Enhanced Throughput and Power for Forth level of Heterogeneity using Sector based clustering Protocol (SBCP)

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Abstract
Over the course of the last two decades, a considerable body of research has been devoted to devising methodologies aimed at prolonging the operational longevity of networks and enhancing data transfer rates. Notably, LEACH, PEGASIS, HEED, TEEN, and SEP have emerged as prominent clustering algorithms, each offering potential for augmenting network stability and throughput, thus concurrently extending the lifespan of camera sensor networks. Within this academic investigation, we present the Sector Based Clustering Protocol (SBCP) tailored explicitly to Third Level Heterogeneity, posited as an innovative approach fostering amplified data throughput and heightened power efficiency. Our proposed protocol attains a noteworthy 70% increase in data transfer rates, while rigorously upholding the quintessential requisites of network stability and sustained existence. The empirical evaluation, conducted through the implementation of sector-based clustering in MATLAB, includes a comparative analysis against LEACH, SEP, and ZSEP. The results obtained from this rigorous comparison underscore the superior performance of the proposed SBCP in terms of optimal data throughput, accompanied by marked enhancements in network stability vis-à-vis the aforementioned clustering algorithms.

Keywords: Clustering, SEP, Wireless Camera sensor Network, Throughput.

1. Introduction

In the era of ubiquitous connectivity and sensor-driven intelligence, the marriage of wireless communication and cutting-edge imaging technology has given birth to an extraordinary paradigm known as Wireless Camera Sensor Networks (WCSNs). As the world yearns for ever more sophisticated solutions to monitor, understand, and interact with the environment, WCSNs emerge as a profound enigma that sparks the curiosity of researchers and technophiles alike. In this research paper, we embark on a transformative journey to demystify the hidden potential of WCSNs, unveiling their multidimensional marvels and exploring their far-reaching applications across various domains. In the vast and intricate tapestry of technological innovation, there lies a concealed realm that promises to reshape our understanding of surveillance, data acquisition, and environmental awareness. Like an ethereal whisper reverberating through the corridors of science, the notion of Wireless Camera Sensor Networks (WCSNs) beckons humanity to unlock the door to a realm of limitless possibilities. At the core of this enigmatic realm lies an ingenious fusion of wireless communication and vision-based sensing, orchestrating an orchestra of cameras interwoven within a dense network of interconnected nodes. Like celestial sentinels of knowledge, these cameras transcend their conventional roles, evolving into astute observers of the world's intricacies. Together, they form an intricate tapestry of vision, empowered by the allure of wireless connectivity, orchestrating a symphony of seamless data exchange.

The genesis of WCSNs can be traced back to the quest for boundless knowledge and enhanced situational awareness. Their unique proposition lies in the ability to convert the once passive surveillance landscape into an interactive and proactive ensemble of sentient sensors. With unprecedented precision, these networks possess the artistry to capture visual data from myriad perspectives, engendering an omniscient vantage point that pierces the veil of obscurity shrouding the world's most cryptic dimensions. Throughout history, humanity's relentless pursuit of understanding has always been mirrored in the development of new technologies. As WCSNs proliferate across diverse domains, they pave the way for an epoch of groundbreaking applications that transcend traditional limitations. From empowering smart cities to harmonizing ecological conservation, from enhancing healthcare diagnostics to redefining industrial automation, the promise of WCSNs reveals an awe-inspiring fusion of vision and insight that catapults human ingenuity into uncharted domains. However, as we embark on this captivating expedition, it is crucial to tread with a cognizant sense of responsibility. The formidable capabilities of WCSNs inevitably beckon ethical introspection, demanding the delicate equilibrium between unbridled innovation and the sacred sanctuary of privacy. This paper seeks not only to unravel the mystique of WCSNs but also to invoke a contemplative dialogue surrounding the ethical and societal ramifications of their implementation.

