OPTIMIZED RESOURCE MANAGEMENT AND DYNAMIC ROUTING PROTOCOL FOR WIRELESS SENSOR NETWORKS THROUGH LOAD BALANCING, PACKET SCHEDULING, AND INTELLIGENT CLUSTERING

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SUMMARY

Heterogeneous Wireless Sensor Networks (HWSNs) are pivotal for providing weather-related event data, enabling universal location access, and facilitating remote monitoring through multi-hop transmission. Efficient energy utilization is critical in ensuring the optimal functioning of HWSNs. Previously, Compressive Sensing (CS) technology was established to enhance communication efficiency within HWSNs. While previous methods were effective in managing energy consumption and reducing transmission delays across network devices, the increased number of devices has impacted their efficacy. Consequently, energy becomes a vital limitation in constructing HWSNs. In order to address these challenges, this study introduces Load Balancing and Packet Scheduling with Intelligent Clustering based Improved Routing Protocol (LPICR). This integrates load balancing, packet scheduling, intelligent clustering, and enhanced routing techniques. The protocol is structured into three main categories: intelligent route selection, load balancing-based Cluster Head (CH) selection, and path scheduling. Initially, an efficient opportunistic routing is conducted by the intelligent route selection process. This routing method minimizes data forwarding during communication and significantly decreases energy consumption in the HWSN. Furthermore, by using a load balancing-oriented procedure for selecting cluster heads, the system achieves efficient determination of cluster heads and construction of clusters, resulting in the most efficient use of energy in communication. Path scheduling reduces the probability of delays by facilitating effective data flow between the source and destination in the HWSN. The NS2 platform is used to implement the proposed LPICR-HWSN protocol. The calculation of the result and comparison analysis is considered for the parameters are Data loss rate, communication time, packet success rate, malicious detection ratio, throughput, Routing overhead and energy efficiency. The results are thoroughly investigated by accounting for factors like the quantity of nodes and the varying speed of the network. To assess the efficacy of this proposed protocol, we conduct a comparative analysis using established methodologies such as CDAS-WSN, EEPC-WSN, TCCS-WSN, and MTODS-HWSN. The results suggest that the proffered LPICR-HWSN model demonstrates superior performance compared to previous methods.

KEYWORDS

Heterogeneous wireless sensor networks (Hwsns), Intelligent clustering, Energy efficiency, Path scheduling, and Multi hop transmission

NOMENCLATURE

LPICR	Intelligent Clustering based Improved Routing Protocol
HWSN	Heterogeneous Wireless Sensor Networks
CH	Cluster Head
F	Frequency
CS	Compressive Sensing

1. INTRODUCTION

This is normally the first section in the main body of the text. This section and all subsequent sections and sub-sections should be numbered manually. Automatic numbering systems must not be used. Wireless sensor networks (WSNs) are increasingly utilized in environmental monitoring, where they detect occurrences and generate event packets. These packets are then transmitted to appropriate sinks to administrator’s notification [1]. WSNs often consist of multiple sensors detecting various events and can coexist in the same area. For example, an intelligent building might deploy sensors for managing hallway lights and indoor temperature, while a hospital uses sensors to monitor patients [2]. These co-located WSNs form a heterogeneous network where each WSN employs its own set of sensors and routing paths. Improving routing efficiency in heterogeneous WSNs by allowing sensors to relay packets for other WSNs could potentially increase sensor density and reduce distances between neighbors. However, challenges arise due to the varying transmission powers among nodes, resulting in non-uniform communication ranges and difficulty in identifying problematic nodes [3]. Energy heterogeneity, reflecting variations in nodes' initial energies, significantly affects computational and link heterogeneity, demanding additional energy resources [4].

Studies addressing energy imbalance explore scenarios where sensors are visited by a mobile sink, forwarding either no data or some data. For instance, one approach involves creating a route to visit each sensor and collect data immediately. However, challenges persist, including potential depletion of the mobile sink's energy, extended data-gathering processes, and potential buffer overflow in static sensors [5]. In heterogeneous WSNs, nodes possess varying energy levels, while sink nodes exhibit greater processing power, storage capacity, and rechargeable batteries. Managing sensor nodes with limited battery power presents a significant challenge, necessitating communication support, efficient routing, Quality of Service (QoS), fault tolerance, and security in WSN applications. Figure 1 illustrates the fundamental operation of a heterogeneous WSN.

Communication protocols is an essential role in determining the performance of HWSNs to optimizing their energy consumption can significantly enhance their longevity. Hierarchical clustering, location-based, data-centric, and quality-of-service-aware protocols are the primary categories of routing protocols in HWSNs. The LEACH protocol is widely used for hierarchical clustering in various applications. The LEACH algorithm utilises a clustering technique to segment the network into separate groups, each of which is supervised by a CH. The choice of the CH is determined by assessing the remaining energy levels of the nodes. The main objective of the protocol is to equitably allocate power consumption among nodes by providing each node with an equal chance to become a CH. Optimizing energy utilization in LEACH can extend the network's lifespan by maintaining a continuous connection between sensors and the sink node, thereby achieving the primary objective of data transmission while enhancing the durability of the network [6].

The study introduces a new protocol called Load Balancing and Packet Scheduling with Intelligent Clustering based Improved Routing Protocol (LPICR). The objective of LPICR is to improve energy efficiency by establishing uninterrupted connectivity between sensor nodes and base stations, hence extending the network's lifespan. The contribution of this study lies in the development of LPICR, which seeks to address energy optimization challenges in HWSNs, ensuring better energy utilization and network sustainability.

- In order to facilitate efficient communication within Compressive Sensing (CS) technique-based Heterogeneous Wireless Sensor Networks (HWSNs), a novel approach named Load Balancing and Packet Scheduling with Intelligent Clustering based Improved Routing Protocol (LPICR) has been proposed.
- The LPICR approach enhances the conventional Ad hoc On-demand Multipath Distance Vector (AOMDV) protocol by implementing an intelligent path scheduling method aimed at minimizing data forwarding. This improvement involves an effective forwarder node selection model, significantly reducing routing overhead within the network.
- Furthermore, the load balancing-based CH selection process effectively manages the mobility of heterogeneous nodes, resulting in decreased energy consumption and reduced communication delays.
- Moreover, the path scheduling process optimizes the scheduling of transmissions in a predetermined manner, effectively handling network mobility. This optimization contributes to enhanced packet delivery ratio and throughput within the HWSN network.

The paper unfolds in six sections, each contributing essential insights to the study. In Section 2, the focus is on outlining the limitations within heterogeneous networks, succinctly summarized within Table 1. Moving on to Section 3, fundamental aspects of network construction are discussed in detail, providing a foundational understanding for subsequent discussions. Section 4 offers an in-depth exploration of the LPICR-HWSN approach, elucidating its components and intricacies. Shifting to Section 5, a comprehensive performance analysis is conducted, evaluating metrics

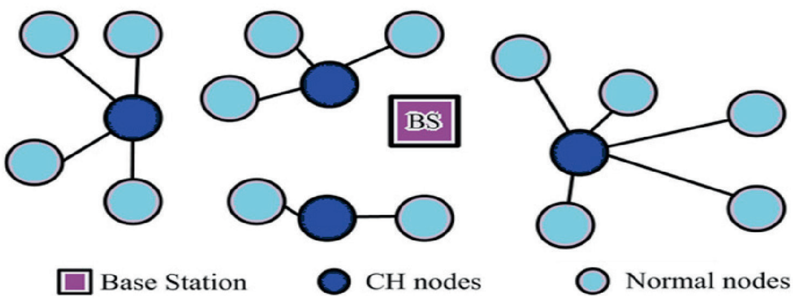

Figure 1. HWSN's basic operations

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concerning node count variations and speed fluctuations. This analysis includes a comparative assessment against previously studied methodologies like CDAS-WSN, EEPC-WSN, TCCS-WSN, and MTODS-HWSN. Finally, Section 6 encapsulates the study's conclusions, distilling key findings and implications drawn from the research.

2. RELATED WORKS

Yuvraj et al. in [7] proposed the EESCA-WR algorithm, aiming to reduce network power consumption in heterogeneous networks by introducing efficient structured clustering with relay. Employing strategies like a threshold-based GL rotation and hybrid GL selection policy, the approach creates homogeneous and heterogeneous networks, addressing power consumption limitations and coverage area issues. However, drawbacks include increased packet loss. In their study, Nileshkumar et al. introduced a cross-layer variant of AODV that aimed to prolong network lifetime. They achieved this by incorporating the Score method into the Network layer [8]. This method collects collision data and connection quality data from the MAC layer and Physical layer respectively, to help in making informed routing decisions. Nevertheless, it experiences issues with packet loss.

Sadrishojaei et al. in [9] introduced a novel clustering based location prediction routing protocol for MIoT utilizing

Table 1. Overview of related works

Ref.No	Methodology	Benefits	Drawbacks
[7]	An efficient, structured clustering Method	Minimum Energy Consumption	Limited coverage region
[8]	AODV Method	Enhances the network lifespan	Higher Packet loss
[9]	Clustering and routing based on location prediction for multiple mobile sinks (CLRP-MMS)	Improves Network throughput	High processing Time
[10]	Heuristic-based routing technique	Improves Network lifespan	Higher power utilization
[11]	An energy-efficient path design method	Increases network lifetime	High power consumption
[12]	Introduces the smart-energy-efficient routing protocol (ESEERP)	Minimize the End to End delay	Data loss is high
[13]	Lines-of-Uniformity based Enhanced-Threshold (LUET) Method	Reduces power Utilization	Encounters issues with packet delivery ratio
[14]	ETERS routing technique	Reduces delay and improves throughput	High power consumption
[15]	Neuro-Fuzzy-Based Routing Protocol	Increases throughput and data delivery ratio	Consumes more processing time
[16]	Query-Driven Clustering (QDC) protocol	Improves network lifetime	Limited coverage region
[17]	Energy-Efficient Data Gathering a Cluster Tree Model (CTEEDG)	Increase network lifetime and data success ratio	Improves computational cost and time
[18]	Balancing traffic strain method	Improves network lifetime	High complexity
[19]	Quasi-Oppositional Butterfly Optimization Algorithm	Energy efficiency is high	High packet loss
[20]	Clustering data utilizing heuristic search	Expands network lifetime	Experiences minimum throughput
[21]	A decision tree-based method	Ensures high security	Encounters high packet loss
[22]	A Weighted Markov Clustering Protocol	Ensures high throughput	Possesses limited coverage area
[23]	Hybrid K-means algorithm and the genetic algorithm	Better throughput, and longer lifespan	Increased processing time

multiple mobile sinks (CLRP-MMS). This technique reduces energy usage and enhances throughput and network longevity, albeit at the expense of high computational costs. Khalid Haseeb et al. [10] proposed the SEHR protocol for WSN to secure data and optimize routing, minimizing network disconnection and link failures. While enhancing network throughput, this protocol leads to increased energy consumption. In [11], Bilal al-Kassem et al. provided an effective path design method using MOEAs to augment network lifetime and connectivity. However, it results in high power consumption. Rani et al. provided an enhanced ESEERP approach in [12] that enhances network lifetime and connectivity, albeit with increased packet loss. Tanvi Sood et al. introduced LUET and its variant (LUET|R) in [13], aiming to improve coverage and energy efficiency in clustering. Yet, it fails to prevent delayed packet delivery. In [14], Tayyab Khan et al. proposed ETERS for WSN to eliminate unknown attacks, offering improved latency and throughput, albeit at the expense of increased power consumption. Thangaramya et al. in [15] introduced a Neuro-Fuzzy Rule Based Cluster Formation and Routing Protocol to enhance secure routing, achieving improved throughput and latency at the cost of high computational expenses.

