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SSFSCE: Design of a Sleep Scheduling based Fan Shaped Clustering Model to enhance working Energy Efficiency of WSN

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Abstract— To enhance energy level in WSN is a research requirement, which assists in improving their lifetime over a series of communications. To achieve this target, a various variety of clustering & sleep scheduling models are discussed by researchers. Most of these models deploy static clustering & sleep scheduling operations, which limits their applicability & scalability levels. Moreover, dynamic clustering & scheduling models are highly complex, which reduces temporal QoS performance under real-time use cases. In order to reduce the probability of these issues, this text discusses design of the proposed Sleep Scheduling based Fan Shaped Clustering Model to enhance working Energy Efficiency of WSN. The proposed model initially deploys a Grey Wolf Optimization (GWO) Method for dynamic sleep scheduling via temporal performance analysis. The GWO Method models a fitness function that combines temporal usage levels, temporal Quality of Service (QoS), and temporal energy levels. Based on this modelling process, nodes were categorized into wake & sleep nodes, which were further clustered via destination-aware Fan Shaped Clustering (FSC), that assisted in improving QoS performance under multiple scenarios. The FSC Model was combined with a QoS-aware routing model, that assisted in selection of routing paths that can achieve low delay, high throughput, and high packet delivery with higher energy efficiency levels. Efficiency of the model was tested on node & network conditions, and its QoS performance was checked in terms of communication delay, consumption of energy, level of throughput, and Packet Delivery Ratio (PDR) levels. On the basis of these comparative evaluations, it is observed that the new proposed model is able to enhance end-to-end delay by 8.5%, reduce level of energy by 15.5%, while increasing throughput by 8.3%, and PDR by 1.5%, thus making it useful for a different real-time conditions.

Keywords- Wireless, Clustering, Destination, Source, PDR, GWO, Throughput, Energy, Delay, QoS.

I. INTRODUCTION

Sleep scheduling in Wireless Sensor Networks (WSN) is used for design of highly energy efficient networks. This process allows infrequently used nodes to be shifted from awake state to sleep state, which assists in reducing their power consumption levels. To carry this task, a wide variety of models are proposed by researchers, which integrate bioinspired optimizations, linear optimizations, predictive analysis, etc. to the design process. A typical sleep scheduling model that uses a combination of cluster head formation along with fuzzy logic [1] is depicted in figure 1, wherein node redundancy levels are used to perform wakeup & sleep operations. The model groups each node into clusters via different fuzzy membership functions, which assists in identification of sleep & wakeup time for different node types. The wakeup nodes collect aggregated data and forward it to destination nodes via an efficient Quality of Service (QoS) aware routing process. To implement this routing process, the model uses node density & other network parameters that assist in estimation of highly efficient routing paths. In case of node failures, the model selects alternate paths, which allows it to integrate fault tolerant via “Directed Acyclic Graphs” (DAGs), and other graph modelling processes.

Such models also use “Time Division Multiple Access” (TDMA) slots that are presently accessible by different node types. These nodes are able to utilize them as these slots are now open. The way by which the nodes communicate data from themselves to the CHs has been simplified as a direct consequence of this improvement. The procedure gets less complex as a consequence of this. The CHs will transport the data either to other nodes or to CHs after that phase is complete in order to close the node-to-node communication loops. Models substitute measurements of distance and energy level with features that are relevant to the environment in which the program is being executed in order to carry out application-specific routing and communications. Conditions like temperature or humidity may be among them. To mention just a few of the myriad possible components that make up these context-specific features [2, 3, 4], throughput, packet delivery

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ratio (PDR), and routing overheads are just a few examples. The overview of such models, their subtleties, benefits, and limitations, as well as prospective new study fields, are presented in the part that follows. It was observed that these models' applicability and scalability are constrained by the fact that the majority of them use static clustering and sleep scheduling processes. The excessive complexity of dynamic clustering & scheduling methods also hinders temporal QoS performance for real-time use cases.

