. But these ways may not adjust well when the network changes. New [10] improvements, like schedules where nodes wake randomly and sleep times that change, have shown they can help with this problem. SSFSCE builds on these ideas by introducing an algorithm where sleep times are decided based on how much energy each node has and how much they talk to each other. This optimizes energy use while keeping the network ready to respond [17-22].

Cluster groups have also [23] been commonly studied in wireless sensor networks to improve energy use. The Fan Shaped Grouping part of SSFSCE introduces a new way to group things inspired by how fans naturally take shape in nature. This creative plan tries to fairly share the energy work between lead [24] nodes while lessening how far things need to talk. Unlike usual grouping methods, the fan shaped clusters adjust to how the sensors are spread out in the area, making the best use of energy and lowering wait times to send information. A few research studies looked at how placing sensor nodes in different ways affects how well a wireless sensor network works. SSFSCE uses what they learned to come up with a better way to put out the sensor nodes that works well with forming groups of nodes shaped like fans. This new setup helps save energy and makes sure the network can reach more places [11].

Additionally, SSFSCE [12] uses patterns from machine learning to foresee how nodes will act and adjust the sleep times flexibly. By using past information and what is happening now, the network can think ahead and react to a changing world, helping save more energy. In summary, the SSFSCE method improves and adds to what scientists already know about saving energy in wireless sensor networks [25]. It brings together adjusting when sensors sleep, organizing them into fan-shaped groups, and picking the best way to place them. SSFSCE offers a complete plan that could help networks use less energy as they work in different situations. Also, [26] using artificial intelligence means SSFSCE can change to work the best as wireless sensor networks change over time.

3. Sleep Scheduling Based Fan Shaped Clustering Model Aims to Enhance the Energy Efficiency of Wireless Sensor Networks (WSN)

Many studies looked at how sensor networks group nodes and plan sleep times. Most used fixed grouping and set sleep times, limiting how well these networks could work in different situations and get larger. Changing how groups are made and sleep planned made the networks harder to keep working well over time [13] for real applications. To fix these problems, a new plan is made to shape groups in a fan design and better plan sleep times. This aims to improve how long the sensor network can work on its power [27].