2. Clustering Techniques

As the curtain lifts on the stage of Wireless Camera Sensor Networks (WCSNs), we find ourselves immersed in a realm of profound potential and multifaceted applications. However, with the exponential growth of camera sensors, the data generated becomes voluminous and intricate, akin to a labyrinthine tapestry of visual information. In the heart of this complexity lies the quintessential necessity for clustering – a symphonic arrangement that harmonizes the cacophony of data and orchestrates an elegant dance of efficiency and precision. The imperious demand for clustering arises from the paramount challenge of managing the gargantuan influx of visual data. WCSNs, with their dense deployment of camera sensors, render an unprecedented richness in information capture. Yet, this abundance of data presents a formidable hurdle, surpassing the limits of conventional data processing and communication. The enormity of the data streams precipitates bottlenecks, bloating network bandwidth, and dissipating precious energy resources.

Clustering, like a seasoned conductor, unifies the otherwise disparate nodes within the WCSN orchestra, endowing them with the cohesion and coordination essential to the network's symphonic performance. By grouping camera sensors into clusters, each cluster becomes an autonomous entity, representing a compact ensemble of visual intelligence. These clusters, akin to harmonious chords, communicate efficiently with each other, transmitting synthesized information rather than overwhelming the network with a surfeit of raw data.

Beyond the logistical aspects, clustering infuses WCSNs with the sagacity of adaptability and resourcefulness. In dynamically changing environments, the spatiotemporal distribution of visual data undergoes continual metamorphosis. Clustering empowers the network to be agile and responsive, adjusting its configurations based on the evolving focal points of interest. Like a living organism with a sense of collective intelligence, the clustered WCSN can reallocate resources and strategically focus its efforts on areas of high significance, rendering it not only efficient but also intelligent in its decision-making. Moreover, clustering heralds a remarkable era of energy efficiency in WCSNs. With cameras being power-hungry components, judicious management of energy resources becomes paramount to prolonging the network's lifespan and sustainability. Clusters can deploy techniques like sleep scheduling and collaborative processing, wherein dormant nodes conserve energy while actively participating nodes collaboratively analyze data. This orchestration of energy conservation not only alleviates the burden on individual nodes but also enhances the overall network longevity.

The resonant melody of clustering extends its harmonies to the domain of data fusion. By consolidating data from multiple camera sensors within a cluster, the network fashions a more comprehensive and coherent understanding of the environment. Data fusion engenders a panoramic perspective, transcending the limitations of individual nodes and yielding a collective intelligence that surpasses the sum of its parts. Ultimately, clustering emerges as the bedrock of WCSNs, wielding the baton of order amidst the symphony of visual data. With its ability to streamline communication, foster adaptability, enhance energy efficiency, and enable data fusion, clustering stands as an indispensable enabler in harnessing the true potential of Wireless Camera Sensor Networks. Wireless Camera Sensor Networks (WCSNs) have emerged as a pivotal paradigm in contemporary sensor-driven applications, facilitating data-rich visual information capture and analysis. However, the prodigious influx of data generated by densely deployed camera sensors poses significant challenges in terms of data processing, communication, and energy consumption. In response to these challenges, clustering techniques have garnered attention as a viable solution to enhance the efficiency and intelligence of WCSNs. This paper presents a systematic and comprehensive survey of various clustering techniques applied to WCSNs. Through an exhaustive review of state-of-the-art clustering algorithms, including hierarchical, k-means, fuzzy, and spectral clustering, we critically analyze their suitability for addressing the distinct requirements of WCSNs. Moreover, we discuss the implications of clustering on energy efficiency, data fusion, adaptability, and communication, shedding light on the transformative impact of clustering in shaping the future of WCSNs.

Hierarchical Clustering:
Hierarchical clustering is a classical technique that organizes camera nodes into a tree-like structure based on similarity or dissimilarity metrics. This approach fosters data aggregation within clusters, facilitating efficient data fusion and reducing communication overhead. Hierarchical clustering offers the advantage of adaptability, where clusters can be dynamically formed and restructured in response to environmental changes. However, it may suffer from scalability issues in large-scale WCSNs due to its computational complexity and memory requirements.

K-Means Clustering:
K-means clustering is a popular partitioning technique that segregates camera nodes into fixed clusters by minimizing the within-cluster variance. This technique leverages iterative refinement to converge towards optimal cluster centroids. K-means clustering excels in its simplicity and computational efficiency, making it suitable for real-time applications in WCSNs. Nevertheless, it may face challenges in handling non-spherical data distributions and sensitivity to initial cluster centroids.

