Energy Optimization Of Dynamic Routing Protocol In Heterogeneous Wireless Sensor Network Using Energy Efficient Delay Sensitive Technique

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Abstract: - Improving the energy efficiency of Wireless Sensor Networks (WSNs) is crucial for sustainable operation. Therefore, this research explores new concepts of optimized dynamic routing protocols. In careful analysis and empirical comparisons, how could clustering techniques address the WSNs' heterogeneity peculiarities while accounting for energy preservation? This study suggests attractive directions to alleviate energy overheads and prolong the network lifetime, acknowledging the dynamic nature of WSNs. New adaptive techniques are proposed using a hierarchical architecture with the cloop and collective intelligence among sensor nodes. Follow us on Twitter for more updates! With the conventional approaches migrating to Enhanced Energy-Aware Dynamic Sensor routing, a significant enhancement can be observed in static network setups. EEDS outperforms existing schemes and guarantees high packet delivery ratios, low data loss rates, minor end-to-end delays, and greater network throughput. EEDS enables enhanced efficiency due to energy saving and network operations optimization. Upon dynamic network settings, EEDS is a constructive version, further emphasizing the efficiency of WSN operation and address. In this paper, we demonstrate new directions for robust and energy-efficient WSN infrastructure, laying a foundation to propel the operation of IoT applications across India and beyond.

Keywords: Wireless Sensor Networks (WSNs), Energy Optimization, Dynamic Routing Protocols, Clustering Technique

Introduction

As the WSN landscape constantly depreciates, the priority of researchers working on this technology domain remains to optimize every joule by achieving better network efficiency and lifetime as much as possible for seamless operation. This need is exacerbated in the case of heterogeneous WSNs because nodes with different characteristics and functionalities coexist. This paper explores the proposal of combining dynamic routing protocols and clustering in an orchestrated way to solve this energy optimization problem effectively, provided that we consider such environments diverse and highly volatile networking.

Explores the provincial resourcefulness in energy optimization for dynamic routing within heterogeneity WSNs employing clustering methodologies. We aim to traverse the maze in WSNs, exploring intricate interactions among dynamic routing schemes, energy efficiency findings, and cluster structure placement as our contribution. In this multi-pronged investigation, we aim to shed light on new routes by which energy starvation can be alleviated and network resilience enhanced while advancing relevant system-level performance benchmarks.

Our investigation is well-grounded in that it acknowledges that WSNs are inherently heterogeneous, with nodes ranging greatly in computational capabilities, communication modalities, and energy

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constraints. In this regard, the performances of dynamic routing protocols and clustering strategies need to be considered in terms of how well they meet their specific requirements when implemented into heterogeneous WSNs.

Our considered investigation is focused on clustering techniques, a known affordance for enabling localized communications and minimizing overhead while enhancing resource utilization in WSNs. By introducing logical groupings of sensor nodes, such clustering strategies move the processing focus away from an individual centralized collection point and onto a decentralized data management process that can result in significant energy saving and network scalability. This paper evaluates the performance and feasibility of dynamic routing protocols in heterogeneous WSN environments. Dynamic routing protocols are advantageous for saving energy, optimizing data transmission paths, and enhancing the reliability of networks by their characteristics to adapt themselves automatically to various network situations from topological dynamics or traffic patterns [2]. We wish to demystify the operation of these protocols within heterogeneous WSN environments by closely examining their actual performance under empirical evaluations and, eventually, theoretical analyses. Along with technical aspects, this study is aware of the real-world difficulties and implementation complexities surrounding energy optimization efforts in heterogeneous WSNs. Various elements must be carefully orchestrated, from network topology design intricacies to node heterogeneity management subtleties, to optimize the exploitation of energy-efficient routing in WSNs.By synthesizing insights extracted from existing work, empirical studies, and theoretical frameworks this study aims to provide a holistic overview of energy optimization in dynamic routing protocols within heterogeneous WSNs with clustering as the foundational technology. Our goal is to influence the further developments of WSN technology by exploring energy optimization strategies in detail and highlighting implications across different application domains, hence building up a sustainable, capable-of-resilient-efficient network infrastructure for the IoT era and beyond.

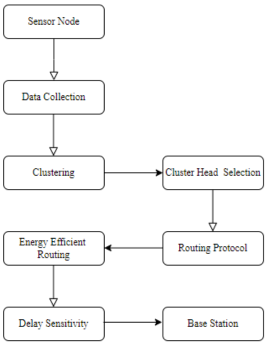

Figure 1. Flow of data from sensor nodes through various stages of processing

Node deployment has been characterized as a critical determinant of network lifetime and coverage in the high-detailed area of WSNs. In this paper, we dive deep into the labyrinth of WSN deployment methodologies and encapsulate their diversity in static and dynamic deployment paradigms.

Static: In static deployment, nodes essentially remain stationary for their lifetime. We must perturb many different things intentionally and carefully to get maximal coverage for workers with minimal energy consumption. Node positioning optimization becomes necessary given the context of application deterministic or random deployment strategies, respectively. In such cases, deterministic methodologies are excellent. Still, in the event of difficulties (e.g., environmental crises or rescue operations), a random deployment will be necessary where sensor nodes are randomly scattered, and further self-organization will be established.