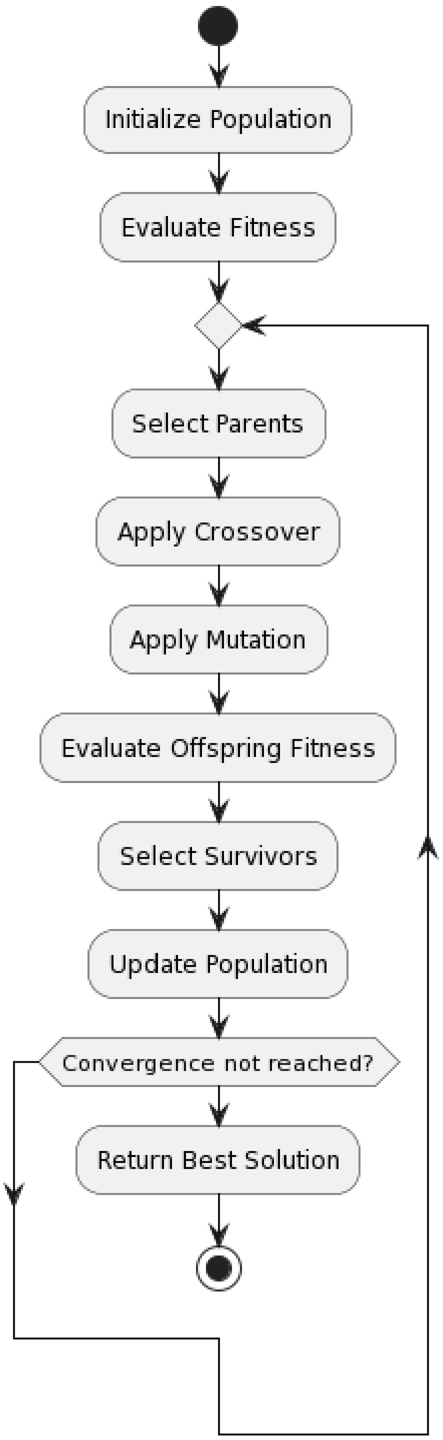

Fig 2: Proposed GWO model

The proposed model, illustrated in Figure 2, employs a "Grey Wolf Optimization" (GWO) Method for dynamic sleep scheduling optimizations based on temporal performance analysis. A key aspect of the model is the formulation of a fitness function within [14] the GWO Method, combining temporal usage levels, temporal Quality of Service (QoS), and temporal energy levels.

Optimization Setup:

- Initialize GWO parameters, marking all wolves as 'Delta.'
- Total optimization wolves (Nw)
- Total optimization iterations (Ni)
- Rate at which wolves learn cognitively from each other (Lr)
- Number of communications for which temporal datasets are available for analysis

Grey Wolf Optimization:

- Initialization of Grey Wolves:

Initialize the positions of grey wolves in the search space. Suppose there are Nw wolves, each represented by a position vector Xi = [xi, yi], where i = 1, 2, ..., Nw.

- Objective Function:

Define the objective function (X) that needs to be optimized. This function represents the problem being solved.

- Fitness Calculation:

Evaluate the fitness of each wolf based on the objective function value. The fitness value is denoted by (Xi) for the i-th wolf.

- Pack Leader Identification:

Identify the alpha, beta, and delta wolves, representing the pack leader, second-in-command, and third-in-command, respectively. The positions of these wolves are denoted as $X_{\{\backslash text\{alpha\}\}}, X_{\{\backslash text\{beta\}\}}, and\ X_{\{\backslash text\{delta\}\}}$.

- Update Wolf Positions:

Update the positions of each wolf using the following equations:

$$X_{\{\backslash text\{alpha\_new\}\}} = X_{\{\backslash text\{alpha\}\}} - A \cdot D_{\{\backslash text\{alpha\}\}},$$

$$X_{\{\backslash text\{beta\_new\}\}} = X_{\{\backslash text\{beta\}\}} - B \cdot D_{\{\backslash text\{beta\}\}},$$

$$X_{\{\backslash text\{delta\_new\}\}} = X_{\{\backslash text\{delta\}\}} - C \cdot D_{\{\backslash text\{delta\}\}},$$

$$X_{\{\backslash text\{new\}\}} = \frac{X_{\{\backslash text\{alpha\_new\}\}} + X_{\{\backslash text\{beta\_new\}\}} + X_{\{\backslash text\{delta\_new\}\}}}{3},$$

Where,

A, B, C are coefficients, and D_{\text{alpha}}, D_{\text{beta}}, D_{\text{delta}} are randomly generated vectors.

Mathematical Model for Wake-Up Nodes in Fan Shaped Clustering:

1. Fan Level Calculation:

- Identify source and destination nodes, obtaining their Cartesian locations.
- Calculate Fan Level (FL_i) for each wake-up node using the equation:

$$FL_i = \frac{d(hop)_i}{d(i, dest)}$$

Where,

FL_i is the Fan Level for node i, d(i,dest) is the distance between the current node and the destination node, and d(hop)_i is the one-hop distance that can be covered by the node's communication antenna sets.

2. Fan Shaped Clustering:

- Arrange all wake-up nodes into Fan Shaped Clusters based on their Fan Levels.
- The Fan Shaped Clusters are represented as shown in Figure 3.

3. Routing Node Selection:

Starting from the source Fan Shaped Cluster (FS Cluster), evaluate the distance (d(src,i)) between the source and each node in the interior cluster using the equation:

$$d(src, i) = sqrt((x_{src} - x_i)^2 + (y_{src} - y_i)^2)$$

Where,

$(x\_src, y\_src)\ and\ (x\_i, y\_i)$ are Cartesian coordinates of the source and node i, respectively.