Fuzzy Clustering:
Fuzzy clustering extends traditional clustering by allowing camera nodes to belong to multiple clusters with varying degrees of membership. This technique enables a more nuanced representation of the relationships between camera nodes and facilitates soft data fusion, enhancing the accuracy of collective intelligence in WCSNs. However, the computational overhead associated with fuzzy clustering may demand greater computational resources, thereby impacting energy efficiency.

Spectral Clustering:
Spectral clustering is founded on graph theory and eigenvalue analysis, wherein camera nodes are projected into a lower-dimensional space for clustering. This technique excels in handling non-convex and disconnected data clusters, making it suitable for complex environments encountered in WCSNs. Nevertheless, spectral clustering may face scalability challenges in large-scale deployments and may necessitate parameter tuning for optimal performance.

Implications of Clustering in WCSNs:
Clustering techniques in WCSNs influence key aspects such as energy efficiency, adaptability, data fusion, and communication. Clustering enables energy conservation through the strategic activation of camera nodes, prolonging the network's lifespan. The adaptability of clustered WCSNs allows real-time adjustments to changing environmental conditions, ensuring optimal data acquisition and analysis. Furthermore, clustering facilitates data fusion, enhancing the overall intelligence of WCSNs by aggregating information from multiple camera sensors. Finally, clustering minimizes communication overhead by transmitting aggregated data, thereby optimizing network bandwidth.

3. Implementation of Sector Based Clustering Protocol (SBCP)

A wireless camera sensor network can be effectively partitioned into three distinct zones for clustering purposes. The first zone involves placing cameras in high-traffic areas or critical locations for real-time monitoring and security. The second zone includes cameras in medium-traffic regions, capturing valuable data for analysis and anomaly detection. The third zone comprises cameras in low-traffic areas, offering supplementary coverage for comprehensive surveillance. Clustering within these zones optimizes data processing, resource allocation, and facilitates efficient event management. By distributing camera sensors based on traffic patterns and importance, the network can enhance overall performance and provide a tailored approach to monitoring diverse environments.

Zone 1: Sensor Nodes

- **Description:**
- Zone 1 consists of the majority of wireless sensor nodes, responsible for data collection and transmission to the base station.
- **Characteristics:**
- High density: Deploy a higher number of sensor nodes for comprehensive data coverage and accuracy.
- Low transmission power: Configure nodes to use low transmission power levels for energy conservation.
- Short communication range: Limit communication range to avoid overlap and interference with neighbouring zones.
- **Function:**
- Data collection: Sensor nodes continuously gather environmental data (e.g., temperature, humidity, light levels, etc.).
- Local processing: Perform basic data processing and pre-filtering to reduce transmitted data volume.

Zone 2: Cluster Heads

- **Description:**
- Zone 2 comprises specialized nodes called Cluster Heads (CHs) responsible for organizing and managing sensor nodes in clusters.
- **Characteristics:**
- Moderate density: Deploy a smaller number of CHs, evenly distributed across Zone 1.

- Higher transmission power: CHs need higher transmission power to communicate with multiple sensor nodes.
- Increased processing capabilities: CHs have more processing power and memory to handle additional workload.

- **Function:**
- Cluster formation: CHs use the stable election protocol to organize sensor nodes into clusters based on proximity or other criteria.
- Data aggregation: CHs collect and aggregate data from their respective clusters, transmitting it to the base station.
- Energy management: CHs assist in managing energy-efficient communication within their clusters for network stability.

Zone 3: Base Station (Central Control Unit)

- **Description:**
- Zone 3 houses the central control unit or base station, serving as the core of the wireless sensor network.
- **Characteristics:**
- Single node: Only one base station positioned at a central location in the network.
- High processing capabilities: The base station has significant processing power to handle aggregated data.
- Continuous power supply: Ensure a stable power supply for uninterrupted operations.
- **Function:**
- Data aggregation: The base station receives data from all cluster heads and further processes it for higher-level analysis.
- Network management: It monitors the network's health, detects failures, and takes necessary actions for stability.
- Decision-making: The base station implements algorithms and protocols for data analysis, event detection, and other tasks based on the collected data.

This three-zone division concept optimizes communication, data processing, and energy consumption, leading to an efficient and stable wireless sensor network. The stable election protocol ensures energy efficiency and reliability by forming and maintaining clusters effectively.