Yadong Gong et al. in [16] introduced the QDC protocol to improve WSNs' power efficiency and network lifespan with minimal coverage area. Kalaivanan et al. proposed the CTEEDG approach in [17], employing fuzzy logic for CH selection to improve network lifetime and throughput, though at the cost of higher energy consumption. Ramin et al. recommended a novel clustering technique in [18], improving the network's lifetime but adding complexity. Nageswara Rao et al. in [19] introduced a quasi-oppositional butterfly optimization algorithm to increase WSN's lifetime and energy efficiency, encountering high packet loss.

YU HAN et al. provided a meta-heuristic-based clustering protocol using the Harmony Search Algorithm in [20], aiming to enhance network longevity but experiencing increased packet loss. Putty Srividya et al. in [21] proposed a decision tree-based method to secure WSNs but faced issues related to high packet loss. Abbad et al. suggested a Markov clustering protocol in [22] for data security, yet achieving a minimal coverage area. Shashi Bhushan proposed a hybrid method combining GA and K-means algorithms in [23], achieving improved performance metrics like throughput and energy efficiency, albeit with increased computational time. Table 1 provides a concise overview of the previous studies.

3. PRELIMINARIES

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3.1 NETWORK MODEL

Clustering is crucial for optimising Heterogeneous Wireless Sensor Networks (HWSNs) as it enhances the longevity and effectiveness of Cluster Heads (CHs) in these networks. As sensors gradually deplete their power post data transmission, clusters characterized by common attributes naturally form.

The proposed method commences by selecting nodes with residual energy levels notably exceeding the network's average. Subsequently, employing the k-means clustering algorithm generates around 20 CHs from these chosen nodes. Each of these CH sets undergoes an evaluation using a fitness function. Post-assessment, the CH set exhibiting the highest value according to the fitness function is selected. Any additional nodes sharing similarities are then linked to the nearest CH within this chosen set. The effectiveness of this method heavily relies on the attributes chosen to define the fitness function's performance during the clustering process. These attributes significantly influence the efficacy of the fitness function in optimizing the selection of CHs and subsequent node connectivity within the HWSN.

- A correlation exists between the residual energy of CHs and reduced transmission delay: higher CH residual energy leads to shorter delays.
- The linked nodes exhibit uniform energy levels due to the standard deviation of errors among these interconnected nodes.
- Variations in the standard deviation impact the lifespan of CHs.
- The median distance among nodes and their corresponding CHs.

Higher delay results from less residual energy, and conversely, more residual energy leads to reduced delay. The methodology section extensively analyzes CH evaluation through the fitness function. Cluster formation occurs subsequent to the identification of suitable CHs. Upon receipt of a message from the relevant CH, each node sends a join message based on signal strength and node-CH distance. Communication links are established between CHs and the BS for data transmission. The proposed algorithm engages with diverse nodes varying in energy levels and hardware functionalities. Regular CH identification is conducted to extend network lifespan, considering network heterogeneity and residual energy. The determination of the ideal placement between the BS and

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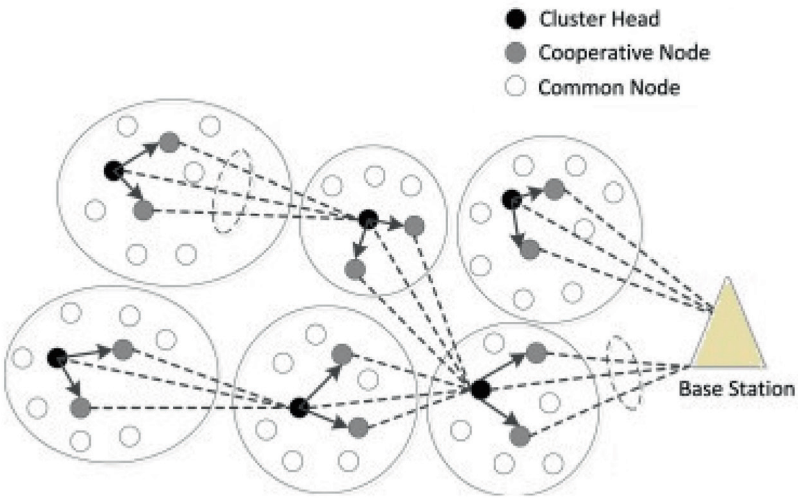

Figure 2. Structure of heterogeneous network

CHs is achieved via route identification. Figure 2 visually represents the model of the heterogeneous network.

3.2 ENERGY MODEL

This research primarily focuses on slot allocation and the diverse radio usage states of nodes, involving transmission, reception, listening, and sleep modes at different network levels such as lower-level nodes, Cluster Heads (CH), and network-wide sink nodes. It delves into energy considerations for reception (Erx) and transmission $p_{tx}(d)$, represented by

$$P_{tx}(d) = m*\left(\varepsilon d^{\alpha} + E_a\right)L, and\ E_{rx} = m*_{Ea.} \tag{1}$$

where m denotes the packets, L signifies slots, d represents distance, ε stands for the transmitter amplifier, and α is the path loss exponent in a multi-path network.

3.3. DELAY MODEL

The delay model encompasses myopic and non-myopic scheduling mechanisms to determine packet transmission times for source nodes and CHs to the sink. Equations such as

$$T_{ch} = \left(\left(\frac{n}{k}\right) - 1\right)L \tag{2}$$

predict the time for sorting packets, and

$$T_{Vbs} = m*L*L' \tag{3}$$

calculates the slots for CH-to-Base Station data transfer. The total time for collecting packet from source to BS is given by

$$T_{total} = T_{Vch} + T_{Vbs} = \left[\left(\left(n, \frac{N}{m}\right) - 1\right) + M\right]L*L' \tag{4}$$

In general, the actions of nodes and CHs are coordinated throughout the time windows where 1 ≤ L, L' < T_{total}.

4. PROPOSED LPICR-HWSN METHOD

This Compressive Sensing (CS) technique-based HWSN is called Load Balancing and Packet Scheduling for an Enhanced Routing Protocol (LPICR), and it consists of three main segments: Intelligent path selection, Load balancing-oriented CH selection, and Path scheduling. This division aims to enhance communication standards. The next sections provide a full explanation of each of these segments, which cover the operational workflow of the proposed LPICR-HWSN system as seen in figure 3.

4.1 AOMDV PROTOCOL INTELLIGENT PATH SELECTION

The process of intelligent path selection serves to increase the routing performance and extend the network lifetime within Heterogeneous Wireless Sensor Networks (HWSN) while reducing routing overhead. This method employs opportunistic routing to determine potential hop nodes for forwarding data to the BS node. The criteria utilized to identify a potential forwarder node include:

- Reception of RREQ broadcast by neighboring nodes from the source node.
- Replay of load, energy, and neighboring node information by a node.
- The originating node accepts both one-hop and two-hop neighbour replays.
- Refreshment of a table by the source node containing nearby node details.

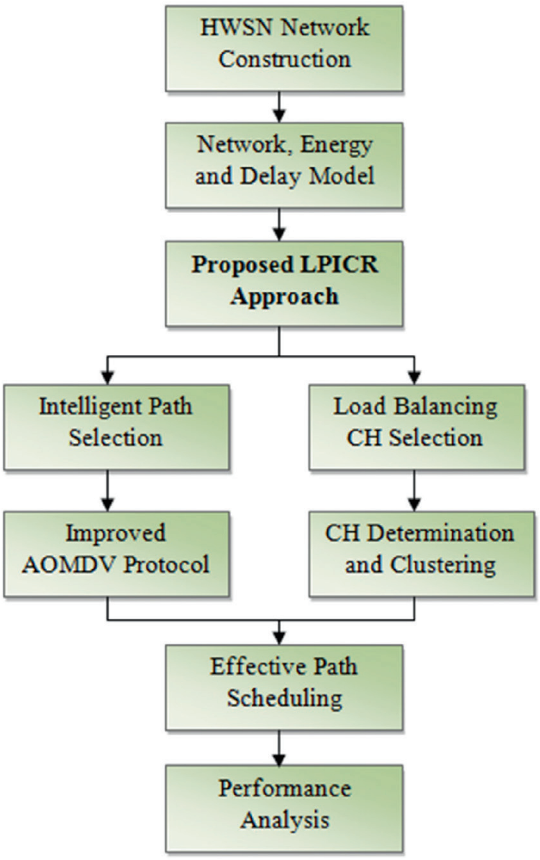

Figure 3. Work flow of proposed LPICR-HWSN

- Opportunistic hopping to the nearest neighboring node towards the sink node, considering factors like minimal load, high energy, and maximum neighbors.
- Creating a routing path from the source to efficiently transmit data packets to the destination node.
- Decreasing the packet loss and minimizing routing overhead by utilizing this dependable channel.

Selection of Forarder node

In the proposed opportunistic routing method, a forwarder node is identified based on two key factors: its residual energy and its proximity to the sink node. However, relying solely on distance for selection might prove ineffective, especially in hazardous areas. The current algorithm lacks consideration for other crucial node parameters. As networks broadcast, opportunistic routing escalates routing costs within densely populated networks, consequently diminishing network longevity.