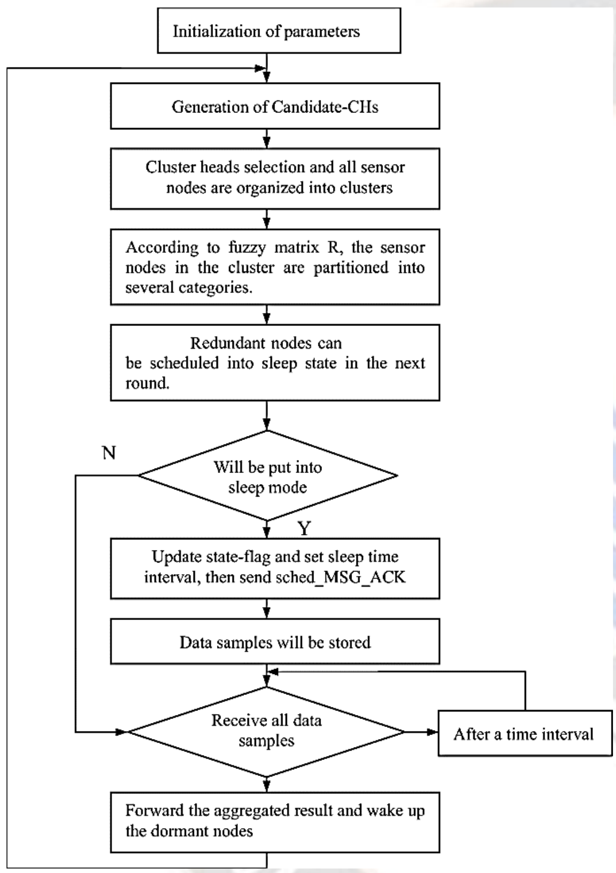

Figure 1. Flow of a typical sleep scheduling energy aware routing model

This text suggests development of a Sleep Scheduling based Fan Shaped Clustering Model to increase the Energy Efficiency of WSN in order to get around these restrictions. The proposed model uses a "Grey Wolf Optimization" (GWO) Method for temporal performance analysis-based dynamic sleep scheduling. This article concludes with a number of observations that encourage reflection on the examined suggested model as well as a number of recommendations for methods to improve their real-time performance. The article's concluding part contains these insights and recommendations. These conclusions and suggestions, which may be used in many contexts, are given out for the readers in the paper's conclusion for different use cases.

II. LITERATURE REVIEW

Researcher proposed a variety of models for improving routing performance via clustering & sleep scheduling processes. For instance, work in [5, 6] propose use of "Trust-Aware and Energy-Aware Clustering Method with Stochastic Fractal Search" (TECMS), and "Wireless Energy Balancer" (WEB), which assists in improving clustering performance via energy optimizations. But these models are highly complex, which limits their applicability for large-scale networks. To overcome this issue, work in [7] proposes use of "Low-Energy Dynamic Clustering" (LEDC) which assists in improving clustering performance via dynamically grouping nodes based on destination node locations. Similar models are discussed in [8, 9, 10], which propose use of "Voronoi Adaptive Clustering" (VAC), Fuzzy Inferences, and "Chaotic Lion Swarm Optimization" (CLSO), that integrate bioinspired computing with low complexity routing processes. Extensions to these models are discussed in [11, 12, 13], which propose use of Hierarchical Clustering, Uneven Clustering, and sensor node's training for intellectual data transmission by using of clustering and reinforcement learning (SARSA), which aim at reducing complexity while maintaining higher QoS for multiple scale networks.

Models that propose use of "distance- and energy-constrained k-means clustering scheme" (DEKCS) [14], "Bayesian Clustering with Collaborative Online Edge Caching" [15], "Coyote Optimization with Fuzzy Logic" (COFL) [16], Improved Soft-k-Means [17], and "Unequally Clustered Multiple Hop Routing via Fuzzy Logic" (UCM RFL) [18] are discussed, which assist in integration of multiple routing metrics for optimization of cluster formation performance under large-scale networks. Similar models are discussed in [19, 20], which propose use of Geometric Analysis, and Nearest Neighbour Distance Distributions for enhancing routing under multiparametric optimization scenarios. But these models are highly complex, which limits their applicability to small & medium scale networks. To overcome this limitation, work in [21, 22, 23] proposes use of "Enhanced Clustering Hierarchy Approach" (ECHA), novel "ranked-based clustering" (NRC), and Multiple Machine Learning techniques for integrating low complexity and high QoS levels during the routing & cluster formation processes. Work done in [24, 25, 26] also proposes such models via use of "Coverage-Guaranteed Unequal-Sized Clustering", "Energy Aware Adaptive Kernel Density Estimation", and Fuzzy Clustering, each of which aim at minimizing network errors during large-scale communications. Extensions to these models are discussed in [27, 28, 29, 30] wherein use of "Exposure-Path Prevention, second-fold clustering" (SFC), "Energy-Efficient Mobility-Based Cluster Head Selection", and "Particle Swarm Optimization with