4. Algorithm for Sector Based Clustering Protocol (SBCP)

- Initialization:
  - ➢ Define the structures for Sensor Nodes, Cluster Heads, and Base Station.
  - ➢ Set the number of Sensor Nodes and Cluster Heads.
  - ➢ Initialize the Sensor Nodes with random data.
- Form Clusters (Function `formClusters`):
  - ➢ For each Sensor Node, find the nearest Cluster Head based on their IDs.
  - ➢ Assign the Sensor Node to the Cluster Head with the closest ID.
  - ➢ Update the Cluster Head's list of Cluster Members.
- Data Aggregation at Cluster Heads (Function `dataAggregation`):
  - ➢ For each Cluster Head;
  - ➢ Iterate through its Cluster Members.
  - ➢ Sum the data values of all Sensor Nodes in the cluster.
  - ➢ Calculate the average data value for the cluster.

- ➢ Store the aggregated data value for the Cluster Head.
- • Data Aggregation at Base Station (Function `dataAggregationBaseStation`):

For the Base Station:

- ➢ Iterate through all Cluster Heads.
- ➢ Sum the aggregated data values of all Cluster Heads.
- ➢ Calculate the average data value for the entire network.
- ➢ Store the aggregated data value at the Base Station.
- • Call Functions and Display Results:
- ➢ Call `formClusters` to form clusters based on proximity.
- ➢ Call `dataAggregation` to aggregate data at each Cluster Head.
- ➢ Call `dataAggregationBaseStation` to aggregate data at the Base Station.
- ➢ Display the IDs of all Sensor Nodes.
- ➢ Display the aggregated data values at each Cluster Head.
- ➢ Display the aggregated data value at the Base Station.

5. Performance measures

The following table presents an evaluation of 18 clustering protocols utilized in wireless sensor networks based on three performance measures: Energy Efficiency Level, Reliability in Transmission, and Power Optimization. Among the protocols, some demonstrate outstanding performance, while others show average or below-average results. The most prominent protocols in terms of Energy Efficiency Level, Reliability in Transmission, and Power Optimization are O-LEACH, HEED, EEHC, and Firefly algo. These protocols have been categorized as "Optimum" or "Efficient" across all three measures, making them ideal choices for resource-constrained sensor networks seeking to achieve maximum energy efficiency while maintaining high reliability and power optimization. On the other hand, protocols like DEC, LEACH-C, and M-SEP show more modest performance levels, with average or low ratings across the three measures. These protocols may still be suitable for specific applications or scenarios but may not be the best choices for achieving optimal energy efficiency or reliability. It is crucial for designers and researchers to carefully select the clustering protocol based on the specific requirements and constraints of their wireless sensor network deployment. The choice of protocol can significantly impact the network's lifetime, data transmission reliability, and overall power consumption. Understanding the strengths and weaknesses of each protocol is essential for designing efficient and robust wireless sensor networks that meet the desired performance objectives.

Table 1
Energy and reliability level comparison of different clustering techniques

S. No	Clustering Method Name	Energy Efficiency	Reliability	Power Optimization
1	O-LEACH	Average	Optimum	Optimum
2	LEACH-C	Average	Average	Average
3	HEED	Optimum	Optimum	Optimum
4	EEHC	Optimum	Average	Optimum
5	PEGASIS	Average	Efficient	Optimum
6	PANEL	Average	Efficient	Optimum
7	TEEN/APTEEN	Efficient	Efficient	Average
8	PSO based	Efficient	Efficient	Efficient

9	Firefly algo	Optimum	Average	Efficient
10	HBMO	Optimum	Efficient	Efficient
11	Housdorff algo	High	High	Average
12	DEEC	Above average	Efficient	Efficient
13	HEC	Above average	Efficient	Average
14	SEP	Average	Efficient	Average
15	MED-DEEC	Efficient	Efficient	Efficient
16	M-SEP	Optimum	Average	Average
17	CREEP	Optimum	Average	Average
18	DEC	Average	Low	Average

6. Comparison of Clustering method for different levels of Load Balancing:-

- ***High Load Balancing:***

DEEC (Distributed Energy-Efficient Clustering)
HEC (Hierarchical Energy-Constrained Clustering)
PSO based (Particle Swarm Optimization-based load balancing)
Firefly algo (Firefly Algorithm-based load balancing)