Dynamic deployment, on the other hand, requires additional resources to optimally locate sensor nodes, i.e., with the help of IDs other than sensors, e.g., robots, especially in dangerous or inaccessible deployed areas. However, dynamic node deployment requires additional overhead than static. The narrative walks through the complexities of resource usage in WSNs, from node deployment to network topologies. It includes a new network topology based on the common WSN communication patterns, which modifies and re-equips traditional methods. Bus and tree topologies are compared with mesh or grid configurations, each offering unique benefits but also energy costs in scalability.

Clustering is a key strategy in energy-efficient WSN deployments since it allows for localized communication, self-organization, and resource optimization. We compare single-hop star, multi-hop mesh, and hierarchical structures as clustering schemes that can improve network efficiency and reliability. Implementing energy-efficient routing schemes is more important, but it is harder with changed configurations and deployment scenarios. This article studies design issues, problems, and types of routing protocols concerning network lifetime in general and energy saving. Then, to save energy and be more efficient in energy consumption, the first chapter, based on routing protocol design issues, introduces the first chapter, focusing on the Network layer and how it can help us achieve lower power usage. Different routing protocols, starting from LEACH to PEGASIS and TEEN, are critically analyzed to extend the network lifetime while consuming energy in a balanced manner. At the beginning of this journey into the WSN mazes, we highlight how crucial energy-efficient routing schemes are in alleviating resource limitations and extending network lifetime; these schemes also serve as a driver for pursuing further improvements on efficient use within what may come to the advancement of each sensor technology. This research tries to answer these questions using different empirical evaluations and theoretical analyses by shedding light on new ways of sustainable, resilient, and efficient WSN infrastructures.

I. Literature Survey

This is an extensive review of the seminal work in areas related to WSNs that provide a better understanding of routing protocols, mobility models, and energy-efficient mechanisms. Examples include a survey by Al-Karaki and Kamal (2004), which summarizes routing schemes, as well as Ren et al. (2011) presents an Energy-Balanced Routing Protocol (EBRP), which can achieve more efficient data gathering in many types of applications[18]. Mamalis (2014) suggests a Path-Constrained Mobile Sink to enhance network lifetime with limited sink mobility. Moreover, Nasr and Khan (2020) proposed a new Connectivity Enhancement Algorithm to solve the partitioning problems for collecting intermittent data. This work collectively helps improve and enhance WSNs, essential for deploying wireless sensor networks across various modern technology platforms.

Table 1. Literature work

Author(s)	Algorithm/Method	Outcome	Application
Cherappa(2023)	ASFO and a cross-layer-based expedient routing protocol	Energy-efficient clustering and routing	Wireless sensor networks
Feng, X., et al. (2023)	Vulnerability-aware task scheduling	Enhanced edge intelligence for trajectory analysis	Intelligent transportation systems
Lin, H., et al. (2023)	Adaptive multi-copy relaying	Improved delay tolerance	Vehicular networks
Nirmala Devi (2023)	Trust-aware optimized clustering	Reliable routing protocol	MANET
Soundararajan(2023)	Metaheuristic optimization	Node localization and multihop routing with mobile sink	Wireless sensor networks
Bangotra (2022)	Trust-based opportunistic routing	Secure intelligent routing	Wireless sensor networks
Kaidi (2022)	Dynamic levy flight chimp optimization	Optimization algorithm	Knowledge-Based Systems
Nagaraju(2022)	Energy optimization	Secure routing	IoT applications
Natesan (2022)	Hybrid mayfly-Aquila optimization	Energy-efficient clustering	Wireless sensor networks
Refaee (2022)	Fit-FCM	Trust and energy-aware cluster head selection	UAV-based wireless sensor networks
Renuga Devi(2022)	Trust-based energy routing protocol	Energy-efficient secure transmission	Wireless sensor networks
Wang (2022)	Artificial rabbits optimization	Engineering optimization	Various engineering problems
Nasr (2020)	Disconnected cluster connectivity	Time-critical data collection	Partitioned wireless sensor networks

Palak Keshwani (2020)	OPF-AOMDV protocol	Performance analysis	Wireless sensor networks
Alassery, F. (2019)	EERSM	Energy-efficient multi-hop routing	Wireless sensor networks
Holzwarth, F., et al. (2018)	Fault detection methodology	Fault detection	Wireless sensor networks
Sachan (2018)	Virtual-MIMO communication	Energy-efficient communication	Cluster-based cooperative wireless sensor networks
Rubel (2018)	Clustering approach	Priority management	Wireless sensor networks
Alnawafa (2018)	Multi-hop routing techniques	Energy efficiency	Wireless sensor networks
Divya Upadhyay (2018)	Maximum probability theory	Time synchronization	Wireless sensor networks