In this approach, forwarder nodes are chosen based on neighbor coverage knowledge, considering various factors such as the forwarder node's and energy levels in comparison to those of the BS. Optimizing broadcasting in dense networks becomes feasible through Neighbor Coverage Knowledge, effectively reducing routing costs. The suggested routing algorithm optimizes the hop node selection process by factoring in load, energy, neighbor coverage, and distance, ensuring efficiency even in challenging terrains. This method significantly establishes a robust path while conserving energy, thereby enhancing the routing algorithm's performance. Ultimately, this routing strategy extends the network's lifespan by maximizing efficiency and adaptability across various network conditions.

Consider the scenario where the source node (Node 0) transmits data packets to reach the sink node (Node 7) through intermediate nodes (Nodes 1 and 2) within the network. The source nodes assess their load, energy, and neighbor coverage to designate the appropriate neighbor as the hop node.

For instance, if Node 2 possesses fewer neighbors route to the sink node, higher energy levels, and lower load compared to Node 1, Node 2 would be selected as the next hop. Following this selection, Node 0 communicates a request to Node 2. Similarly, Node 2 broadcasts data packets to its neighboring nodes and identifies the most suitable hop or forwarder node to transmit data to the sink node.

In this instance, the established reliable path from Node 0 to 7 follows the sequence: 0-2-4-6-7. This algorithm's implementation maximizes both the network's lifetime and broadcasting efficiency by strategically choosing hop nodes based on load, energy, and neighbor coverage assessments.

4.2 LOAD BALANCING-BASED CH SELECTION

Balancing the load during CH selection primarily aims to minimize energy consumption and alleviate delays. This approach is segmented into distinct phases, which are delineated as follows:

CH Determination:

The process entails the selection of CHs from the deployed sensor nodes within the area. Initially, the comparison is performed between the average residual energy (E_{mean}) and each individual node's residual energy (E_{rde}). Nodes with $E_{rde} > E_{mean}$ are shortlisted for further assessment. Subsequently, the selection process identifies 20 sets of CHs based on predetermined preferences. Among these sets, the one demonstrating the highest fitness function value, obtained after applying the fitness function to these sets, will be selected.

The steps involved in determining the CHs are outlined as:

Step 1: Computation of Delay: The delay is computed using the inverse correlation between residual energy and delay. It is expressed as

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$$Delay = \left(\frac{\left(E_{start} - E_{rde} \right)}{E_{start}} + r \right) * RNTD \,, \tag{5}$$

where E_{rde} represents residual energy, E_{start} denotes initial node energy, RNTD signifies Round Trip Delay.

Step 2: Standard Deviation of E_{res} : This step manages the uneven distribution of residual energy between CHs.

The standard deviation of E_{res} is calculated as

$$E_{res}\, Stddev = \sqrt{\frac{\sum_{k=1}^{CH_{s_{num}}} \left(E_{res_k} - E_{res_{avg}} \right)^2}{CH_{s_{num}}}} \tag{6}$$

Step 3: Determination of standard CH Distance: The distance between each node and its related CH is calculated as the average.

$$CH_{Dist_{Avg}} = \frac{\sum_{k=}^{n} Distance_{(Sensor_k - CH)}}{n} \tag{7}$$

Step 4: Difference in Cumulative CH Ratings over Time: It displays the difference in remaining lifetimes among the CHs.

$$CH\_life\_Avg = \frac{\sum_{k=1}^{CH_{s\_num}} \left(E_{remain_{CH_k}} / E_{Trans\_needed} \right)}{CH_{s\_num}} \tag{8}$$

$$Std\_CH\_life = \sqrt{\frac{\sum_{k=1}^{CH_{s\_num}} \left(Life_k - CH\_life\_avg \right)^2}{CH_{s\_num}}} \tag{9}$$

Step 5: Maximum Distance to BS: The maximum distance from a CH to the Base Station (BS) is identified.

$$Max\_Dist\_BS = MAX\left(DIST_{CH_k - BS} \right) \tag{10}$$

Step 6: Fitness Assessment: The fitness value is evaluated as

$$\begin{aligned} Fitness\,Value &= 0.3 * F1 + 0.15 * F2 \\ &\quad + 0.15 * F3 + 0.2 * F4 + 0.2 * F5 \end{aligned} \tag{11}$$

whereby the average CH distance (F3), standard deviation of eres (F2), maximum CH to sink distance (F5), delay (F1), and standard deviation of eres (F4) are combined in a weighted manner.

Step 7: Selection of CHs: The CHs with the greatest fitness value, determined after iterating through these steps a certain number of times, are selected as the final set of Cluster Heads.

Cluster Formation

After the Cluster Heads (CHs) have been chosen, any remaining shared nodes are connected to the CHs that are nearest to them in terms of geographical proximity. This linking process utilizes received signal intensity to estimate the distance between the nodes.

Algorithm 1. To produce an optimal set of CHs

```
Input: Attributes values
Output: Optimal set of CHs based on fitness
Start
for all the sensors, k do
if (Eres (k) > (network) Eres)
add node k in the group of CH
end
Set CHs produced in CH Group
for all nodes in CH Group do
    for all CH identify phases do
                Calculate Latency;
Evaluate Residual Energy Dispersion;
Measure Typical CH Distance;
Calculate Variation in CH evaluation Life Expectancy;
Calculate Standard Deviation of CHs' Lifetimes;
        end
end
choose a random value from 0 to 1;
Assign the fitness values of the first and second nodes as S
(Fit Value) and T (Fit Value) respectively.
for All nodes in CH Group do
        if (S (Fit Value) > T (Fit Value))
        Node S has normal fitness;
S is chosen as CH and displayed;
End
End
```

The execution of cluster formation and selection of CHs is carried out in various WSN environments using the aforementioned techniques. This approach significantly enhances the network's energy efficiency and facilitates increased data transmission within specific timeframes, thereby maximizing the network's throughput in the proposed HWSN.

4.3 PATH SCHEDULING

The proposed approach emphasizes minimizing computational and communication overhead in interconnected systems by coordinating node activities at a community level and CH at the wider level. It entails allotting Collision-free Slots for transmitting accumulated data packets from nodes to CHs and subsequently to the sink. This method leverages both Myopic and Non-myopic scheduling techniques to reduce energy consumption and delay. The methodology utilizes a framework, as depicted in Figure 4, to synchronize collision-free slots.

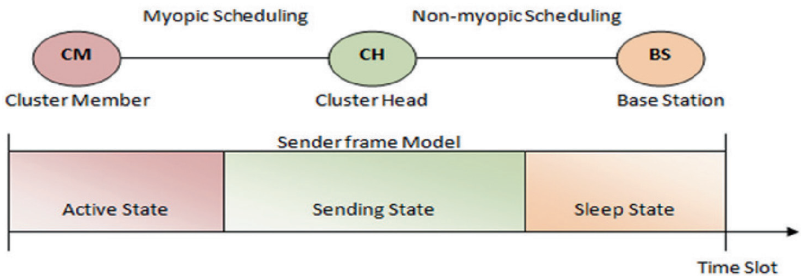

Figure 4. Procedure for frame utilization

Time Division Multiplexing (TDMA) is employed to plan node and CH actions, logically dividing transmission and reception periods ("Ts" and "Tr") into halves based on allocated time slots "L," which are synchronized across the network nodes. The total duration "T" comprises both Tr and Ts, denoted as T = Tr + Ts. During the certain period "T," Node vi generates a variable quantity of packets, rvi. These packets are sent from the node to the CH and then routed to the sink at the CH level. This approach organises tasks without overlaps by taking into account the current channel status. At time instance t=0, each node is assigned a specific number of slots (L). The transmission function for message transmission is determined based on nodes generating 'm' packets without collision, ensuring efficient and collision-free communication.

$$f\left(f\left(t\right),S\right)=\sum_{m\in M}W_{m}\left\{f_{m}\left(t\right)\nexists S,\ f_{m}\left(t\right)\neq V_{ch}\right\} \tag{12}$$

Where weight of the message is ' W_m ', $f(t)=f_m(t)$ is the channel's state, the 'S' dictating each node's activity during the grouped packet transfer process. The channel's status transitions following the Time slot "T" which is mathematically represented by (13).

$$f_{m}\left(t+1\right)=\begin{cases}f\left(f_{m}\left(t\right)\right) & if\ f_{m}\in S\left(t\right)\\ f_{m}\left(t\right) & otherwise\end{cases} \tag{13}$$

Utilizing the outlined calculations, an efficient path scheduling method is implemented to significantly mitigate occurrences of packet loss and routing overhead during the communication process within the HWSN (Hybrid Wireless Sensor Network). By leveraging these calculations and employing an optimized path scheduling strategy, the network aims to minimize packet loss and reduce the associated routing overhead, enhancing the overall reliability and efficiency of communication in the HWSN environment.

4.4 COMPRESSIVE SENSING AND RECONSTRUCTION ERROR

The signal acquisition procedure in a compressive sensing wireless sensor network has many stages, primarily relying on an approximate gradient descent approach for signal reconstruction.

- Initially, all sensor nodes within the wireless sensor network synchronize their timing. Each node captures the incident signal over a specific time duration 'T,' represented as a matrix 'X.' This matrix represents the signal generated by the event. To compress information, sparse basis matrices are constructed using discrete cosine transformation, enabling data reduction across the network.
- Subsequently, each sensor node constructs a prediction of a signal vector under the matrix for the time duration 'T' to achieve signal compression. Sampling matrices are generated for each sensor network to measure the signals. The flattened signal element is projected under the sampling matrix to generate 'Y' signal. This under-sampling process arises from the non-square nature of the sampling vector.
- The network's base station gets the compressed sampled signal 'Y' from the member nodes, together with the sampling matrices. Subsequently, it utilises the approximation gradient method to restore the signal's sparse structure and reconstructs it by introducing the discrete cosine affine transformation method.
- When processing the compressive signal 'Y,' the central node employs the PRG (Proximal Residual Gradient) technique to gradually and accurately provide the genuine solution of 'Y' signal. Initially, a unit matrix is generated the length which is equal to that of the signal vector. The selection of the convergence criteria has a substantial effect on the efficiency and processing time. Hence, the use of the optimum convergence criteria guarantees the utmost efficiency in programme execution.