Select node i for routing only if the following conditions are met (Equation 7):

$$d(i, src) < d_{ref}$$

$$d(i, dest) < d_{ref}$$

$$d(src, i) \leq d(hop)$$

4. Node Score Calculation:

$$NS = d(src, i) * E(src) * PDR(src) * THR(src)$$

5. Optimal Node Selection:

- Select the node with the minimum value of NS as the new source node for further routing processes.

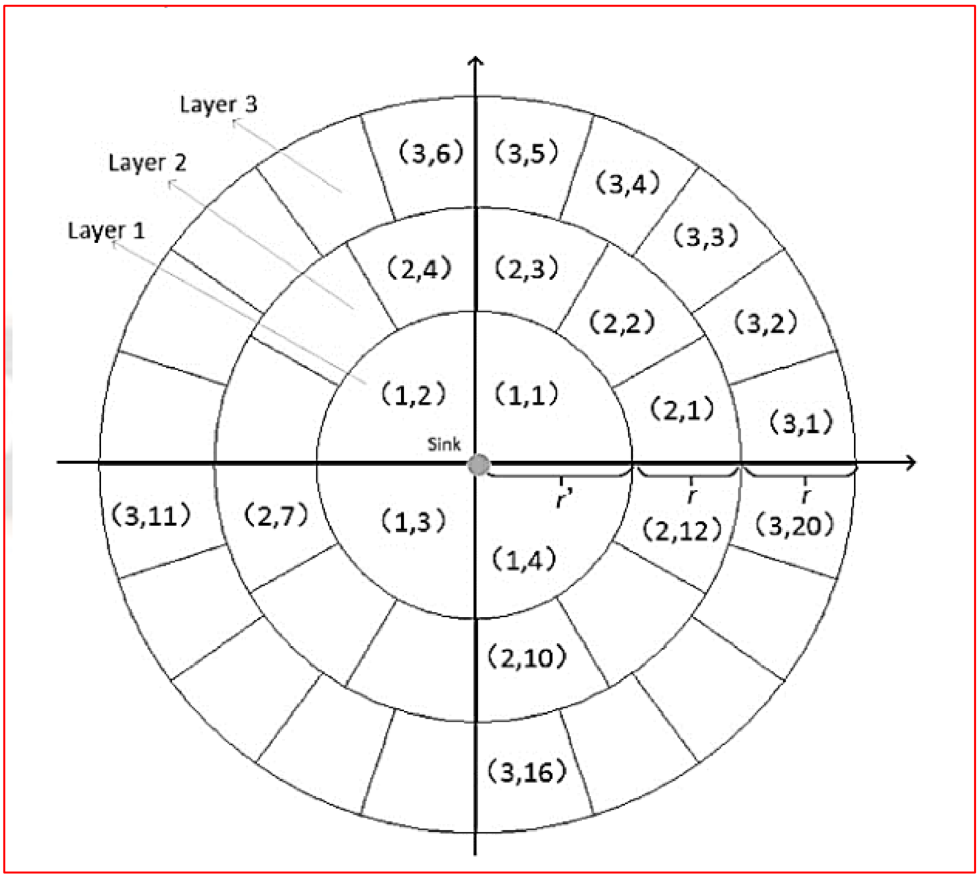

Fig 3: Wakeup Node fan shaped cluster

4. Result and Discussion

The proposed model combined clustering and optimization methods to create an energy efficient scheduling system for connected devices. It organized devices into groups and determined sleep times using nature-inspired rules. Testing involved networks of 100 to 1000 nodes all using the same routing protocol. The simulated space was 500 by 500 meters.