II. Methodology

The EEDS algorithm results from the fault diagnosis challenge in WSNs. Even though the continued evolution of faulty nodes complicates the issue managed due to energy drainage conditions, it takes an extended period to reform the routes, and more delays accumulate. Furthermore, the faulty nodes reduce the network potential and raise energy usage, thus decreasing the network life. The EEDS employs particle swarm optimization to find the best direction between the source and target nodes. Communication coordinative techniques employ the AOMDV protocol, which uses sound residual energy in node interception. The approach is validated based on the network energy drain and time spent during node faults, including algorithm flowcharts, fault diagnosis models, network energy, and the PSO description. Particle Swarm Optimization is a flock or fish group behavior related to human thinking. The PSO functions as a group of stochastic variables organized in established patterns. The PSO is derived from the thematic schematization of the rapid motion, outright orientation, and collapsibility of the bird’s iterations. Dr. Kennedy and Dr. Eberhart initiated the PSO in 1996, and it is used in function optimization, neural network teaching, radial-based neural networks, tuning fuzzy systems, and engineering layouts. The PSO particle is illustrated as a possible solution. These particles initiated with random positions have standing. The idea of the PSO comes from a group of birds that try to find a food source. Since these birds do not know where the food is situated, they compare their positions with each other. PSO iteratively adjusts these positions based on fitness evaluation. From these evaluation outcomes, these birds interchange their positions. Due to these evaluation movements, PSO strives to find the optimum solution.

3.1 Network Model

The nodes start to be distributed randomly in the sensor field as a homogeneous network with the same and poor initial energy. Some of these nodes show stationary and some dynamic behaviors as well. Nodes are not replaceable or can be recharged once deployed because of energy constraints. Node assignment is random, and data are sent to random receiver nodes. The experiments consist of static nodes with different data transmission rate levels and dynamic nodes with varying speeds. It randomly communicates with a constant bit rate and uses the UDP protocol. Although the amount of energy is almost the same at the initial stage, some nodes exhaust first as their role is that of communication routers.

3.2 Energy Model

The experimental setup adopts an efficient radio and energy dissipation channel, incorporating free space and multipath fading channels for effective energy utilization. Energy consumption for transmitting data over distances is computed using an Equation. The energy dissipation at the receiver for receiving data is measured accordingly.

$E_{TX}(M,D) = M.E_{elect} + M.\epsilon_{fs}.d^2 \quad \text{if } d \leq d_0$

$M.E_{elect} + M.\epsilon_{mp}.d^4 \text{ if } d > d_0$

The proposed algorithm considers soft faults in sensor nodes, distinguishing between hard and soft faults based on their communication capabilities and operational integrity. A sensor's fault probability is defined, reflecting discrepancies between readings and actual conditions.

$p = P(S = \neg x | A = x)$

3.3 Selection of Optimized Node

Particle Swarm Optimization (PSO) draws inspiration from collective animal behaviors, minimizing individual efforts while maximizing group efficiency. PSO iteratively refines particle positions based on personal and global best solutions. Each particle tracks its personal and global best positions to optimize its trajectory. The PSO algorithm initializes a swarm of random particles, iteratively refining their positions and velocities to converge toward an optimal solution. The inertia weight constantly adjusts to balance local and global exploration to maximize convergence. This study uses an adaptive PSO algorithm that dynamically modifies the inertia weight for each iteration to find the ideal number of cluster heads in sensor networks.

$P_i = [P_{i,1}, P_{i,2}, P_{i,3} \ldots\ldots\ldots.. P_{i,D}]$

$Vnew_{,i} = w * V_i + c_1 * r_1 * (Xpbest_i - X_{i,d}) + c_2 * r_2 * (Xgbest - X_i)$

$X_{new,d} = X_{old,d} + V_{new,d}.$

$W = w_{initial} -$ (Max. Iteration – Current Iteration) / Total number of Iterations

3.4 Designing the Fitness Function

How well the nodes are selected by their fitness function will determine how good algorithms outperform WSNs. The proposed function considers two crucial WSN features: energy spent on transferring data between sensor nodes and energy consumption due to the aggregation and transmission of sensor packets toward receiver nodes. We formulated the equations to represent energy consumption between sensor nodes in each zone by involving factors of every Node within a specific zone and its distance. Such a calculation is necessary to assess the energy dynamics of the network.

3.5 Energy Consumption between Sensor Nodes and Zones

Equations delineate the process for computing energy consumption between sensor nodes and zones. A function, F(Kj,Ck), evaluates this energy expenditure, considering parameters such as energy levels, distance, and threshold distances. The meticulous calculation accounts for the varying energy states within different zones, essential for optimizing node selection strategies.

Energy consumption between the sensor nodes and zones [F(Kj, Ck)] is given as:

In WSN, Emin and Emax are minimum energy decay, respectively.

For the kth zone, use Ck.

The function S outputs the minimum distance of the jth node in the kth zone, with one indicating that this is a node located at position j-th within the given field and zero otherwise. The threshold distance is marked as a d0 symbol

3.6 Energy Consumption between Zones and Base Station

Equations are provided to extend the energy computation framework for inter-zone and base station (BS) energy consumption. This difference is measured in terms of energy expenditure, which involves a function denoted as G(Ck, BS) that includes the distance between zones and the BS. The comprehensive review of energy use in the network ensured optimal transmission pathways were developed, taking a holistic perspective.

3.7 Total Energy Consumption (Fitness Function)

The Equation combines the output of computed energy expended from both services as the total consumed volume, which is used to derive the fitness function. E1 denotes the energy consumption on intermediate nodes composing the routing path, and E2 indicates the energy consumption between the sender/receiver pair. Sender-receiver distance affects energy consumption by setting μ a vital parameter to optimize transmission efficiency. An additional fitness function corresponding to f1 above produces an overall node selection scheme with a reduced learning curve for WSN-based algorithms.