5. PERFORMANCE ANALYSES

The experimental evaluation of our proposed LPICR for HWSN is conducted in this section. Multiple scenarios are executed to assess the performance of LPICR, considering diverse parameters. The evaluation encompasses various performance metrics including malicious detection ratio, packet delivery rate, packet loss, end-to-end delay, throughput, routing overhead, communication cost, and energy efficiency,. These metrics are analyzed across

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Table 2. Parameter settings

Input Parameters	Values
Simulator	NS2
Total Number of nodes	100
Total Number of BS	1
Total Coverage area	1000*1000 m
Simulation Time	200ms
Type of Antenna	Omni directional antenna
Type of Queue	DropTail
Transmission rate	200KB
size of Packet	300KB
Communication range	30m
Initial Power	100 Joules
Transmission Power	0.500 Joules
Receiving Power	0.050 Joules

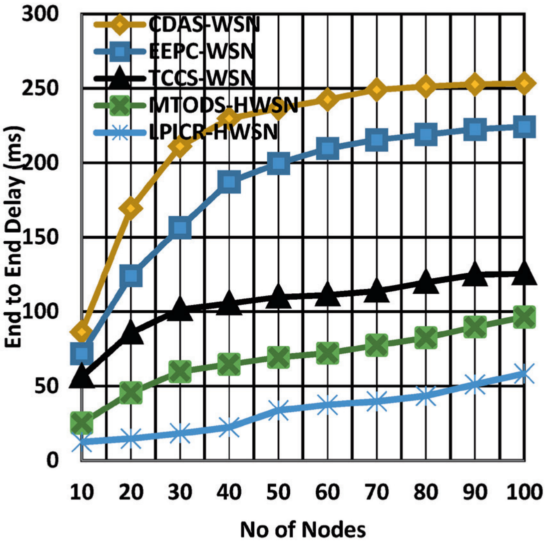

Figure 5. End to end delay

different scenarios involving varying node counts and operational speeds within the HWSN. The network simulation uses the NS2 simulator, which employs Object-oriented Tool Command Language (OTCL) and C++ for front and back end respectively. In order to conduct a thorough comparison, the obtained findings are compared to those obtained from earlier techniques such as TCCS, CDAS, EEPC, and MTODS. The evaluation of results is conducted by the study of input parameters specified in table 2.

5.1 PERFORMANCE ASSESSMENT BASED ON NUMBER OF NODES

This section provides simulation results that showcase various node configurations for different methodologies, such as CDAS-WSN, EEPC-WSN, TCCS-WSN, MTODS-HWSN, and the proposed LPICR-HWSN. The analysis covers a wide range of parameters, including end-to-end latency, communication cost, packet success rate, malicious detection rate, packet loss rate, energy efficiency, throughput, and routing overhead.

5.1.1 End-to-End Delay Calculations:

In this assessment, LPICR-HWSN's performance is compared to recent research, particularly focusing on its effectiveness concerning end-to-end Delay. Figure 5 illustrates that proffered LPICR-HWSN achieves notably lower end-to-end Delay compared to previous methods like CDAS-WSN, EEPC-WSN, and TCCS-WSN. These earlier methodologies primarily emphasize enhancing packet delivery ratio without achieving optimal energy efficiency. Subsequently, MTODS-HWSN is developed, targeting security and energy efficiency but doesn't maximize throughput effectively. Addressing device mobility is essential inside the HWSN architecture to optimise route selection and load balancing during communication. In response to this requirement, the proposed LPICR-HWSN is introduced in this study, aiming to optimize delivery ratio, throughput, and efficiency. Through effective load balancing and path scheduling, LPICR-HWSN demonstrates reduced delay generation compared to previous approaches.

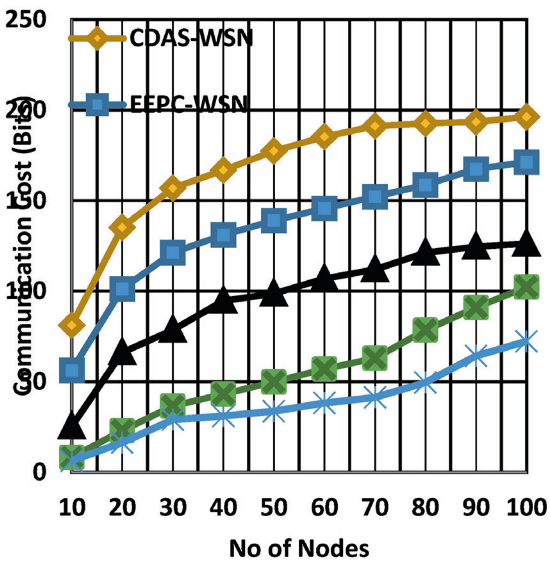

Figure 6. Communication cost

5.1.2 Communication Cost:

The reduction in communication costs within the HWSN network presents opportunities to augment the overall value of data transmission. Illustrated in Figure 6, the efficiency of communication costs quantifies the effectiveness in this domain. The findings distinctly showcase that the suggested

LPICR-HWSN remarkably decreases communication costs compared to other techniques, namely CDAS-WSN, EEPC-WSN, TCCS-WSN, and MTODS-HWSN. The proffered LPICR-HWSN, significantly amplifies the network's delivery rate and throughput. The clustering process plays a pivotal role in enhancing network efficiency. Consequently, the proffered LPICR-HWSN demonstrates notably lower communication costs in contrast to previous methodologies.

5.1.3 Malicious Detection Ratio:

The malicious detection ratio represents the process of identifying malfunctions induced in the network. Figure 7 illustrates the analysis of packet loss ratios across various approaches, including CDAS-WSN, EEPC-WSN, TCCS-WSN, MTODS-HWSN, and the proposed LPICR-HWSN. The graphic clearly illustrates that the LPICR-HWSN strategy outperforms conventional solutions.

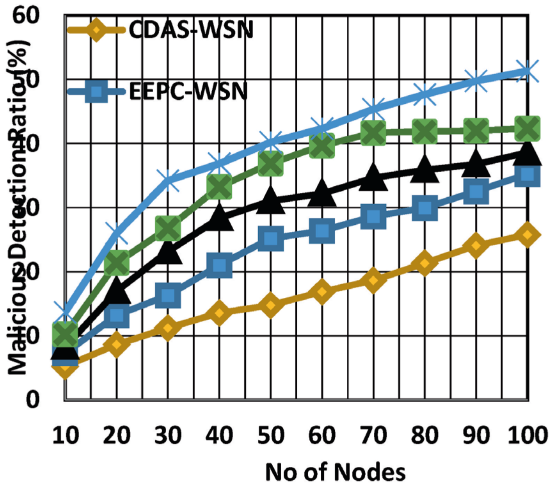

Figure 7. Malicious detection ratio

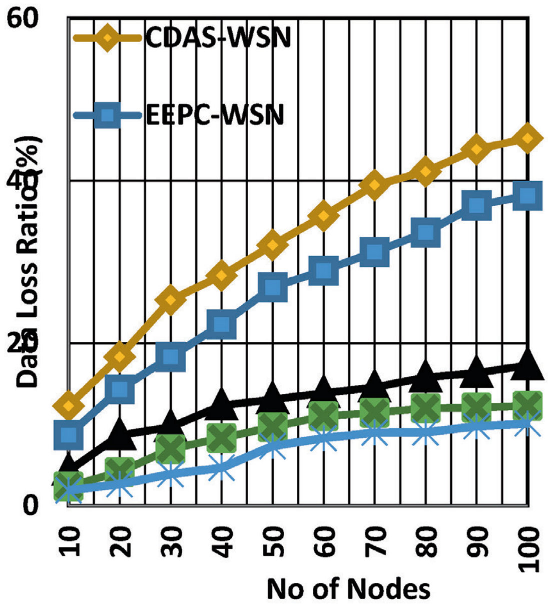

Figure 8. Packet loss rate

5.1.4 Packet Loss Rate:

The packet loss ratio represents the count of unsuccessful data transmissions occurring between the sources and the destination during communication. Figure 8 illustrates the analysis of packet loss ratios across different approaches, namely CDAS-WSN, EEPC-WSN, TCCS-WSN, MTODS-HWSN, and the proffered LPICR-HWSN system that was developed. The graphic clearly illustrates that the LPICR-HWSN strategy outperforms conventional solutions in terms of packet loss rate. The efficiency of LPICR-HWSN in minimizing packet loss is attributed to its practical path scheduling process. This process ensures that mobile devices traverse predefined paths while effectively managing their loads, thereby minimizing packet loss in contrast to earlier approaches.

5.1.5 Data Success Rate:

The data delivery ratio is a measure of the successful transmission of data from the source to the sink. Figure 9 illustrates the evaluation of data delivery ratio in various approaches, such as CDAS-WSN, EEPC-WSN, TCCS-WSN, MTODS-HWSN, and the proffered LPICR-HWSN. According to the chart, LPICR-HWSN has the highest data success ratio when evaluated to previous methods. The heightened data success ratio in LPICR-HWSN can be credited to its balanced load-based data transmission and efficient path scheduling process. These techniques significantly reduce packet loss and delay, leading to a higher packet delivery ratio within the network compared to earlier methodologies.

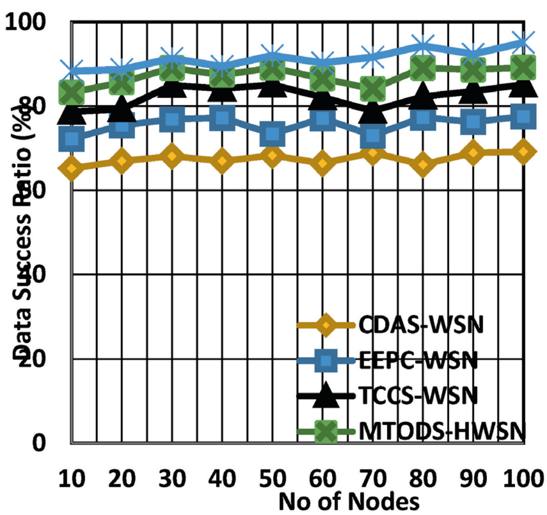

Figure 9. Data success rate

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5.1.6 Overhead Calculations:

The routing overhead refers to the amount of data that is transmitted between the source and destination during the process of data sharing. Figure 10 demonstrates the measurement of routing overhead for various approaches, such as CDAS-WSN, EEPC-WSN, TCCS-WSN, MTODS-HWSN, and the proffered LPICR-HWSN, followed by a thorough performance analysis. The figure demonstrates that the proffered LPICR-HWSN has the lower routing overhead when evaluated to other standard methods. The result may be allocated to the suggested methodology that includes a proficient path-scheduling procedure grounded on the TDMA paradigm. Hence, the proposed LPICR-HWSN significantly diminishes the network's overhead calculation.