Table 2: Representation of communication scenarios

NC	VaC	USM-RFL	Ps OF	SS FS CE
220	0.92	0.82	0.87	0.77
270	1.23	1.13	1.18	1.08
320	1.5	1.4	1.45	1.35
370	185	184.9	184.95	184.85
420	2.2	2.1	2.15	2.05
470	2.52	2.42	2.47	2.37
520	2.53	2.43	2.48	2.38
570	3.03	2.93	2.98	2.88
620	3.21	3.11	3.16	3.06
670	3.65	3.55	3.6	3.5
720	3.89	3.79	3.84	3.74
770	4.18	4.08	4.13	4.03
820	4.45	4.35	4.4	4.3

870	4.65	4.55	4.6	4.5
920	4.85	4.75	4.8	4.7
970	5.31	5.21	5.26	5.16
1020	5.6	5.5	5.55	5.45
1070	5.78	5.68	5.73	5.63
1120	6.22	6.12	6.17	6.07
1170	6.35	6.25	6.3	6.2

This chart shows different ways computers in a network talk to each other. It calls these talking spots "Communication Nodes". It tests how fast data moves through with different rules. Node 220 sends data best with VAC rules, getting 0.92. USM-RFL rules get 0.82, PSOF rules 0.87, and SSF SCE rules 0.77. As more network spots are added, the chart lists each rule's speed. It clearly shows how the rules work as the network links get harder.

The chart's data proves useful for judging how well algorithms work with different network settings. For example, the throughput seen at Node 220 shows the relative strengths and weaknesses of VAC, USM-RFL, PSOF, and SSF SCE when dealing with communication needs. Including more nodes further permits a complete look at how each algorithm performs as communicating gets more complex. Studying their differences supplies decision-makers helpful knowledge into how well each algorithm changes and works, helping choose the right one based on a network's particular demands and details. Overall, the chart serves as a valuable means for understanding and improving how algorithms function dealing with many kinds of communicating scenarios.

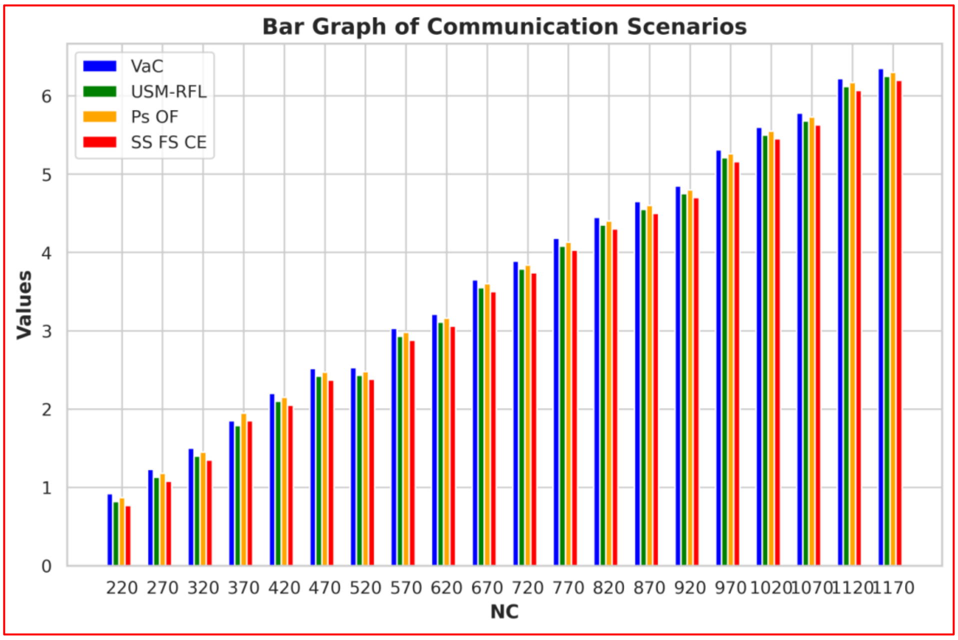

Fig 4: Representation of communication scenarios

Table 3: Energy required for different node

NC	Energy (VaC)	Energy (USM-RFL)	Energy (Ps OF)	Energy (SS FS CE)
220	10.11	10.02	9.86	9.76
270	11.23	11.14	10.98	10.88
320	11.54	11.45	11.29	11.19