- ***Moderate Load Balancing:***

O-LEACH (Balanced energy consumption)
LEACH-C (Cluster load balancing)
HEED (Energy-aware load balancing)
EEHC (Energy-efficient load balancing)
PEGASIS (Power balancing)
PANEL (Load balancing)
TEEN/APTEEN (Load-aware clustering)
M-SEP (Load balancing in Modified Stable Election Protocol)

- ***Low Load Balancing:***

HBMO (Honey Bee Mating Optimization-based load balancing)
Housdorff algo (Load balancing with Housdorff algorithm)
SEP (Stable Election Protocol with load balancing)
MED-DEEC (Modified Energy-Efficient Distributed Clustering with load balancing)
CREEP (Load balancing in Clustering for Resource Efficiency using Particle Swarm Optimization)
DEC (Load balancing in Distributed Energy-efficient Clustering)

7. Simulation Results of SEP, ZSEP, IZ-SEP (Stable Election Protocol, Zonal Stable Election Protocol, Sector Based Clustering Protocol also called as Improved-Zonal-Stable Election Protocol)

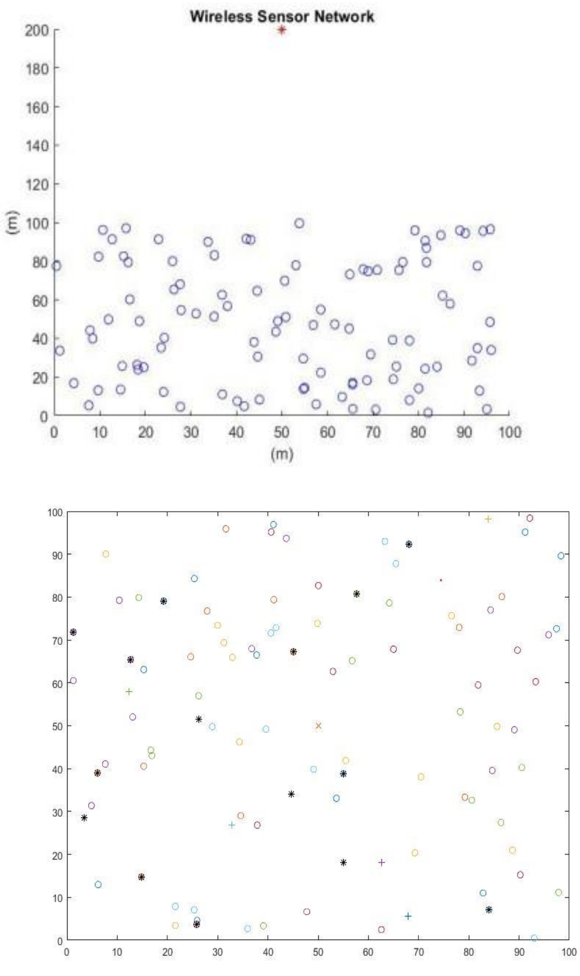