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Fuzzy" (PSOF), which aim at reducing node density under large scale networks. The importance of clustering decision making has been reported by many researchers in varied fields. Some of them being E-LEACH protocol for energy efficient in wireless sensor network model [31]. A model of "Bioinspired Routing Model with Fan Clustering" for WSN (BRMFC) [32] model performs destination-aware Fan Shaped Clustering (FSC) and groups nodes based on their distance measures. Another Model propose "Energy Efficient Backup Node Assisted Routing" (E2BNR) [33] finds the best backup node by analyzing the statistical relationship between energy harvesting & consumption rates. Similar models that use Interval "Type-2 TSK Fuzzy Logic Theory" [34] are discussed, but these models use static clustering and sleep scheduling operations, which restricts their applicability and scalability levels. The high complexity of dynamic clustering & scheduling models also hinders temporal QoS performance for real-time use cases. To overcome this limitation, next section proposes design of a novel Sleep Scheduling based Fan Shaped Clustering Model to improve Energy Efficiency of WSN. The proposed model is evaluated for validating its real time performance under different use case in terms of different network parameters.

III. DESIGN OF THE PROPOSED SLEEP SCHEDULING BASED FAN SHAPED CLUSTERING MODEL TO IMPROVE ENERGY EFFICIENCY OF WSN

According to the literature review, majority of the current models use static clustering and sleep scheduling operations, which restricts their applicability and scalability levels. The high complexity of dynamic clustering & scheduling models also hinders temporal QoS performance for real-time use cases. This section discusses design of a Sleep Scheduling based Fan Shaped Clustering Model to increase the Energy Efficiency of WSN in order to get around these restrictions. The proposed model is visualized in figure 2, where it can be observed that the model uses a "Grey Wolf Optimization" (GWO) Method for temporal performance analysis-based dynamic sleep scheduling optimizations.

Temporal usage levels, Temporal "Quality of Service" (QoS), and Temporal Energy Levels are combined to model a fitness function in the GWO Method. Based on this modelling process, nodes were divided into wake and sleep nodes. These nodes were then clustered using "destination-aware Fan Shaped Clustering" (FSC), which helped to improve QoS performance in a variety of scenarios. In order to select routing paths that can achieve low delay, high throughput, and high packet delivery with higher energy efficiency levels, the FSC Model was combined with a QoS-aware routing model.

The model initially deploys a GWO based sleep scheduling process, which assists in estimation of wakeup and sleep cycles for different node types. The GWO Model works via the following process,

- To start the optimization process, setup following GWO Parameters, while marking all Wolves as 'Delta',
  - Total optimization Wolves = N_w
  - Total optimization iterations = N_i
  - Rate at which Wolves will learn cognitively from each other = L_r
  - Number of communications for which temporal datasets are available for analysis = N_c