III. ALGORITHM

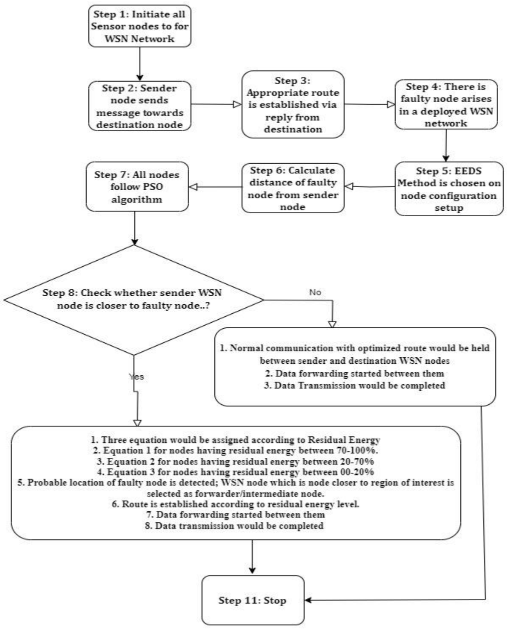

Figure 2. Algorithm Flowchart

Steps of Simulation

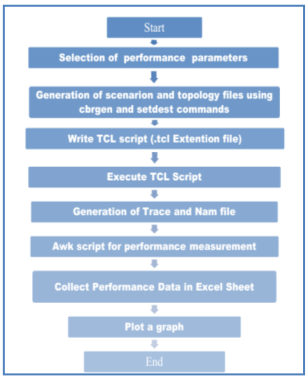

Figure 3 : NS-2 Simulation Steps

4.1 Execution Steps for AWK Script

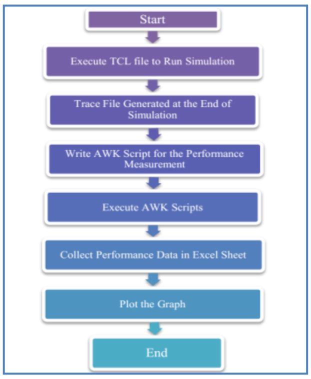

Figure 4: AWK Script execution

4.2 Static Scenario of EEDS method

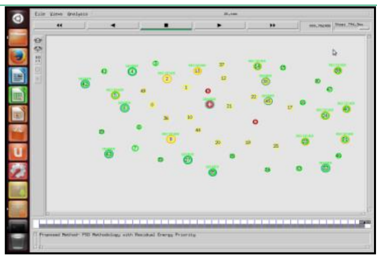

Figure 5 : Static Scenario- Experiment 1 for data rate=2000kbps

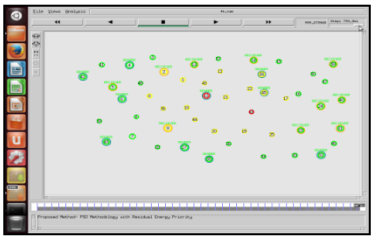

Figure 6: Static Scenario- Experiment 2 for data rate=4000kbps

Figure 7 : Static Scenario- Experiment 3 for data rate=6000kbps

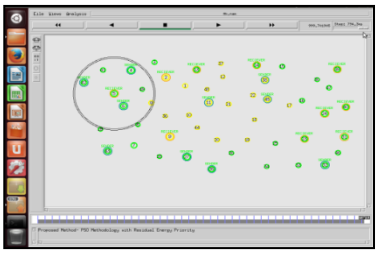

Figure 8: Static Scenario- Experiment 4 for data rate=8000kbps

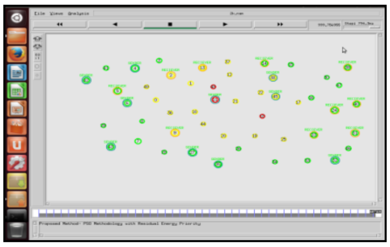

Figure 9: Static Scenario- Experiment 5 for data rate=10000kbps

4.3 Dynamic Scenario of EEDS method

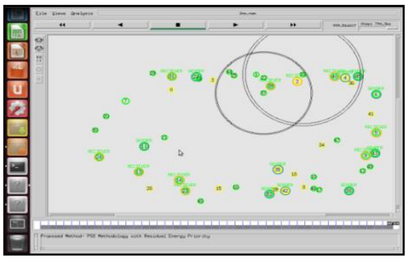

Figure 10: Dynamic Scenario- Experiment 1 for node velocity= 2m/s

Figure 11 : Dynamic Scenario- Experiment 2 for node velocity= 4m/s

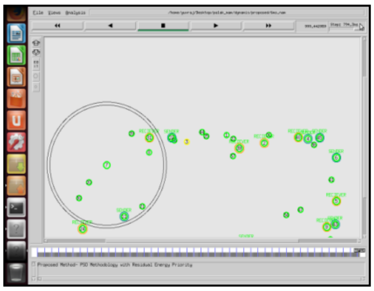

Figure 12 : Dynamic Scenario- Experiment 3 for node velocity= 6m/s

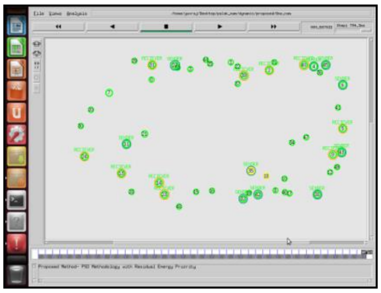

Figure 13 : Dynamic Scenario- Experiment 4 for node velocity= 8m/s

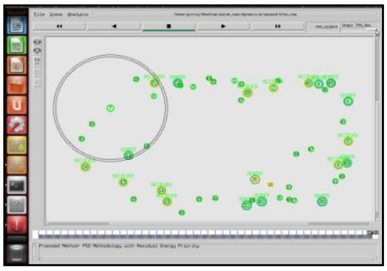

Figure 14: Dynamic Scenario- Experiment 5 for node velocity= 10m/s

IV. Result

Throughput is the most basic network performance metric because it shows the average data rate forwarded correctly and, finally, to the destination. This may be a wavelength lawsuit of the transfer links efficiency; hence, it means the data travels continuously without interfering due to several factors, which include bits per second or packets per second, which depends on a high throughput compared to its alternative. Hence, we liken it to a well-functioning traffic flow.

Throughput (bits/sec) = (Total no. of received packets at destination * packet size) /(Total Simulation Time)

Packet Delivery Ratio It describes the effectiveness of the routing protocol; hence, it means the amount of data successfully received at the destination compared to the amount of data sent; thus, it works smoothly as a tuning orchestra. The Packet Loss Ratio describes the inefficiencies in your packet transmission; hence, it measures the lost data packets and then divides them to arrive at a conclusion.

Any energy management protocol is measured by paying attention to Energy Consumption, which becomes a severe issue of ad-hoc networks. Energy consumption reflects the cost of sending and receiving sending and receiving data, which is essential for keeping the network and node alive. Wireless networks require prolonged operation and keeping every node active; efficient energy management is critical for survival.

Transmit a packet:

TxEnergy = txPower x (packet size/bandwidth)

Received packet:

RxEnergy = rxPower x (packet size/bandwidth)