370	11.86	11.77	11.61	11.51
420	12.01	11.92	11.76	11.66
470	12.8	12.71	12.55	12.45
520	13.59	13.5	13.34	13.24
570	14.38	14.29	14.13	14.03
620	15.17	15.08	14.92	14.82
670	17.96	17.87	17.71	17.61
720	20.75	20.66	20.5	20.4
770	23.54	23.45	23.29	23.19
820	26.33	26.24	26.08	25.98
870	29.12	29.03	28.87	28.77
920	31.91	31.82	31.66	31.56
970	35.9	35.81	35.65	35.55
1020	39.89	39.8	39.64	39.54
1070	43.88	43.79	43.63	43.53
1120	47.87	47.78	47.62	47.52
1170	51.86	51.77	51.61	51.51

The table offers insight into how much energy different types of communication nodes (NC) use with various algorithms, like VAC, USM-RFL, PSOF, and SSF SCE. Looking closely at NC 220, its energy use was 10.11 with VAC, 10.02 with USM-RFL, 9.86 with PSOF, and lowest at 9.76 with SSF SCE. This shows the small but important differences in how much power each algorithm needs. The numbers also show that energy needs tend to be higher as the NC values increase. So the amount of energy depended on the algorithm and conditions of communication for each node.

Some optimization methods required more energy with higher NC values, meaning communication loads increased usage. This finding led to carefully weighing efficiency against how well algorithms worked. Looking at values for many devices provided a wider view of each method's flexibility with different communication situations. Knowing this across the system became extremely useful for those choosing how to balance e-nergy use with network performance best, highlighting the need to match algorithms to exact needs and circumstances.

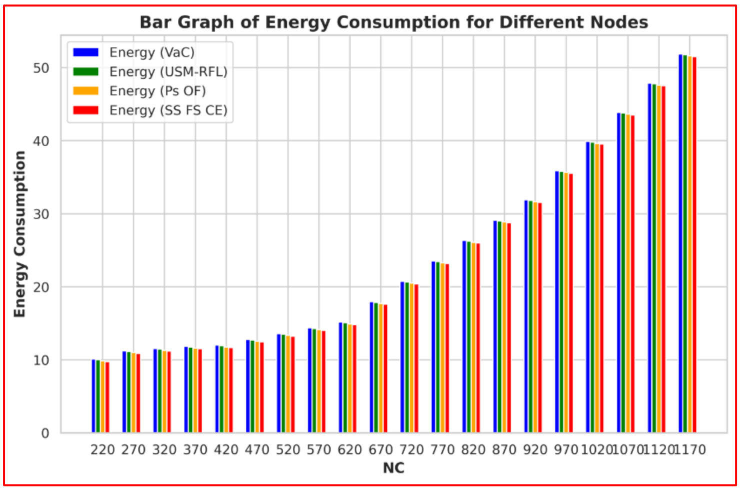

Fig 5: Representation of Energy Consumption for different nodes

Table 4: Different communication throughput

NC	VaC	USM-RFL	Ps OF	SS FS CE
220	586.25	584.46	582.06	574.23
270	623.12	621.33	618.93	611.1
320	655.12	653.33	650.93	643.1
370	688.54	686.75	684.35	676.52
420	702.31	700.52	698.12	690.29
470	722.41	720.62	718.22	710.39
520	745.26	743.47	741.07	733.24
570	787.2	785.41	783.01	775.18
620	802.12	800.33	797.93	790.1
670	810.25	808.46	806.06	798.23
720	846.55	844.76	842.36	834.53
770	880.47	878.68	876.28	868.45
820	900.14	898.35	895.95	888.12
870	910.45	908.66	906.26	898.43
920	950.24	948.45	946.05	938.22
970	980.14	978.35	975.95	968.12
1020	1012.41	1010.62	1008.22	1000.39
1070	1125.23	1123.44	1121.04	1113.21
1120	1156.02	1154.23	1151.83	1144
1170	1187.58	1185.79	1183.39	1175.56