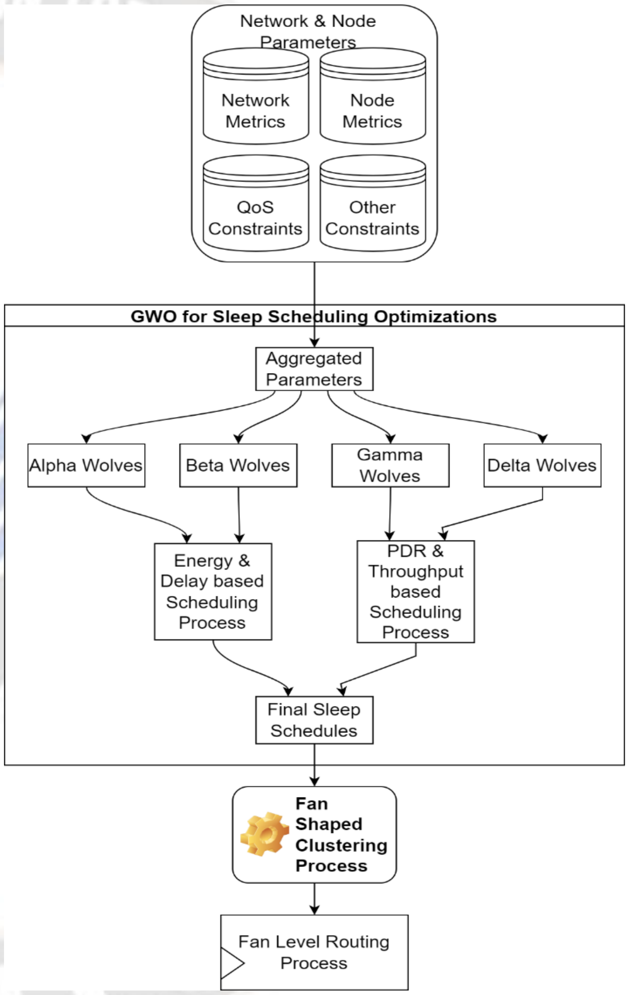

Figure 2. Overall flow of the Sleep Scheduling based Fan Shaped Clustering Model for efficient routing operations.

- Iterate through all the N_i iterations, and modify all 'Delta' Wolves via following process,
  - Modify sleep cycle (SC) for all nodes via equation 1,

$$SC = STOCH(SC_F * L_r, L_r) \dots (1)$$

Where, SC_F represents Sleep Cycle Factor for each node, and it evaluated via equation 2,

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$$SC_F = \sum_{i=1}^{N_c} \frac{THR_i}{Max(THR)} + \frac{PDR_i}{Max(PDR)} \dots (2)$$

Where, THR represents temporal throughput, and PDR represents temporal packet delivery ratio during temporal communications.

- Based on this sleep cycle, initiate N_c dummy communications via a simulation, and estimate Wolf fitness via equation 3,
- $f = \sum_{i=1}^{N_c} \frac{THR_i}{Max(THR)} + \frac{PDR_i}{Max(PDR)} + \frac{Max(EC)}{EC_i} + \frac{Max(D)}{D_i} \dots (3)$

Where, THR represents temporal throughput, PDR represents temporal packet delivery ratio, EC represents energy consumption, and D represents delay needed during temporal communications.

- Evaluate such fitness levels for all 'Delta' Wolves, and at the end of each iteration calculate fitness threshold via equation 4,

$$f_{th} = \sum_{i=1}^{N_w} \frac{f_i * L_r}{N_w} \dots (4)$$

- Once an iteration is completed, then reconfigure Wolf status as follows,
  - "Mark Wolf "as 'Alpha', if $f > 2 * f_{th}$
  - "Mark Wolf" as 'Beta', if $f > f_{th}$
  - "Mark Wolf" as 'Gamma', if $f > L_r * f_{th}$
  - Else, "Mark Wolf" as 'Delta'

Repeat these steps for all iterations, and select highest fitness Alpha Wolf, which provides sleep cycles for all nodes. Use these sleep cycles to put nodes into 'Sleep' and 'Wake Up' modes, which will assist in conserving energy & improving network lifetime under real-time conditions. The 'Wake Up' nodes are clustered via Fan Shaped Clustering (FSC), which works via the following process,

- Identify source & destination nodes, and obtain their Cartesian locations
- Based on these locations and 1-hop distance, identify Fan Level for each 'Wake Up' node via equation 5,

$$FL_i = \frac{d(i, dest)}{d(hop)_i} \dots (5)$$

Where, FL represents node's Fan Level, while $d(i, dest)$ represents distance between current node & destination node, and $d(hop)$ represents one hop distance that can be covered by the node's communication antenna sets.