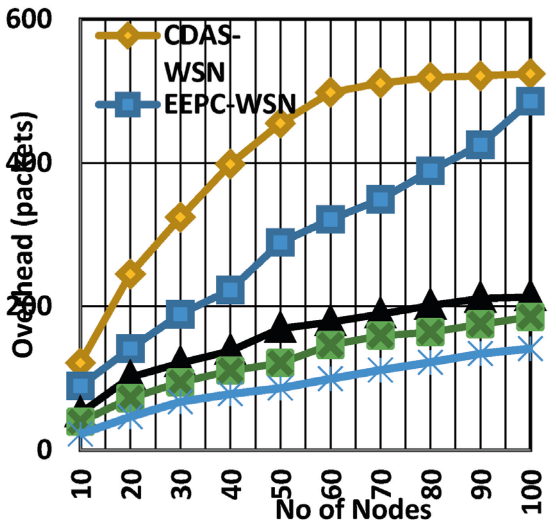

Figure 10. Routing overhead

5.1.7 Energy Efficiency:

Energy efficiency, in this context, refers to the assessment of the residual energy retained in each node. Figure 11 portrays the evaluation of energy efficiency across methodologies such as CDAS-WSN, EEPC-WSN, TCCS-WSN, MTODS-HWSN, and the newly proffered LPICR-HWSN, followed by a subsequent performance analysis. The graphical representation demonstrates that LPICR-HWSN outperforms prior methods by achieving superior energy efficiency. This success can be attributed to the load balancing-based clustering process integrated into LPICR-HWSN. The efficient determination of Cluster Heads (CHs) and formation of clusters significantly contribute to enhancing the network's energy efficiency. This approach optimizes CH selection and cluster creation, thereby augmenting the overall energy efficiency of the network.

5.1.8 Throughput:

Throughput refers to the total number of packets transmitted from the source to the destination at any given period of time. Figure 12 illustrates the throughput measurements for existing techniques, CDAS-WSN, EEPC-WSN, TCCS-WSN, MTODS-HWSN, and the proffered method LPICR-HWSN. The LPICR-HWSN methodology involves an efficient cluster formation and a predefined path selection process. These strategies ensure optimized cluster establishment and path definition, ultimately leading to maximized throughput compared to the previous approaches.

5.2 RESULTS AND DISCUSSION BASED ON NUMBER OF NODES

In this section, a thorough examination of various existing methods is provided, such as CDAS-WSN, EEPC-WSN, TCCS-WSN, MTODS-HWSN, and the proffered

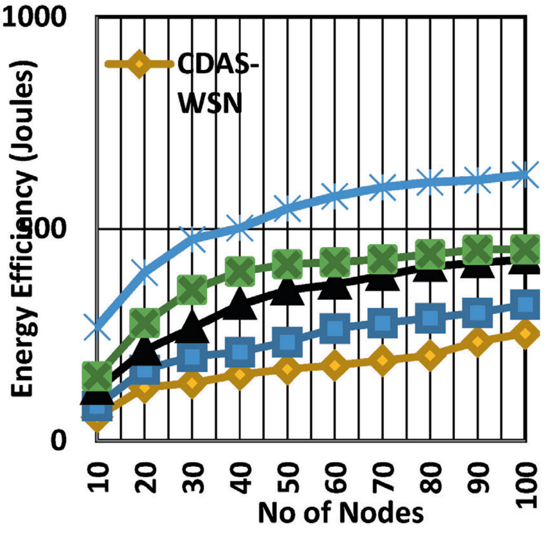

Figure11. Energy efficiency

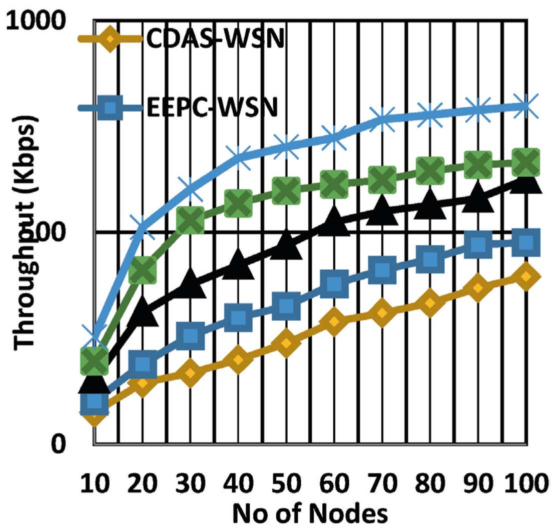

Figure 12. Through put

LPICR-HWSN. The simulation technique covers various parameters for comparison, such as malicious detection ratio, communication cost, data success rate, processing time, packet loss ratio, overhead, energy efficiency, and throughput. Table 3, 4, and 5 provide a clear and comprehensive evaluation of the various criteria.

The proposed LPICR-HWSN outperforms several prior methods. Specifically, LPICR-HWSN demonstrates a significantly higher malicious detection ratio of 51.33%, surpassing CDAS-WSN, EEPC-WSN, TCCS-WSN, and MTODS-HWSN by 25.63%, 16.13%, 12.83%, and 9.97% respectively. Additionally, LPICR-HWSN achieves a notable reduction in communication cost, operating at 72.31 bits, which outperforms CDAS-WSN, EEPC-WSN, TCCS-WSN, and MTODS-HWSN by 123.89 bits, 98.69 bits, 53.69 bits, and 29.69 bits respectively. Moreover, LPICR-HWSN demonstrates an impressive data success ratio of 95.11%, showcasing its superior performance by surpassing CDAS-WSN, EEPC-WSN, TCCS-WSN, and MTODS-HWSN by 25.88%, 17.61%, 9.01%, and 5.88% respectively in terms of successful data transmission.

The performance metrics for various network types display distinctive values. Specifically, in terms of End-to-End Delay (ms), CDAS-WSN recorded 252.2 ms, while EEPC-WSN exhibited 223 ms, TCCS-WSN measured 124.4 ms, MTODS-HWSN reached 95.28 ms, and LPICR-HWSN showcased the lowest delay at 57.33 ms. Regarding Data Loss Ratio (expressed in percentage), CDAS-WSN experienced a rate of 44.23%, EEPC-WSN had 37.1%, TCCS-WSN recorded 16.2%, MTODS-HWSN exhibited 11.28%, and LPICR-HWSN achieved the lowest ratio at 9.11%. Additionally, in terms of Overhead (counted in Packets), CDAS-WSN operated with 523 packets, EEPC-WSN with 485 packets, TCCS-WSN with 212 packets, MTODS-HWSN with 184 packets, and LPICR-HWSN showcased the least overhead with 140 packets.

From the table 5, The Energy Efficiency and Throughput metrics for various WSN types reveal distinctive values. In terms of Energy Efficiency measured in Joules, CDAS-WSN demonstrates 124.13 Joules, EEPC-WSN records 167.02 Joules, TCCS-WSN exhibits 212.36 Joules, MTODS-HWSN shows 276.92 Joules, and introduced

Table 3. Performance measures of malicious detection rate, communication cost, and packet success rate

No of nodes	Malicious Detection Rate (%)					Communication Cost (Bits)					Data Success Ratio (%)				
10	4.13	6.17	7.14	9.13	12.57	80.12	55.1	24.1	7.26	5.23	64.15	71.1	77.5	82.18	87.21
20	7.55	12.1	15.8	20.28	24.02	134.2	99	65.2	21.0	16.38	66.98	75.4	79.3	85.69	88.69
30	10.1	15.3	22.1	25.78	34.21	155.7	120	77.6	35.4	28.97	68.16	76.8	85.0	89.11	91.32
40	12.4	20.0	27.3	32.26	35.77	164.6	129	93.4	42.2	31.06	66.98	77.2	84.1	87.44	89.45
50	13.6	24.1	30.0	35.89	39.22	175.4	137	97.5	48.7	33.68	68.31	73.4	85.1	89.12	92.02
60	15.7	25.3	31.1	38.66	41.34	184.5	143	104	54.8	38.31	66.44	77.1	82.1	86.59	90.33
70	17.5	27.6	33.6	40.68	44.26	190.6	151	108	62.0	41.33	68.99	73.0	78.8	84.12	91.64
80	20.2	28.9	34.8	40.88	46.55	191.5	157	116	76.5	49.54	66.11	77.3	82.3	89.08	94.31
90	23.1	31.5	35.6	41.01	48.79	192.6	164	124	90.2	64.32	68.94	76.3	83.5	88.67	92.35
100	25.7	35.2	38.5	42.36	51.33	196.2	171	126	102	72.31	69.23	77.5	85.1	89.23	95.11

Table 4. Performance metrics of end to end delay, packet loss ratio, and over

No of Nodes	CDAS-WSN	EEPC-WSN	TCCS-WSN	MTODS-HWSN	LPICR-HWSN	CDAS-WSN	EEPC-WSN	TCCS-WSN	MTODS-HWSN	LPICR-HWSN	CDAS-WSN	EEPC-WSN	TCCS-WSN	MTODS-HWSN	LPICR-HWSN
	End-to-End Delay (ms)					Data Loss Ratio (%)					Overhead (Packets)				
10	85.14	70.6	55.12	24.02	11.21	11.17	7.58	3.28	1.25	0.76	120	88	50	38	21
20	168.3	123	84.66	44.36	13.68	17.33	13.3	7.66	3.11	1.65	244	140	100	71	45
30	210	155	100.3	58.65	17.22	24.31	17.3	8.66	5.97	2.88	323	188	120	93	66
40	228.6	186	104.4	63.59	21.31	27.32	21.3	11.3	7.32	3.66	397	222	137	109	77
50	235.4	198	108.6	68.31	32.69	31.08	25.8	12	8.66	6.31	454	288	168	120	85
60	241.3	208	110	71.08	36.31	34.68	27.9	12.8	10.02	7.31	497	320	177	145	98
70	247.9	214	112.6	76.38	38.64	38.46	30.2	13.5	10.44	7.99	510	348	188	158	110
80	250.3	217	118.6	81.45	42.33	40.12	32.6	14.7	10.98	8.03	518	388	200	163	121
90	251.6	221	123.6	88.66	50.02	42.88	35.9	15.3	11.05	8.77	520	424	210	174	133
100	252.2	223	124.4	95.28	57.33	44.23	37.1	16.2	11.28	9.11	523	485	212	184	140

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Table 5. Performance metrics of energy efficiency and throughput