Total energy consumed:

Total Energy Consumed = Initial energy – Energy left at each node.

End-to-end delay entirely digests the distance between the two nodes; hence, it calculates the average number of packets that take place at both times to reach the destination. Routing Overhead means the frequency of the packet used, hence the bandwidth. This presents the scalability of the protocols since congestion is a concern.

Table 2: Parameters setting of proposed EEDS method

Description	Parameter	Value
Size of Network	Network Field	1000m x 1000m
The total count of nodes inside the domain	Number of nodes	70-100
Nodes' initial energy (in joules)	Eo	0.5 J
Transfer Power (Nano joules/bit)	ETX	50 nJ/bit
Energy of Reception (Nano joules/bit)	ERX	50 nJ/bit
Energy-free area for radio amplification (joules)	Efs	10pJ/bit
Weight inertia	Winit	0.4
Energy Aggregation Data (Nano joules/bit)	EDA	5 nJ/bit/Message
Energy-multipath radio amplifier (joules)	Emp	0.00013pJ/bit
Size of Message	Message Size	512 byte
CH Reference Probability	Po	0.1
Count of iterations	Maximum No. of Iterations	5
Factor of acceleration	c1 = c2	2

Analysis of Simulative Parameters for Static Scenario

Five experiments consisted of static scenarios (with data rates from 2000 bps to 10000 bps) where six parameters, particularly Packet Delivery Ratio (PDR), experimental nodes visualization, and their optimal density location, are watched in the network simulations components. Finally, the subset of PDR results for AOMDV, CDMFD, and EEDS methods are also provided in Table 4.3, with their graph shown in Fig. 4.16. This is the heart of our results: striving for larger PDR values, which suggests better performance. Our analysis indicates that the EEDS method significantly outperforms AOMDV and CDMFD regarding PDR under various data rates. In simpler terms, the EEDS method establishes itself as the dominant technique. It performs better and more elaborately than other methods we used for experiments, marking tremendous success in its aptitude in network simulations.

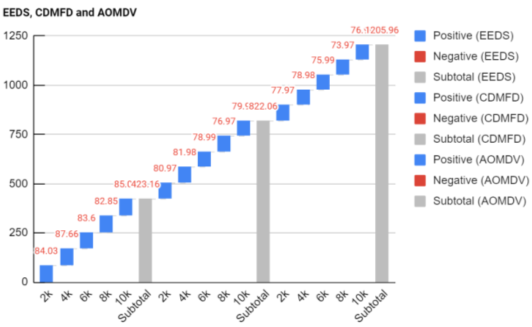

Figure 15: PDR- Static Topology

The Packet Delivery Ratio (PDR) is an important performance metric for optimizing network efficiency over data rates such as 2k to 10k bps. We can see From the results that EEDS has higher PDR percentages in all data rate scenario experiments than CDMFD and AOMDV. It also has high success rates of packet delivery inside the network (PDR 82.85–87.66%), demonstrating improved reliability in such conditions. In contrast, CDMFD and AOMDV techniques possess slightly lower PDR in the range of 73.97% to 81.98% & from 75.99%-78.98 %, respectively. In summary, EEDS is a novel solution that achieves packet delivery across heterogeneous data rates and makes it an attractive choice for network optimization and reliability over other competitor solutions in terms of performance.