- Due to this, all 'Wake Up' nodes will be arranged into Fan Shaped Clusters which are represented in figure 3 as follows,

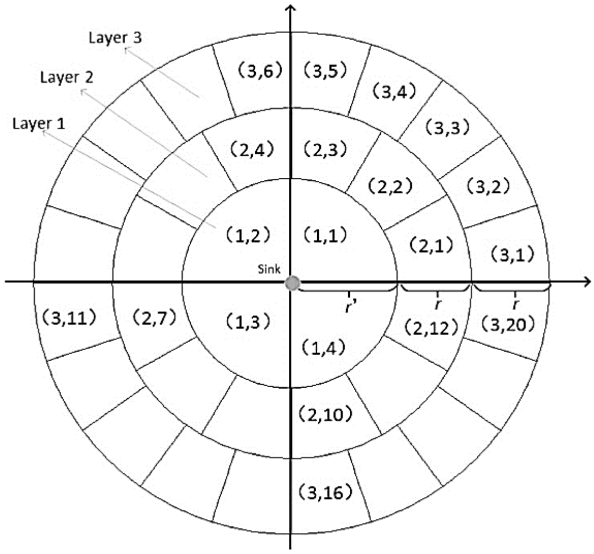

Figure 3. Fan Shaped Clusters for all 'Wake Up' nodes

- Starting from the Source FS Cluster, evaluate distance between source & each node in the interior cluster via equation 6,

$$d(src, i) = \sqrt{(x_{src} - x_i)^2 + (y_{src} - y_i)^2} \dots (6)$$

Where, x, y represents Cartesian coordinates of the nodes.

- Select the node i for routing only if,

$$d(i, src) < d_{ref},$$
$$d(i, dest) < d_{ref} \text{ and}$$
$$d(src, i) \leq d(hop) \dots (7)$$

Where, d_{ref} represents distance between source & destination nodes.

- For all selected nodes, evaluate a node score via equation 8,

$$NS = \frac{d(src, i)}{E(src) * PDR(src) * THR(src)} \dots (8)$$

Where, E represents residual energy levels of the nodes.

- Select node with minimum value of NS, and mark this node as new source node for further routing process
- This process is repeated till destination node is reached, and then routing is performed between selected node sets.

Due to inclusion of distance, energy levels, PDR and Throughput levels, the selected paths are able to maintain higher QoS levels than other path combinations. Performance of the model for different routing combinations can be observed from

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the next section of this text, where it is evaluated w.r.t. state-of-the-art methods under different scenarios.

IV. PERFORMANCE EVALUATION & COMPARISON

The proposed model is able to combine FSC and GWO based sleep scheduling operations, which enables for low levels of energy consumption as well as high levels of PDR, throughput, and communication speeds. In order to evaluate the performance of the proposed SSFSCE model, it was tested with Wireless Multiple Channels, Two Ray Ground propagation, with Wireless Physical Network, and the Mac 802.16 model, which uses Priority Queues and Omnidirectional antennas. All of these tests were carried out in conjunction with Wireless Physical Network. The model was validated on 100 to 1000 nodes, each of which was controlled by the AOMDV routing model. The network size was 500m by 500m, and 1000 bytes were sent in each packet at intervals of 0.0001 seconds. With the help of these common wireless network characteristics, we can look at QoS parameters. Latency, average

“Packet Delivery Ratio” (PDR), “Average Throughput per communication”, and Energy required for communication during each individual transmission are included in these metrics. Results from an examination of the efficacy of the model with 2000 node-to-node communications, which were evaluated to calculate the performance of different routing & clustering models under similar scenarios. Models proposed in VAC [8], USM RFL [18], and PSOF [30] were evaluated for this purpose, and their QoS parameters were averaged for 200 to 2000 communications under 1000 nodes. Based on this strategy, the communication delay for different Number of Communications (NC) can be observed from table 1,