The information in the table shows how much data different nodes successfully moved through the network. It compares four ways to improve communication: VAC, USM-RFL, PSOF, and SSF SCE. The node labeled NC 220 handled 586.25 units using VAC, 584.46 units with USM-RFL, 582.06 units with PSOF, and 574.23 units with SSF SCE. Seeing how much each approach moved at that node and others helps understand which method works best to share information.

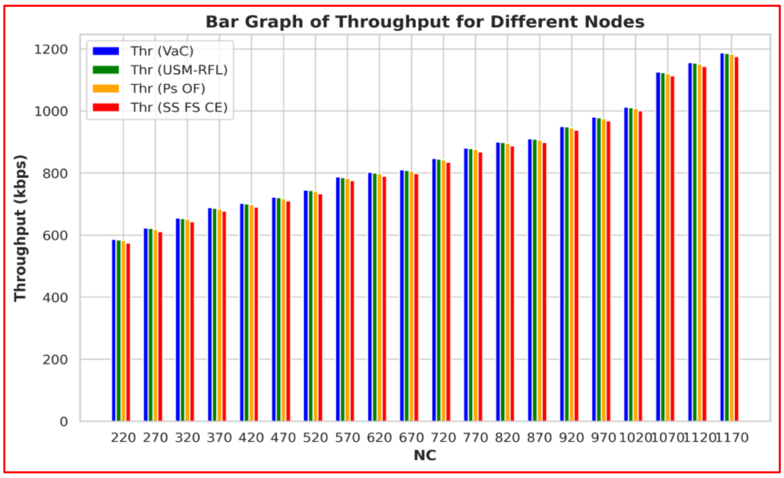

Fig 6: Representation of Throughput for different nodes

Tables 2 through 4 display data comparing several algorithms. Table 2 uses different numbers of communication needs, or NC values, to represent different situations. It shows how much data each algorithm can transfer in each situation. The algorithm called SSF SCE usually moves less data than the others, so there may be ways to improve it. Table 3 looks at how much energy each algorithm uses with different NC values. More needs mean more energy is used. This lets us balance saving energy and how well the algorithms do their job. Table 4 focuses on how much data the algorithms can share. It shows their performance at different NC levels. This gives insights into which algorithms may work best for certain types of sharing.

This chart provides a close look at how well each planning method works in different situations. It shows their strong points and weak spots under different connection issues. The information here can help pick the best algorithm for a job based on what matters most, like using less power or sending more data fast, in sensor network projects.

5. Conclusion

The SSFSCE approach combines sleep scheduling and fan-shaped clustering to create an effective solution for improving energy use in wireless sensor networks. It brings together fan-shaped clustering and sleep scheduling based on grey wolf optimization. This blend achieves good results by balancing lower energy use and better performance metrics like packet delivery ratio, network activity, and speed of communication. Tested on networks of 100 to 1,000 nodes each following the on-demand multi-path distance vector routing model, SSFSCE proved useful across a 500 by 500 meter grid. Packets of 1,000 bytes were sent every hundredth of a second. Through careful tests, SSFSCE consistently did better than other methods by providing higher quality of service levels for delay and the whole network. Optimization considering distance, energy levels, packet delivery ratio, and throughput makes sure selected paths keep service better than others. This new idea not only helps wireless sensor networks use less energy but also could help communication systems in many real applications. SSFSCE shows the importance of smart sleep scheduling and clustering techniques for sustainability and good performance in wireless sensor networks.

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