No of Nodes	CDAS-WSN	EEPC-WSN	TCCS-WSN	MTODS-HWSN	LPICR-HWSN	CDAS-WSN	EEPC-WSN	TCCS-WSN	MTODS-HWSN	LPICR-HWSN
	Energy Efficiency (Joules)					Throughput (Kbps)				
10	55.03	80.94	119.36	151.58	267.11	74.03	101.25	152.49	195.27	252.24
20	124.13	167.02	212.36	276.92	395.92	144.03	188.15	309.82	409.82	511.12
30	135.36	197.43	265.14	355.06	474.11	167.15	254.92	376.25	527.45	600.92
40	154.94	208.46	319.86	398.36	501.11	198.45	297.45	421.15	567.29	674.12
50	168.11	231.95	354.24	415.39	547.99	237.35	325.98	468.15	597.14	701.11
60	176.92	264.14	368.25	419.83	575.92	288.12	377.26	522.95	612.05	721.92
70	188.24	277.14	388.45	427.44	597.24	309.02	410.03	548.92	622.34	765.15
80	200.02	288.13	409.82	438.95	608.03	332.26	435.39	562.92	643.18	775.14
90	55.03	80.94	119.36	151.58	267.11	367.77	470.03	578.11	657.46	787.11
100	124.13	167.02	212.36	276.92	395.92	394.08	474.03	623.19	663.17	796.13

LPICR-HWSN achieves the highest efficiency at 395.92 Joules. In terms of Throughput measured in Kbps, CDAS-WSN operates at 394.08 Kbps, EEPC-WSN at 474.03 Kbps, TCCS-WSN at 623.19 Kbps, MTODS-HWSN at 663.17 Kbps, and proposed LPICR-HWSN attains the highest throughput at 796.13 Kbps. Notably, proposed LPICR-HWSN surpasses all other types significantly in both Energy Efficiency and Throughput.

5.3 PERFORMANCE ANALYSIS BASED ON VARYING SPEED

The simulation results are assessed across a wide range of speeds, ranging from 3 Km/H to 15 Km/H. The comparison study encompasses various measures for the approaches being examined, namely CDAS-WSN, EEPC-WSN, TCCS-WSN, MTODS-HWSN, and the proffered LPICR-HWSN. The evaluation is conducted by metrics, including end-to-end delay, communication cost, routing overhead, data success rate, malicious detection ratio, packet loss rate, energy efficiency, and throughput.

5.3.1 Malicious Detection Ratio:

The detection ratio of several existing approaches like CDAS-WSN, EEPC-WSN, TCCS-WSN, MTODS-HWSN, and the proffered LPICR-HWSN is displayed in figure 13. It's evident from the graph that the LPICR-HWSN method consistently outperforms the other methodologies, maintaining the highest malicious detection ratio even when the speed varies. Despite the decrease in the detection rate with increasing speed in other models, the proposed LPICR-HWSN effectively manages speed variations through an intelligent path scheduling process, ensuring a superior malicious detection ratio.

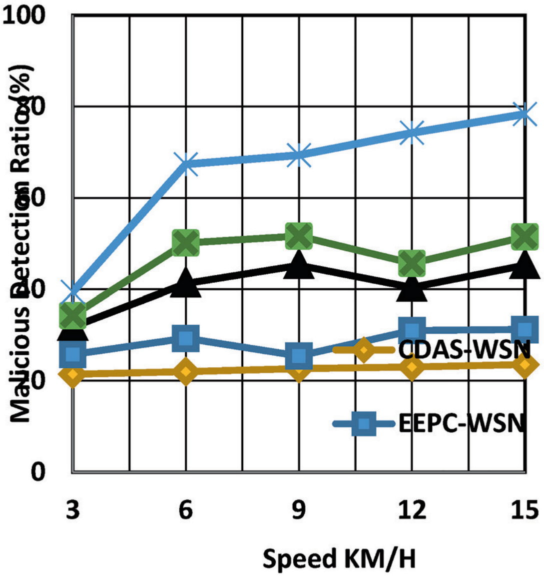

Figure 13. Malicious detection ratio

5.3.2 Communication Cost:

The evaluation of communication costs using various existing approaches, including CDAS-WSN, EEPC-WSN, TCCS-WSN, MTODS-HWSN, and the proffered LPICR-HWSN is shown in figure 14. The graph clearly shows that the LPICR-HWSN method consistently maintains lower communication costs compared to the other methods, even with varying speeds. Typically, an increase in speed tends to elevate communication costs. However, the proposed LPICR-HWSN effectively manages this scenario by employing load balancing and path scheduling processes, resulting in reduced communication costs compared to previous methodologies in the HWSN network as the speed increases.

5.3.3 Data Success Ratio:

The evaluation of the data success ratio across various existing methods, including CDAS-WSN, EEPC-WSN, TCCS-WSN, MTODS-HWSN, and the proffered LPICR-HWSN is shown in figure 15. The visual data indicates

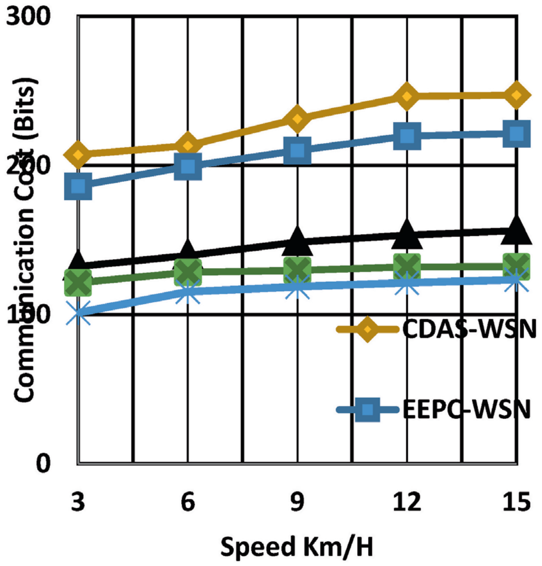

Figure 14. Communication cost

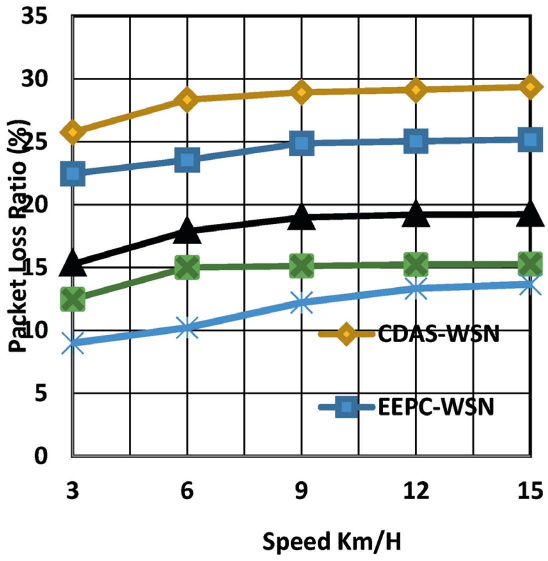

Figure 16. Packet loss ratio

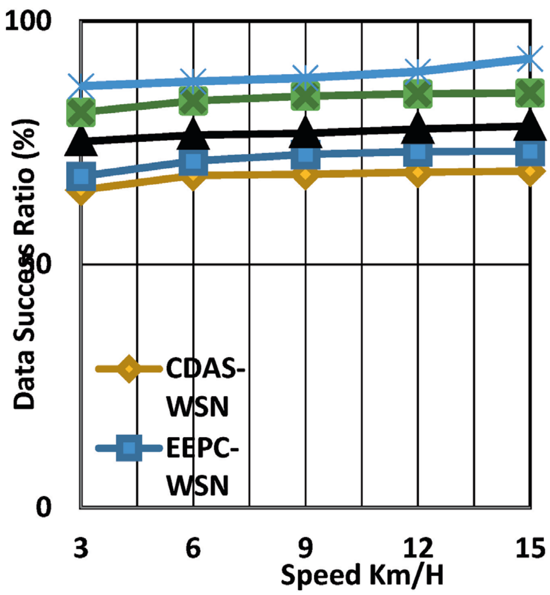

Figure 15. Data success ratio

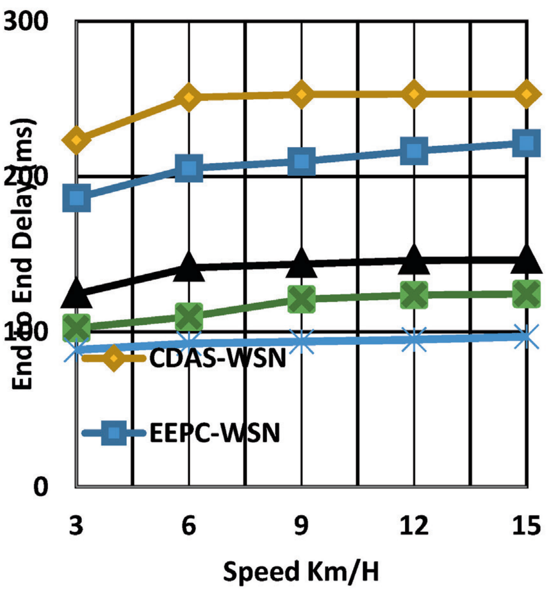

Figure 17. End to end delay

that the LPICR-HWSN achieves the highest success rate in transmitting data compared to the other methods. Despite the typical reduction in data transmission success rates with increasing speed in the HWSN network, the proposed LPICR-HWSN manages path scheduling effectively. This efficient approach significantly enhances the probability of achieving the higher delivery ratio even in high-speed scenarios, outperforming the other methodologies in data success rate.

5.3.4 Packet Loss Ratio:

The packet loss ratio of various existing methodologies, like CDAS-WSN, EEPC-WSN, TCCS-WSN, MTODS-HWSN, and the proffered LPICR-HWSN is shown in figure 16. The graph shows that out of all the methodologies examined, the proffered LPICR-HWSN approach obtains the lower packet loss ratio. With the potential increase in packet loss due to higher speeds during data transmission in any network, the proposed LPICR-HWSN implements effective data transmission models. Consequently, this approach results in a minimal packet loss ratio when compared to the earlier methodologies.

5.3.5 End-to-End Delay:

The evaluation of end-to-end Delay across different methodologies, including CDAS-WSN, EEPC-WSN,

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TCCS-WSN, MTODS-HWSN, and the proffered LPICR-HWSN is shown in Figure 17. The data clearly demonstrates that the proffered LPICR-HWSN obtains a lower end-to-end latency evaluated to other methodologies. As the transmission speed increases in the HWSN network, the delay caused by data transmission usually increases. However, the proffered LPICR-HWSN, effectively reducing the network's Delay when compared to earlier approaches, especially in scenarios involving increased speeds.