NC	**Delay (ms) VAC [8]**	**Delay (ms) USM RFL [18]**	**Delay (ms) PSOF [30]**	**Delay (ms) SSF SCE**
200	0.91	0.89	0.88	0.75
250	1.12	1.09	1.08	0.92
300	1.4	1.37	1.35	1.15
350	1.75	1.71	1.69	1.44
400	2.07	2.02	2	1.71
450	2.4	2.35	2.32	1.98
500	2.73	2.67	2.64	2.25
550	3.03	2.96	2.93	2.5
600	3.29	3.22	3.18	2.72
650	3.51	3.44	3.4	2.9
700	3.79	3.71	3.67	3.13
800	4.08	3.99	3.94	3.36
900	4.36	4.26	4.21	3.6
1000	4.64	4.54	4.49	3.83
1200	4.92	4.82	4.76	4.06
1400	5.21	5.09	5.03	4.3
1600	5.49	5.37	5.31	4.53
1800	5.77	5.64	5.58	4.76
2000	6.05	5.92	5.85	5

Table 1. End-to-end delay for different communications

Based on this evaluation, and figure 4, it can be observed that the proposed model showcased 12.5% faster performance when compared with VAC [8], 10.5% faster performance when compared with USM RFL [18], and 8.3% faster performance when compared with PSOF [30], which makes it highly useful for delay-aware network scenarios.

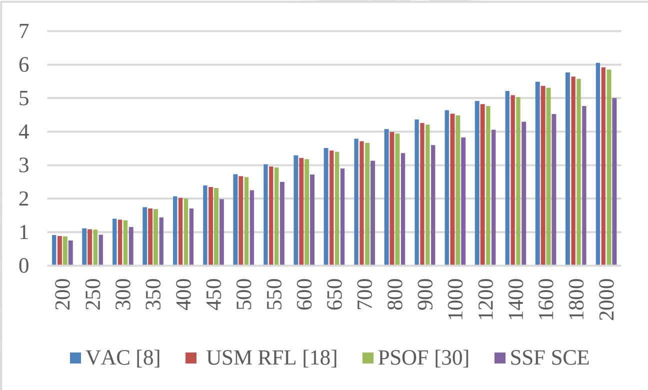

Figure 4. Communication delay for different nodes

The reason for this improvement it use of distance metrics during sleep scheduling & routing processes, which assists in optimizing its real-time network QoS performance levels. Similar to this, the energy consumption can be observed from table 2 as follows,

NC	**Energy (mJ) VAC [8]**	**Energy (mJ) USM RFL [18]**	**Energy (mJ) PSOF [30]**	**Energy (mJ) SSF SCE**
200	10.27	12.24	9.01	6.35
250	12.21	14.59	10.72	7.57
300	14.46	17.30	12.71	8.98
350	16.83	20.16	14.80	10.47
400	19.28	23.10	16.95	12.00
450	21.70	26.01	19.08	13.51
500	23.89	28.67	21.02	14.89
550	26.01	31.23	22.90	16.23
600	28.03	33.68	24.69	17.50
650	30.12	36.21	26.53	18.81
700	32.30	38.83	28.45	20.18
800	34.47	41.46	30.37	21.54

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900	36.65	44.09	32.29	22.91
1000	38.82	46.71	34.21	24.27
1200	40.99	49.34	36.13	25.64
1400	43.17	51.96	38.05	27.00
1600	45.34	54.59	39.97	28.37
1800	47.52	57.22	41.89	29.73
2000	49.69	59.84	43.81	31.10

Table 2. Communication energy needed for different nodes

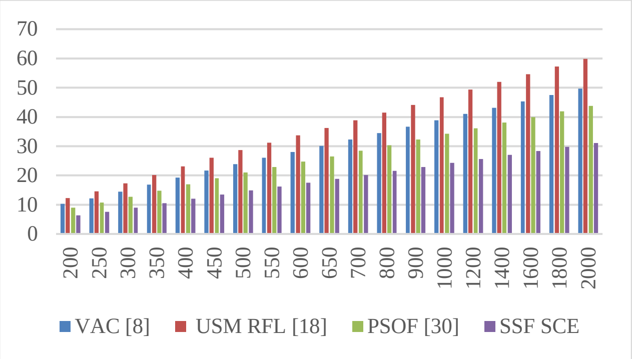

Figure 5. Energy consumed during different communications

Based on this evaluation, and figure 5, it can be observed that the proposed model showcased 28.5% lower energy consumption when compared with VAC [8], 39.4% lower energy consumption when compared with USM RFL [18], and 18.3% lower energy consumption when compared with PSOF [30], which makes it highly useful for low-power network scenarios. The reason for this improvement it use of residual energy levels, and temporal energy consumption metrics during sleep scheduling & routing processes, which assists in optimizing its real-time network QoS performance levels. Similar to this, the throughput performance can be observed from table 3 as follows,