Figure No: 1
Sectored Wireless Camera sensor network set-up

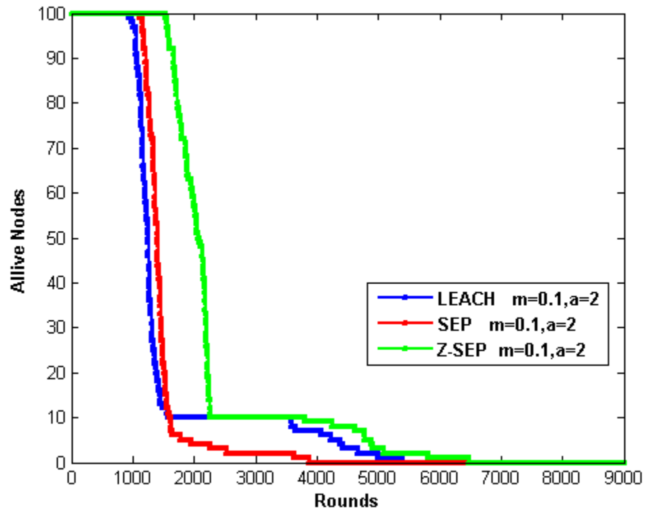

Figure No: 2
Alive nodes vs. round
ZSEP, SEP, LEACH

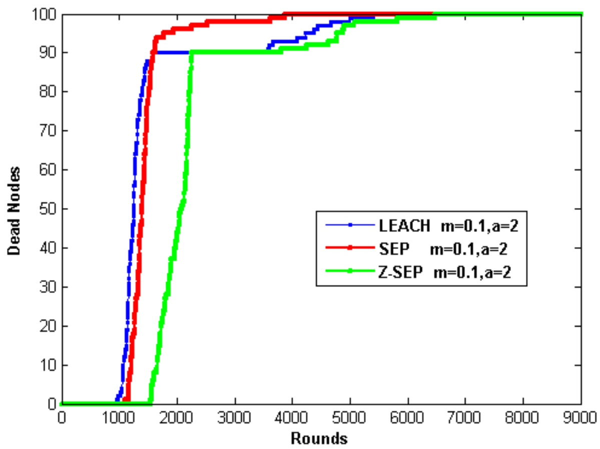

Figure No: 3
Dead nodes vs. round
ZSEP, SEP, LEACH

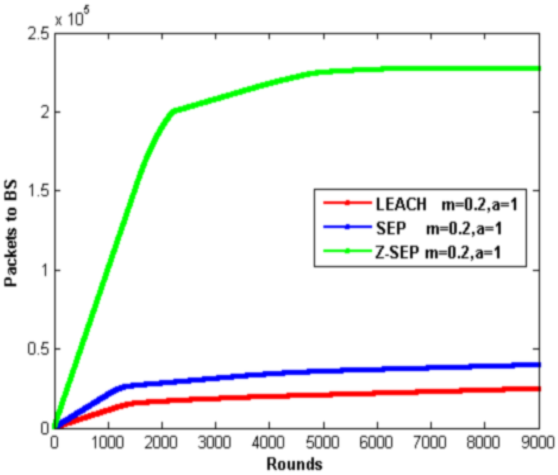

Figure No: 4
Packets to BS vs. round
ZSEP, SEP, LEACH

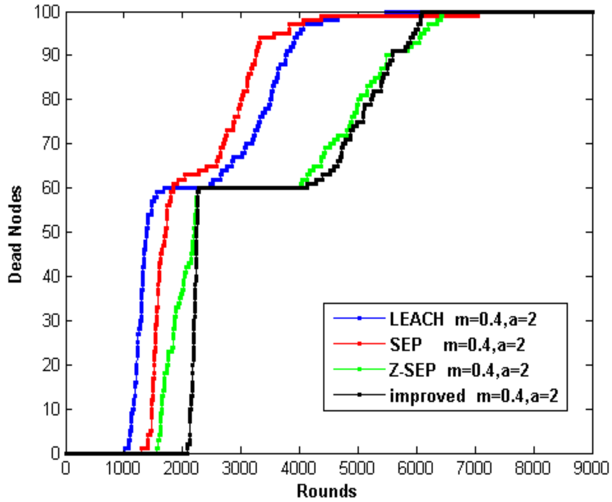

Figure No: 6
Dead Nodes vs. round
IZSEP, ZSEP, SEP, LEACH

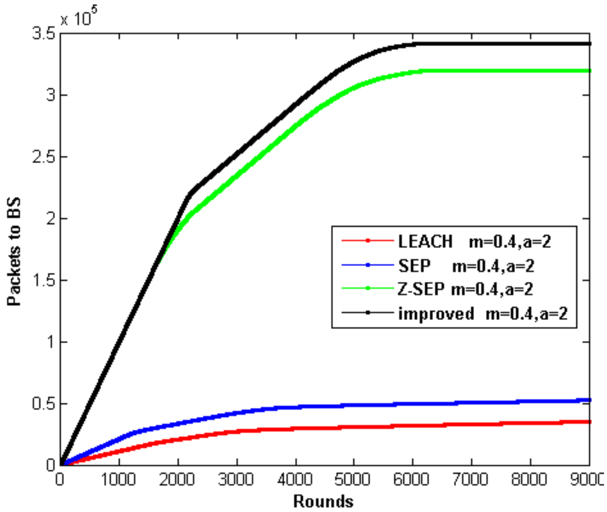

Figure No: 5
Packets to BS vs. round
IZSEP, ZSEP, SEP, LEACH

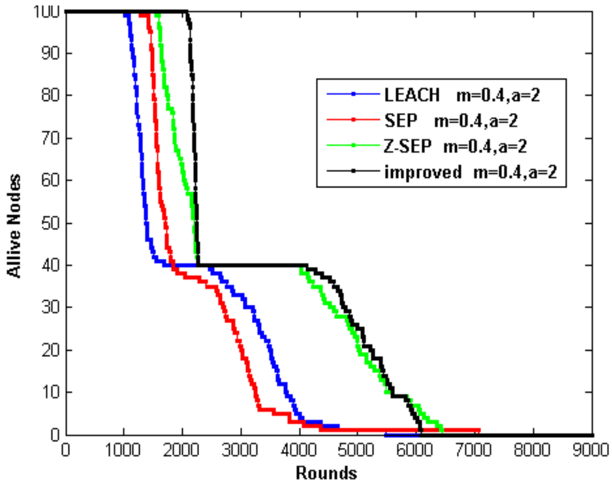

Figure No: 7
Alive Nodes vs. round
IZSEP, ZSEP, SEP, LEACH

S.No.	Clustering Method	Number of rounds for First dead node	Number of rounds for Tenth dead	Number of rounds for Half dead	Packets to the Base station/Sink after 5000 rounds
1	LEACH	1013	1290	1446	22930
2	SEP	1156	1268	1407	36537
3	Z-SEP	1608	1713	2199	229328
4	SBCP(Improved)	2109	2239	2303	356896