5.3.6 Routing Overhead:

The evaluation of routing overhead across various existing methodologies, such as CDAS-WSN, EEPC-WSN, TCCS-WSN, MTODS-HWSN, and the newly proffered LPICR-HWSN. Is shown in Figure 18. The graph demonstrates that the LPICR-HWSN strategy consistently maintains the lower routing overhead when compared to alternative solutions. In general, higher speeds can increase both delays and data forwarding during communication, resulting in increased overhead between the source and destination nodes. However, the proffered methodology implements strategic path selection and load balancing techniques, adeptly reducing the generation of forwarded packets even in scenarios of heightened speeds. Consequently, this mitigates routing overhead within the HWSN network.

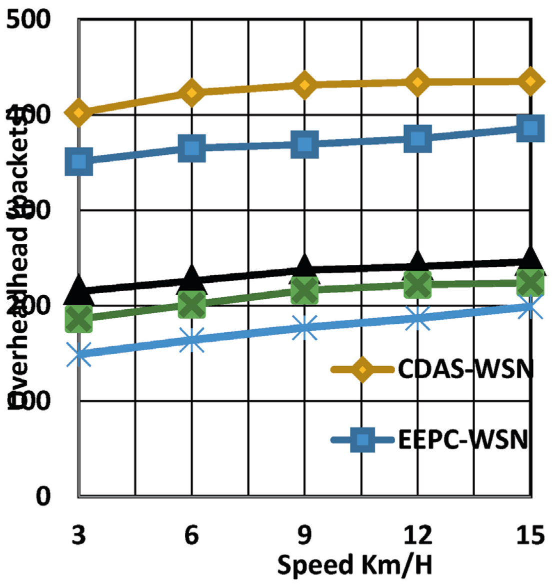

Figure 18. Routing overhead

5.3.7 Energy Efficiency:

The evaluation of energy efficiency across different existing methodologies, like CDAS-WSN, EEPC-WSN, TCCS-WSN, MTODS-HWSN, and the novel LPICR-HWSNis shown in figure 19. The graph validates the proffered LPICR-HWSN demonstrates superior energy efficiency compared to other methods. Normally, higher speeds lead to increased energy consumption during data transmission. However, in proposed method LPICR-HWSN, significantly reduces energy usage, even with rising speeds. This demonstrates the methodology's efficacy in optimizing energy efficiency, even under increased speed conditions in the HWSN network.

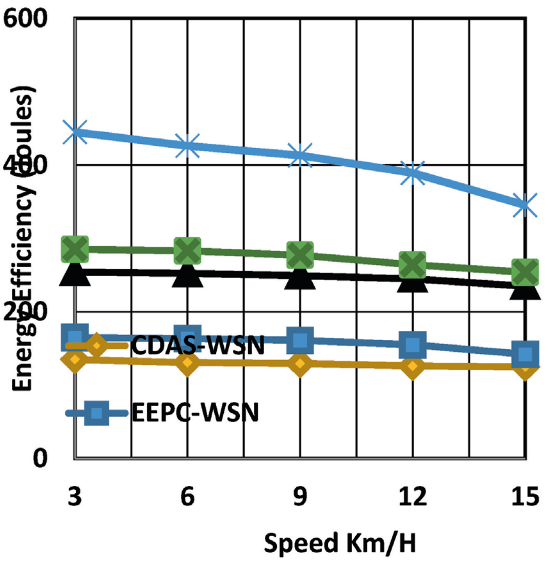

Figure 19. Energy efficiency

5.3.8 Throughput:

Figure 20 illustrates the calculated throughput for different existing methodologies, like CDAS-WSN, EEPC-WSN, TCCS-WSN, MTODS-HWSN, and the proposed LPICR-HWSN. The graph demonstrates that the methods considered, proffered LPICR-HWSN attains

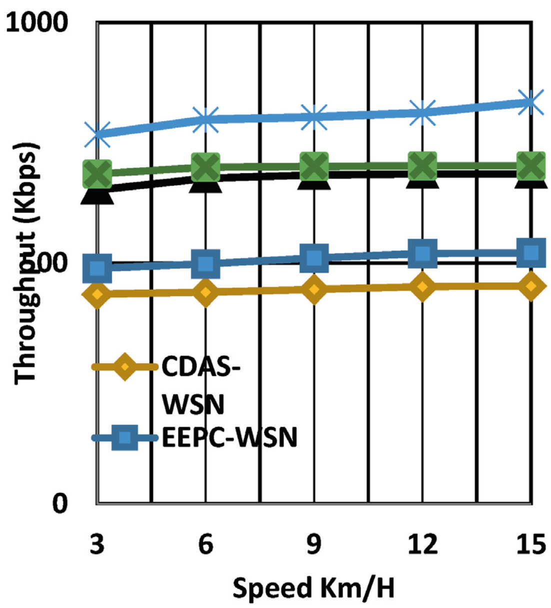

Figure 20. Network throughput

the highest network throughput. Typically, as the speed of communication increases, there is a reduced probability of achieving maximum throughput. However, the proposed LPICR-HWSN, resulting in increased throughput during communication within the HWSN network. This demonstrates the methodology's efficiency in maximizing network throughput, even with varying speeds across the network nodes.

5.4 RESULTS AND DISCUSSION FOR VARYING SPEED

In this subsection, we will analyse the implementation results obtained from various existing methodologies, like CDAS-WSN, EEPC-WSN, TCCS-WSN, MTODS-HWSN, and the proffered LPICR-HWSN. The speeds considered in the analysis range from 3 Km/H to 15 Km/H. This approach encompasses various factors for comparative analysis, including the detection rate of malicious activities, communication costs, success rate of data transmission, communication cost, packet loss rate, overhead, energy efficiency, and throughput. The parameters are clearly depicted in Tables 6, 7, and 8. From the Table 6, in terms of Malicious Detection Ratio, CDAS-WSN demonstrates 22.5%, EEPC-WSN records 30.25%, TCCS-WSN exhibits 44.2%, MTODS-HWSN shows 50.47%, and the proposed LPICR-HWSN achieves a notably higher ratio at 77.35%. Regarding Communication Cost, CDAS-WSN operates at 246 Bits, EEPC-WSN at 220 Bits, TCCS-WSN at 155 Bits, MTODS-HWSN at 131.1 Bits, and the proposed LPICR-HWSN showcases the lowest cost at 122.4 Bits. For Data Success Ratio, CDAS-WSN achieves 68.23%, EEPC-WSN at 72.2%, TCCS-WSN at 77.4%, MTODS-HWSN at 84.27%, and proposed LPICR-HWSN attains the highest success ratio at 91.31%.

Table 6. Performance metrics of malicious detection ratio, communication cost, and data success ratio

Speed (Km/H)	CDAS-WSN	EEPC-WSN	TCCS-WSN	MTODS-HWSN	LPICR-HWSN	CDAS-WSN	EEPC-WSN	TCCS-WSN	MTODS-HWSN	LPICR-HWSN	CDAS-WSN	EEPC-WSN	TCCS-WSN	MTODS-HWSN	LPICR-HWSN
	Malicious Detection Ratio (%)					Communication Cost (Bits)					Data Success Ratio (%)				
3	20.3	24.68	30.4	33.17	38.30	206	185	131	120.3	100.2	64.28	67.1	74.2	80.28	85.66
6	21	28.32	40.2	49.12	66.34	212	198	138	127.3	114.3	67.33	70.2	75.5	82.65	86.64
9	21.6	24.45	44.2	50.65	68.35	230	209	147	128.6	117.6	67.58	71.6	75.9	83.58	87.35
12	22	30.02	39.3	44.66	73.25	245	218	152	131	120.3	67.98	72.2	76.8	84.08	88.64
15	22.5	30.25	44.2	50.47	77.35	246	220	155	131.1	122.4	68.23	72.2	77.4	84.27	91.31

Table 7. Performance metrics of end to end delay, packet loss rate, and routing overhead

Speed (Km/H)	CDAS-WSN	EEPC-WSN	TCCS-WSN	MTODS-HWSN	LPICR-HWSN	CDAS-WSN	EEPC-WSN	TCCS-WSN	MTODS-HWSN	LPICR-HWSN	CDAS-WSN	EEPC-WSN	TCCS-WSN	MTODS-HWSN	LPICR-HWSN
	Packet Loss Ratio (%)					End-to-End Delay (ms)					Overhead (packets)				
3	24.6	21.45	14.5	11.42	7.97	222.3	185	123	101.3	87.22	401	350	214	185	148
6	27.3	22.56	16.8	14.01	9.22	250	204	140	108.6	91.34	422	364	225	200	163
9	27.9	23.89	17.9	14.13	11.22	251.8	208	142	120	92.65	430	368	236	215	176
12	28.1	24.05	18.2	14.24	12.33	252	215	145	122.6	93.89	433	374	240	221	186
15	28.3	24.17	18.2	14.27	12.68	252.1	220	145	123.3	95.87	434	385	245	223	198

Table 8. Performance metrics of energy efficiency and throughput

Speed (Km/H)	CDAS-WSN	EEPC-WSN	TCCS-WSN	MTODS-HWSN	LPICR-HWSN	CDAS-WSN	EEPC-WSN	TCCS-WSN	MTODS-HWSN	LPICR-HWSN
	Energy Efficiency (Joules)					Throughput (Kbps)				
3	134.14	164.17	253.15	284.35	443.86	434.24	488.35	651.16	684.12	766.13
6	130.11	162.77	251.33	282.33	425.26	438.33	497.34	674.94	698.55	797.11
9	128.74	160.12	248.57	276.58	412.14	444.34	509.31	682.21	700.01	802.55
12	125.26	154.12	244.2	263.26	388.34	450.01	519	683.97	701.07	811.34
15	124.12	141.25	234.06	253.12	344.54	451.22	520.35	684.22	701.13	833.11

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From the Table 7, The CDAS-WSN exhibits a Packet Loss Ratio of 28.3%, while EEPC-WSN records 24.17%, TCCS-WSN shows 18.2%, MTODS-HWSN exhibits 14.27%, and the proposed LPICR-HWSN attains the lowest ratio at 12.68%. Regarding End-to-End Delay, CDAS-WSN operates at 252.1 ms, EEPC-WSN at 220 ms, TCCS-WSN at 145 ms, MTODS-HWSN at 123.3 ms, and proposed LPICR-HWSN showcases the lowest delay at 95.87 ms. Concerning Overhead, CDAS-WSN incurs 434 packets, EEPC-WSN at 385 packets, TCCS-WSN at 245 packets, MTODS-HWSN at 223 packets, and the proposed LPICR-HWSN demonstrates the least overhead at 198 packets. Remarkably, the proposed LPICR-HWSN outperforms all other WSN types significantly in Packet Loss Rate, Delay, and Rotuing Overhead, demonstrating superior performance.