NC	Thr. (kbps) VAC [8]	Thr. (kbps) USM RFL [18]	Thr. (kbps) PSOF [30]	Thr. (kbps) SSF SCE
200	568.7	520.5	726.1	838.8
250	673.5	619.4	862.0	997.4
300	796.7	734.2	1020.6	1181.9
350	926.4	855.3	1187.8	1376.4
400	1059.7	979.0	1359.1	1575.2
450	1191.6	1102.0	1529.1	1772.9
500	1310.5	1213.7	1682.8	1952.1
550	1425.9	1321.8	1831.8	2125.6
600	1536.0	1425.1	1974.1	2291.5
650	1650.0	1531.8	2121.2	2462.7
700	1768.4	1642.6	2274.0	2640.6
800	1886.8	1753.3	2426.8	2818.5
900	2005.2	1864.1	2579.6	2996.4
1000	2123.6	1974.9	2732.4	3174.3
1200	2242.0	2085.7	2885.2	3352.1
1400	2360.5	2196.5	3037.9	3530.0
1600	2478.9	2307.3	3190.7	3707.9
1800	2597.3	2418.0	3343.5	3885.8
2000	2715.7	2528.8	3496.3	4063.7

Table 3. Communication throughput achieved during different communications

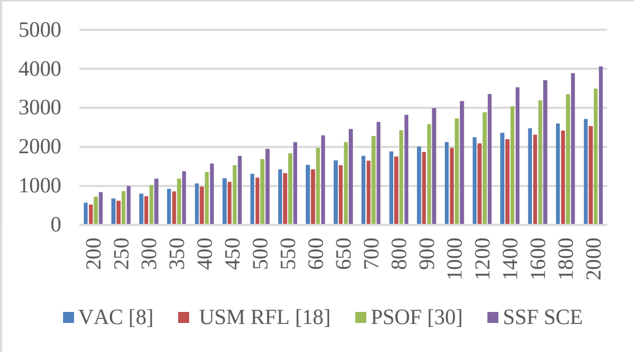

Figure 6. Communication throughput achieved during different communications.

Based on this analysis as shown in figure 6, it will be suggested that the proposed model showcased 16.5% higher throughput when compared with VAC [8], 19.3% higher throughput when compared with USM RFL [18], and 5.9% higher throughput when compared with PSOF [30], which makes it highly useful for high-efficiency network scenarios. The reason for this improvement it use of temporal throughput metrics during sleep scheduling & routing processes, which assists in optimizing its real-time network QoS performance levels. Similar to this, the PDR performance will be summarized in table 3 as follows,

NC	PDR (%) VAC [8]	PDR (%) USM RFL [18]	PDR (%) PSOF [30]	PDR (%) SSF SCE
200	89.2	89.4	91.4	92.2
250	89.3	89.6	91.5	92.4
300	89.3	89.7	91.6	92.5
350	89.4	89.8	91.8	92.7
400	89.5	90.0	91.9	92.9
450	89.5	90.1	92.0	93.1
500	89.6	90.2	92.2	93.2
550	89.7	90.4	92.3	93.4
600	89.8	90.5	92.4	93.5
650	89.8	90.7	92.5	93.7
700	89.9	90.8	92.7	93.9
800	90.0	90.9	92.8	94.0
900	90.1	91.1	92.9	94.2
1000	90.1	91.2	93.0	94.4
1200	90.2	91.3	93.2	94.5
1400	90.3	91.5	93.3	94.7
1600	90.4	91.6	93.4	94.9
1800	90.4	91.7	93.6	95.0
2000	90.5	91.9	93.7	95.2