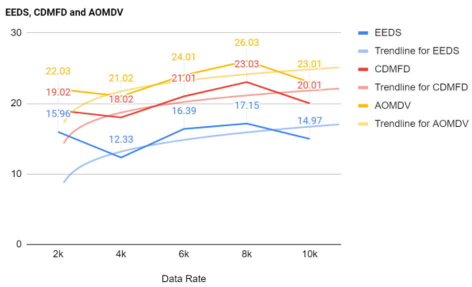

Figure 16 : PLR- Static Topology

This is a critical parameter for network reliability when dealing with network data rates between 2k and to10kb/s, i.e., timeslots. After analyzing the results, it is shown that PLR percentages are consistently lower for EEDS compared to CDMFD and AOMDV at all data rates (Table. ERR). As demonstrated by EEDS, the 12.33% to 17.15 percent range of PLR values indicates good performance at keeping the data intact in the network traffic load distribution[10]. However, the performance of CDMFD and AOMDV carries slightly larger average PLR percentages in contrast with our proposal: between 18.02% to 23.03 % for CDMFD and from 21.02% to 26. Our results were remarkable in concluding that EEDS is the most effective way to reduce packet loss under such variable data rates. It is ideal for improving network reliability and performance [4], beating all its competitors with high margins.

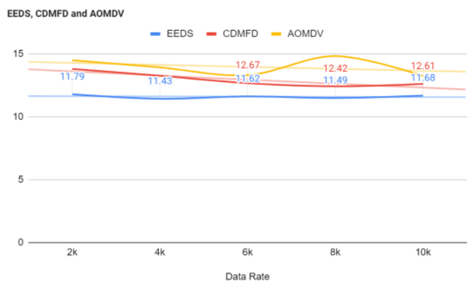

Figure 17: E2E Delay- Static Topology

End-to-End Delay: the Cornerstone of Efficiency in Network Data Rates between 2k &10k bps Further, on close inspection, the EEDS method is getting less End-to-End Delay values than CDMFD and AOMDV by all data rates. EEDS touts End-to-End Delay times between 11.43 ms and 11.79 ms, indicating its ability to speed up data transmission through the network circuitous path(opens new window). On the other hand, CDMFD and AOMDV have a bit higher end-to-end delay-timings between 12.42 ms to 13.8

ms; from another angle, delays vary between 13.. 24 ms to 14.. 82 ms, respectively.-2 These findings underscore the success of EEDS in reducing transmission latency and show that it remains an attractive approach for developing more network-efficient yet low-latency systems compared to existing alternatives.

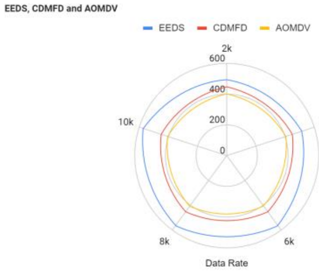

Figure 18: Throughput- Static Topology

Regarding the complex mechanism of network data rates, Google Earth Engine Data Security outperforms its competitors in the proper measurement of Throughput41. Based on the data presented in the table, it is possible to observe that EEDS reveals a more reliable measurement of throughput at all data rates than CDMFD or AOMDV. Specifically, EEDS reveals Throughput values from 494.83 kbps to 574.03 kbps, which means this method ensures that it is possible to monitor and transfer data in the network faster than CDMFD with its Throughput rates from 445.56 kbps to 452.48 kbps; and AOMDV with its Throughput values from 401 kbps to 407.23 kbps34. As a result, EEDS is capable of ensuring better data transfer and flow even when the data rate fluctuates. It is possible to achieve increased efficiency in this measurement unit. This leads to EEDS's better performance than its competitors, which is one of the crucial measures.

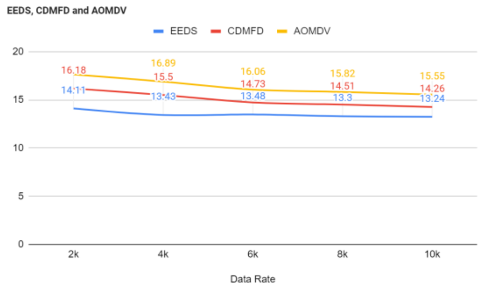

Figure 19 : Energy consumption - Static Topology

Energy Consumption: The efficiency of power utilization, a key benchmark in the complex network dynamics. The EEDS method also has energy consumption values consistently smaller than CDMFD and AOMDV in every data rate. With this, the showcased energy consumption of EEDS ranges between 13.24 joules. It goes to a maximum of reaching 14.11 Joule indicates that it's good at saving power within the network itself · Preen: Energy-saving label assignment mechanism for time-division long-term evolution — Sherien Sengupta et al On the contrary, CDMFD and AOMDV have minimal high energy efficiency with a range of 14.26–16.18 joules, while an average power in-between are approximately equal to 15.55-17.63 Joule. Such observations delineate EEDS's sharp energy minimization efficiency even when data rates vary, thus making it an appropriate choice to bolster network lifetime and sustainability by pushing the field limits in this essential perspective.