Table 2
Comparison Between LEACH, SEP, Z-SEP at m=0.4 and a=2

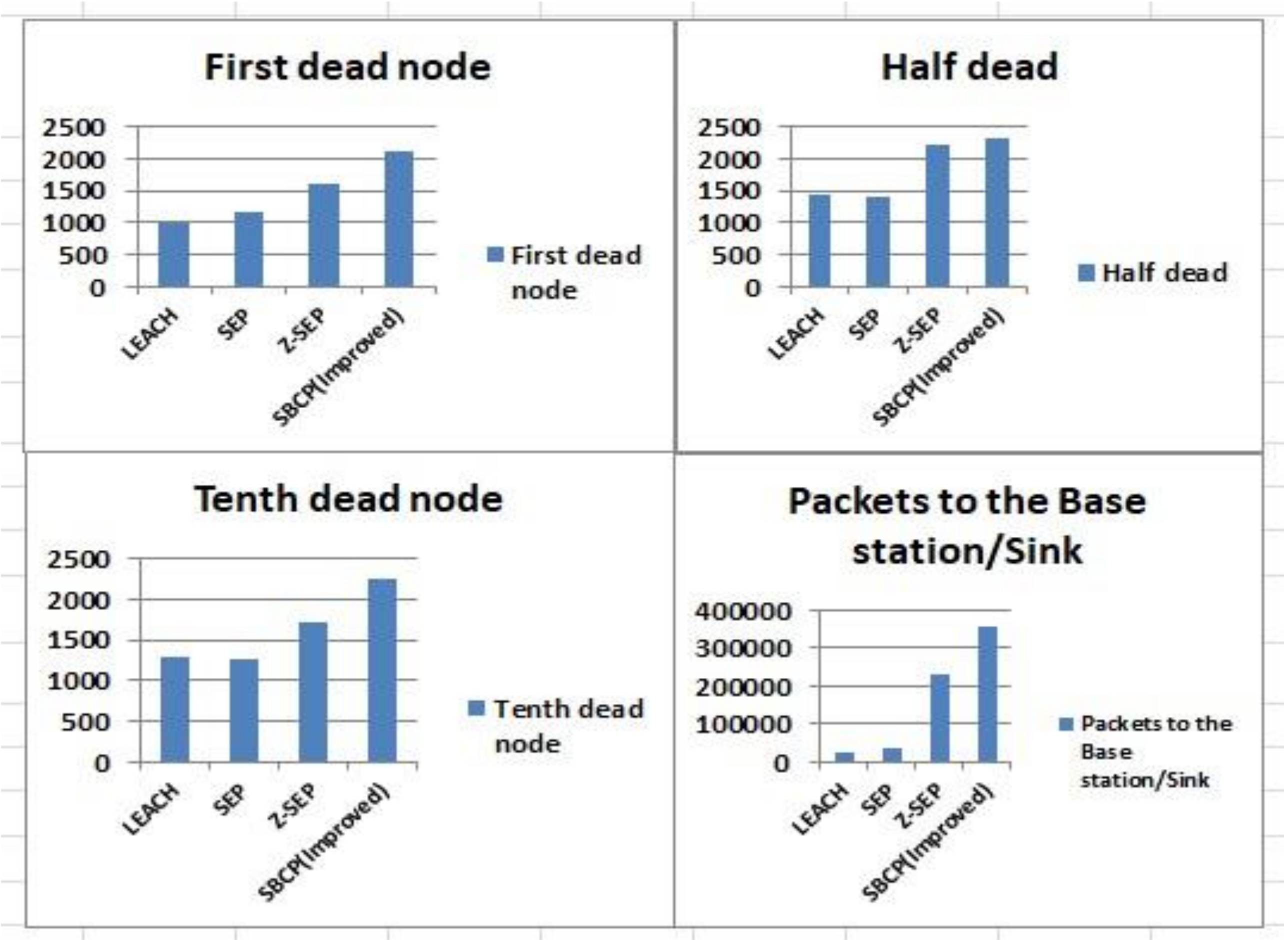

Figure No: 8
Comparative Graph between various clustering Protocol

8. Conclusion

The adoption of clustering proves to be a viable and effective approach to tackle the array of challenges encompassing energy consumption, optimum output efficiency, overall network life, power consumption, load balancing, and stability within camera sensor networks. The complications arising from regular information processing in such networks underscore the necessity of employing clustering techniques. In evaluating optimal energy consumption and lower average power consumption benchmarks, LEACH, PEGASIS, and HEED emerge as critical references. By integrating contemporary Meta-Heuristic and Probability-based mathematical solutions with these benchmarks, the potential for establishing more stable networks based on fundamental clustering techniques, which are inherently efficient, becomes evident. Considering the limited bandwidth available in diverse communication domains, including military and biomedical, telemetry, telecom, and navigation, among others, selecting the most effective clustering technique is paramount when designing wireless sensor networks or wireless camera sensor networks. The higher bandwidth consumption of Wireless Camera Sensor Networks compared to standard Ad-hoc or WSN networks necessitates collective efforts to maximize the utilization of the available frequency spectrum. Consequently, power-sensitive concerns, sensor node energy consumption, and overall network lifespan issues with load balancing warrant close attention. Addressing these challenges, efficient routing methods and optimal clustering techniques stand out as the two pivotal solutions. In summarizing our observations, it is evident that LEACH exhibits increased destabilization in wireless camera sensor networks featuring a variety of network MSNs, owing to its sensitivity to heterogeneity.