Table 4. Communication PDR achieved during different communications

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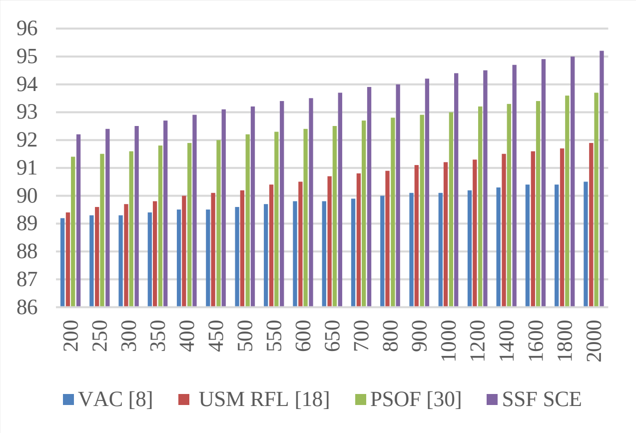

Figure 7. Communication PDR achieved during different communications

As shown in figure 7, we can evaluate and observed that the proposed model have 5.5% higher PDR when compared with VAC [8], 4.9% higher PDR when compared with USM RFL [18], and 1.8% higher PDR when compared with PSOF [30], which makes it highly useful for low error communication network scenarios. The reason for this improvement it use of temporal PDR metrics during sleep scheduling & routing processes, which assists in optimizing its real-time network QoS performance levels. Due to these optimizations, the proposed model is capable for deployment of a wide variety of real-time network scenarios. The suggested model is capable for deployment of networks that require QoS awareness, thus making it highly useful for low-delay, high throughput, low energy and high PDR use cases.

V. CONCLUSION

In this text a highly efficient routing & clustering model that combines sleep scheduling with fan shaped clustering is discussed & tested for different network scenarios. The proposed model initially performs sleep scheduling via introduction of Grey Wolf Optimization (GWO) that calculates sleep cycles for individual nodes based on their temporal performance levels. These sleep cycles are augmented by the FSC based clustering process, which assists in formation of destination-aware clusters. These clusters are analyzed for identification of low energy, low delay, high throughout and high PDR routes. Because of this, the proposed model is able to perform 12.5% faster compared to VAC [8], 10.5% faster compared to USM RFL [18], and 8.3% faster compared to PSOF [30], making it extremely useful in delay-aware network scenarios. The use of distance metrics during sleep scheduling and routing procedures, which helps to optimize its real-time network QoS performance levels, is the cause of this improvement. Additionally, it can demonstrate energy consumption reductions of 28.5%, 39.4%, and 18.3% when compared to VAC [8], USM RFL [18], and PSOF [30], respectively. This makes it an excellent choice for low-power network scenarios. The use of residual energy levels, as well as temporal energy consumption metrics during sleep scheduling and routing processes, contributes to this improvement by helping to optimize the real-time network QoS performance levels. While it was able to achieve throughput increases of 16.5%, 19.3%, and 5.9% when compared to VAC [8], USM RFL [18], and PSOF [30], respectively, making it extremely useful in high-efficiency network scenarios. The use of temporal throughput metrics during sleep scheduling and routing processes, which helps to optimize its real-time network QoS performance levels, is the cause of this improvement. Additionally, compared to VAC [8], USM RFL [18], and PSOF [30] it was able to achieve PDR improvements of 5.5%, 4.9%, and 1.8%, respectively, making it very useful in low error communication network scenarios. The use of temporal PDR metrics during sleep scheduling and routing processes, which helps to optimize its real-time network QoS performance levels, is the cause of this improvement. These improvements enable the proposed model to be deployed in a wide range of real-time network scenarios. The proposed model can be implemented for networks that need to be aware of QoS, which makes it very beneficial for use cases involving low latency, high throughput, low energy, and high PDR levels.

VI. FUTURE SCOPE

In future, researchers can integrate low power protocols that fuse different bioinspired models for further optimizing power consumption levels. Use of Genetic Algorithm, Bee Colony Optimization, Firefly Optimization, etc. can be done, along with their fusion in order to optimize model performance under multiple use cases. Moreover, researchers can also integrate deep learning models for pre-emption of node communications, thereby improving its long-term performance under real-time communication scenarios.

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