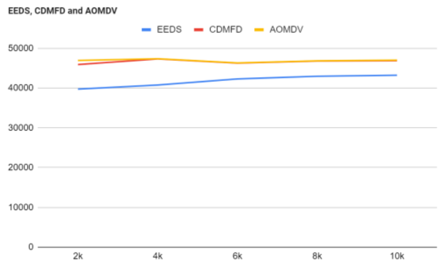

Figure 20: Routing overhead - Static Topology

In an intricate network environment, Routing Overhead becomes a critical metric that addresses the operation mechanisms of routing protocols. Examinating in Note 9, it is clear that the EEDS method displays lower values for Routing Overhead when compared to CDMFD or AOMDV at all rate ranges. This means that EEDS has less routing overhead, showing 39,732 to 43,225 packets during communication loading, indicating its added advantage in handling network traffic better. On the other hand, both CDMFD and AOMDV show a slightly higher routing burden of about 45,910~46,900 packets and 46.314~47.006, respectively. These observations highlight the capabilities of EEDS to improve routing efficiency in changing data rates, even at lower achieved throughput. This attractive feature can be used for network scalability and overhead reduction with a decisive edge over all other algorithms under this critical parameter.

Analysis of Simulative Parameters for Dynamic Scenario

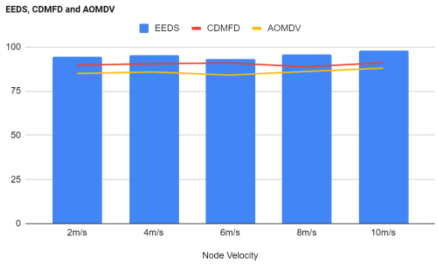

Figure 21: PDR - Dynamic Topology

The Packet Delivery Ratio (PDR) is an essential indicator of network reliability, particularly in dynamic subjects with node velocity ranging from 2m/s up to 10 m/m. On closer examination, the EEDS algorithm shows consistently higher PDR percentages than CDMFD and AOMDV for any node velocity. EEDS demonstrates PDR values of 93.38% to 97.8%, which means it does well on relaying packets while nodes keep moving (speed changes). On the other hand, CDMFD and AOMDV have relatively lower PDR %, 88.77% to 91.16%. Meanwhile, they go down even further in the case of Poor Signal & High-Speed scenarios within a range from ≈84 to over <88 %. These results highlight the EEDS as an efficient technique to guarantee packet delivery in dynamic environments where the node velocity varies. It is a candidate for improving network reliability and performance since it surpasses its competitors regarding this critical issue.

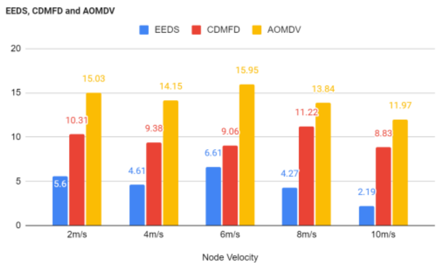

Figure 22: PLR - Dynamic Topology

Regarding reliability in the network, with its very smooth dynamics (between 2m/s and up to speed at a max velocity of around ten m/s), a set of cascaded losses become crucial… among them the Packet Loss Ratio(PLR). EEDS performs better in percentages of PLR against CDMFD and AOMDV for all node velocities, as seen after analyzing the plots. EEDS provides PLR rates of 2.19% and 6.61%, which means EEDS is good at mitigating data loss under different node speed variations[rack14]. In contrast, CDMFD and AOMDV have a slightly higher PLR (%), 8.06% to 11.22%, and 11.97% of 15 O %. This shows that EEDS can improve the data transmission reliability effectively even with mobility of node velocity changes and can be one of the solutions for improving network performance and minimizing loss of data, which sets this method over other approaches in terms of the above critical domain.

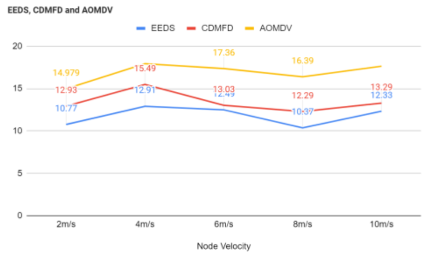

Figure 23: E2E Delay - Dynamic Topology

End-to-end delay becomes an important matrix in the probabilistic node velocities between 2m/s to 10 m/s, which measures how soon data can be successfully transmitted throughout the network. When investigated, it is observed that the EEDS method has an inferior End-to-End Delay value compared to CDMFD and AOMDV for every node velocity setting. EEDS End-to-End Look at DELAY B EEDSEnd -to – end delay starts from 10.37ms, and the highest value of it achieves up to to12.98 indicating that EFFICEINTLY facilitates data transmission speed naively between various node rates within the network. On the other hand, CDMFD and AOMDV exhibit a bit of end-end delay with an approximate value ranging from 12.29ms–15.49ms & 14.979 ms–17.94 ms, respectively. The results of our evaluations emphasize the advantage that EEDS offers over existing solutions in maintaining minimal delays amidst variations as noticeable as these between node velocities and present it as a preferable choice to maximize network efficiency while minimizing delay times, thereby distinguishing itself from other competing methodologies for lower latencies one significantly critical dimension where they are left behind.