Table 8 displays the metrics for Energy Efficiency (Joules) and Throughput (Kbps) for several kinds of WSNs, like CDAS-WSN, EEPC-WSN, TCCS-WSN, MTODS-HWSN, and the proffered LPICR-HWSN. Specifically, for Energy Efficiency: CDAS-WSN demonstrates 124.12 Joules, EEPC-WSN exhibits 141.25 Joules, TCCS-WSN shows 234.06 Joules, MTODS-HWSN records 253.12 Joules, and proposed LPICR-HWSN attains 344.54 Joules. Regarding Throughput: CDAS-WSN operates at 451.22 Kbps, EEPC-WSN at 520.35 Kbps, TCCS-WSN at 684.22 Kbps, MTODS-HWSN at 701.13 Kbps, and proposed LPICR-HWSN showcases the highest throughput at 833.11 Kbps.

6. CONCLUSION

This research presents a novel routing protocol LPICR, designed to improve communication efficiency within sensing-enabled HWSN. The proposed method, LPICR combines efficient path selection and load-balanced CH selection, effectively monitoring network mobility to significantly reduce energy consumption during data transmission. Path scheduling optimizes data transmission in the HWSN network by following predetermined methods. This minimizes routing overhead and delays, resulting in increased creation of data packets and a higher packet delivery rate. The NS2 study evaluates many parameters such as malicious detection ratio, throughput, communication cost, data delivery ratio, routing overhead, computation time, packet loss ratio and energy efficiency. The study investigates varying node counts and speeds while comparing LPICR-HWSN with existing methodologies like CDAS-WSN, EEPC-WSN, TCCS-WSN, and MTODS-HWSN. These findings indicates that the proffered LPICR-HWSN outperforms existing methods across several key aspects: achieving higher malicious detection ratio from 7% to 25%, reducing communication costs from 29 to 124 bits, improving data success ratio from 4% to 24%, decreasing end-to-end delays from 34–189 ms, lowering packet loss ratio from 3%–34%, minimizing routing overhead about 69–225 packets, enhancing energy efficiency from 175–375J, and increasing throughput. The proposed LPICR-HWSN outperforms recent HWSN systems like CDAS-WSN, EEPC-WSN, TCCS-WSN, and MTODS-HWSN across various metrics. The system achieves a significant increase in malicious detection rate, from 25% to 54%. It also reduces communication costs from 9 to 125 bits, improves data success ratio from 6% to 21%, decreases end-to-end delays from 30 ms to 150 ms, reduces packet loss from 1% to 10%, lowers routing overhead from 20 packets to 230 packets, enhances energy efficiency from 90J to 220J, and throughput is increased from 125 Kbps to 375 Kbps. This demonstrates its superior performance in Hybrid Wireless Sensor Networks compared to previous methodologies.

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7. REFERENCES

1. BEHERA, T.M., MOHAPATRA, S.K., SAMAL, U.C., KHAN, M.S., DANESHMAND, M. GANDOMI, A.H., et al. (2019). *I-SEP: An improved routing protocol for heterogeneous WSN for IoT-based environmental monitoring*. IEEE

Internet of Things Journal, vol.7, no.1, pp.710-717, doi: 10.1109/JIOT.2019.2940988.

2. HUNG, L.L., LEU, F.Y., TSAI, K.L. AND KO, C.Y., et al. (2020). *Energy-efficient cooperative routing scheme for heterogeneous wireless sensor networks*. IEEE Access, 8, pp.56321-56332, doi: 10.1109/ACCESS.2020.2980877
3. BHAT, S.J. and SANTHOSH, K.V., (2021). *A method for fault tolerant localization of heterogeneous wireless sensor networks*. IEEE Access, 9, pp.37054-37063, doi: 0.1109/ACCESS.2021.3063160
4. LI, J., LUO, Z. AND XIAO, J., et al. (2020). *A hybrid genetic algorithm with bidirectional mutation for maximizing the lifetime of heterogeneous wireless sensor networks.* IEEE Access, 8, pp.72261-72274, doi: 10.1109/ACCESS.2020.2988368
5. LIN, Z., KEH, H.C., WU, R. AND ROY, D.S., et al. (2020). *Joint data collection and fusion using mobile sink in heterogeneous wireless sensor networks. IEEE Sensors Journal,* vol.21, no.2, pp.2364-2376, doi: 0.1109/JSEN.2020.3019372
6. NAEEM, A., JAVED, A.R., RIZWAN, M., ABBAS, S., LIN, J.C.W. GADEKALLU, T.R., et al. (2021). *DARE-SEP: A hybrid approach of distance aware residual energy-efficient SEP for WSN.* IEEE transactions on green communications and networking, vol.5, no.2, pp.611-621, doi: 10.1109/TGCN.2021.3067885
7. PADMANABAN,Y.and MUTHUKUMARASAMY, M., (2020). *Scalable grid-based data gathering algorithm for environmental monitoring wireless sensor networks*. IEEE Access, 8, pp.79357-79367, doi: 10.1109/ACCESS.2017
8. PATEL, N.R., KUMAR, S., SINGH, S.K., et al. (2021). *Energy and collision aware WSN routing protocol for sustainable and intelligent IoT applications.* IEEE Sensors Journal, vol. 21, no. 22, pp.25282-25292, doi: 10.1109/JSEN.2021.3076192
9. SADRISHOJAEI, M., NAVIMIPOUR, N.J., RESHADI, M. HOSSEINZADEH, M., et al. (2021). *A new preventive routing method based on Clustering and location prediction in the mobile internet of things*. IEEE Internet of Things Journal, vol.8, no.13, pp.10652-10664, doi: 0.1109/JIOT.2021.3049631
10. HASEEB, K., ALMUSTAFA, K.M., JAN, Z., SABA, T. AND TARIQ, U., et al. (2020). *Secure and energy-aware heuristic routing protocol for wireless sensor network.* IEEE Access, 8, pp.163962-163974, doi: 10.1109/ACCESS.2020.3022285
11. AL-KASEEM, B.R., TAHA, Z.K., ABDULMAJEED, S.W. AL-RAWESHIDY, H.S., et al.(2021). *Optimized Energy–Efficient Path Planning Strategy in WSN With Multiple Mobile Sinks*. IEEE Access, 9, pp.82833-82847, doi: 10.1109/ACCESS.2021.3087086
12. DOGRA, R., RANI, S., SHAFI, J., KIM, S. AND IJAZ, M.F., et al. (2022). *ESEERP: Enhanced Smart Energy Efficient Routing Protocol for Internet of Things in Wireless Sensor Nodes*. Sensors, vol.22, no.16, p.6109, doi: 10.3390/s22166109
13. SOOD, T. and SHARMA, K., (2020). *LUET: a novel lines-of-uniformity based clustering protocol for heterogeneous-WSN for multiple-applications.* Journal of King Saud University-Computer and Information Sciences, doi: 10.1016/j.jksuci.2020.09.016
14. KHAN, T., SINGH, K., HASAN, M.H., AHMAD, K., REDDY, G.T., MOHAN, S. AND AHMADIAN, A., et al. (2021). *ETERS: A comprehensive energy aware trust-based efficient routing scheme for adversarial WSNs. Future Generation Computer Systems,* 125, pp.921-943, doi: 10.1016/j.future.2021.06.049
15. THANGARAMYA, K., KULOTHUNGAN, K., LOGAMBIGAI, R., SELVI, M., GANAPATHY, S. KANNAN, A., et al. (2019). *Energy aware cluster and neuro-fuzzy based routing algorithm for wireless sensor networks in IoT. Computer Networks*, 151, pp.211-223, doi: 10.1016/j.comnet.2019.01.024
16. GONG, Y., WANG, J. AND LAI, G., et al. (2022). *Energy-efficient Query-Driven Clustering protocol for WSNs on 5G infrastructure.* Energy Reports, 8, pp.11446-11455, doi: 10.1016/j.egyr.2022.08.279
17. KARUNANITHY, K. AND VELUSAMY, B., et al. (2020). *Cluster-tree based energy efficient data gathering protocol for industrial automation using WSNs and IoT*. Journal of Industrial Information Integration, 19, p.100156, doi: 10.1016/j.jii.2020.100156
18. YARINEZHAD, R. and sABAEI, M., (2020**).** An optimal cluster-based routing algorithm for lifetime maximization of Internet of Things. Journal of Parallel and Distributed Computing, 156, pp.7-24, doi: 10.1016/j.jpdc.2021.05.005
19. MALISETTI, N.R. and PAMULA, V.K., (2020). *Performance of quasi oppositional butterfly optimization algorithm for cluster head selection in WSNs*. Procedia Computer Science, 171, pp.1953-1960, doi: 10.1016/j.procs.2020.04.209
20. HAN, Y., LI, G., XU, R., SU, J., LI, J. AND WEN, G., et al. (2020). *Clustering the wireless sensor networks: a meta-heuristic approach.* IEEE Access, 8, pp.214551-214564, doi: 10.1109/ACCESS.2020.3041118

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21. SRIVIDYA, P. and DEVI, L.N., (2022). *An Optimal Cluster & Trusted Path for Routing Formation and Classification of Intrusion Using Machine Learning Classification Approach in WSN.* Global Transitions Proceedings, doi: 10.1016/j.gltp.2022.03.018

22. ABBAD, L., NACER, A., ABBAD, H., BRAHIM, M.T. ZIOUI, N., et al. (2022). *A weighted Markov-clustering routing protocol for optimizing energy use in wireless sensor networks.* Egyptian Informatics Journal, doi: 10.1016/j.eij.2022.05.001

23. BHUSHAN, S., PAL, R. and ANTOSHCHUK, S.G., (2018), August. *Energy efficient clustering protocol for heterogeneous wireless sensor network: a hybrid approach using GA and K-means.* In 2018 IEEE Second International Conference on Data Stream Mining & Processing (DSMP) (pp. 381-385). IEEE, doi: 978-1-5386-2874-4/18.