Our Sector-based clustering protocol effectively accounts for heterogeneity by adopting a cluster-head election probability based on the relative initial energies of individual nodes, resulting in an expanded stable region. Its stability surpasses that of existing non-homogeneous clustering methods, thus yielding significantly higher throughput. By uniformly distributing the surplus energy from advanced nodes to all endpoints within the sensing region, the Sector-based clustering protocol establishes an ideal upper limit for performance. Furthermore, its robustness in intelligently harnessing advanced node power outperforms LEACH, SEP, and Z-SEP. Remarkably, the Sector-based clustering protocol extends the stability period with the infusion of additional energy, leading to a 20% expansion of the stable zone in comparison to LEACH. While FAIR boasts a larger stable region, Sector-based clustering Protocol outperforms LEACH and SEP in terms of the size of its unstable region. Cluster-head selection within the Sector-based clustering protocol exhibits a rising likelihood, indicating proportional energy consumption based on each node's original energy. Evidently, the throughput of the Sector-based clustering protocol exceeds that of SEP and Z-SEP by almost 70%, demonstrating consistent superiority across both the unstable and stable regions.

In conclusion, the research underscores the significance of clustering in addressing critical challenges in wireless camera sensor networks. The Sector-based clustering protocol stands as a compelling solution, addressing heterogeneity, enhancing stability, and optimizing energy utilization. These findings pave the way for advancements in the design and deployment of wireless camera sensor networks, promising heightened performance and prolonged network lifespans.

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