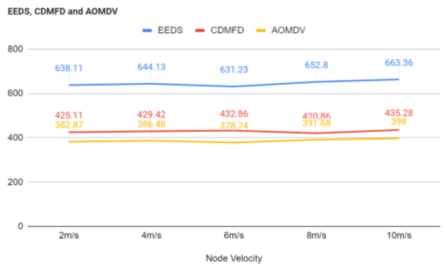

Figure 24: Throughput - Dynamic Topology

In the dynamic symphony of node velocities 2m/s to >10m/s, one crucial measure is finding how well data can transmit over all nodes throughput. When analyzed, the EEDS method presents higher Throughput values concerning CDMFD and AOMDV for all node velocities. Throughput rates with EEDS were labeled from 631.23 kbps to 663.36, indicating a high level of message delivery among differing node speeds (Figure 9). However, CDMFD and AOMDV have low Throughput values of 420.86 kbps to 435.28 kbps and between the frames from about 378.74kbps up to about too much closestpeakrate=398kbs respectively The results obtained highlight the ability of EEDS to accurately optimize data flow also when node velocities are nonconstant, which has been proved to be one main advantage for improving network efficiency in terms of amount and speed," surpassing its competitors with respect this key point.

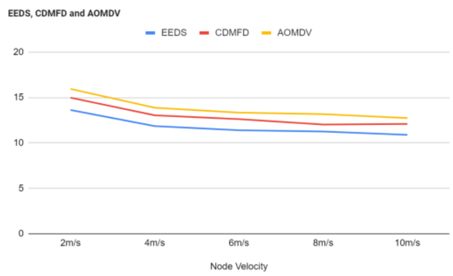

Figure 25: Energy Consumption - Dynamic Topology

Energy consumption is an essential metric for savings regarding power utilization within the network. At the same time, node velocities range between 2m/s and as high as possible, so energy efficiency is a leading priority. Based on the above analysis, we also investigate how Energy Consumption differs among CDMFD and AOMDV from EEDS across different node velocities. EEDS demonstrates power-saving capabilities across different node speed cases and has energy consumption in the range of

10.89 Joules to 13.62 Joules, an indication of its strength on a variable node speeds capability, which is shown by low EDS values as compared with SD-GAfEC (lower bar graphs). On the other hand, CDMFD and AOMDV perform better in terms of slightly more energy consumption from 12.02 J to 14.98 J (CDMFD) and 12.74J to 15.94J (AOMDV). These arguments illustrate EEDS's potent efficacy in adapting to changing communication conditions even when nodes frequently change. Hence, it is a suitable alternative for increasing network longevity and sustainability, which sets it apart from other protocols regarding this critical issue.

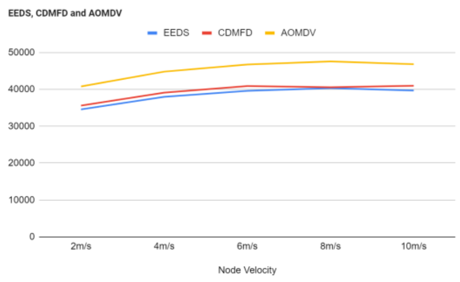

Figure 26: Routing Overhead - Dynamic Topology

Routing Overhead: This is an important metric used to give insights into the efficiency of routing protocols within a network and reflects on how well you can deliver your packets. At the same time, node speeds range from 2m/s-10 m/s. We analyze that the EEDS method always shows Minimum Routing Overhead over CDMFD and AOMDV for all Node velocities. EEDS includes relatively low routing overhead values and is proficient in distributing the traffic over different nodes with diverse speed capabilities (routing overhead ranges from 34,561 up to 40,315 packets). CDMFD and AOMDV have a bit of routing overhead compared with BATSR in CDMSCSs, the former ranging from 35,597 to 40,988 packets, whereas this range is varied between 40.781 and 46.805packets for the latter ones [30]. Together, these results confirm the effectiveness of our EEDS toward routing efficiency even when node velocities change and justify using such an algorithm to scale networks with lower overhead, efficiently outperforming others in this critical dimension.

V. Conclusion

While not related directly to the dynamic part of network configurations, some exciting enhancements in different parameters come from CDMFD over EEDS. In the meantime, EEDS also improves PDR by 6.08% for a high success rate of data transmission, and it effectively reduces PLR by as much as 23.99%, indicating its effort to prevent packet loss in other ways. EEDS also decreases the end-to-end delay by 10.42%, makes data transfer faster, and increases throughput to better flow of information at a rate of up to 20.53%. Besides, EEDS reduces Energy Consumption by 10.41%, improves efficiency, and alleviates the Routing Overhead by up to a factor of 10.31%, enhances managing network works reliably at low data exchange rates for frequent user change thresholds in an IoT environment[]. In contrast, EEDS is the best-performing choice, with higher reliability and less wasted energy in static network scenarios.

This dataset presents a proof of concept as we transfer from CDMFD, capturing these differences more effectively than could be achieved by any static factor alone. EEDS presents a substantial 5.65%increasein Packet Delivery Ratio for ensuring data transmission with higher fidelity and also significantly reduces the packet loss rate (52.29%), inevitably leading to less data loss on transit/media streamlines [8]. Moreover, EEDS decreases end-to-end delay by 12.17%, making data transfer faster and increasing throughput to approximately 50.66% IO for each node every second so that information can pass more rapidly between nodes. EEDS also results in 8.88% less Energy Consumption, making the entire network efficient and reducing Routing Overhead by 2.56%, streamlining network operations. EEDS is a better choice, which, in turn, enhances scalability performance and universal efficiency, particularly for dynamic network environments.

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