Energy-Aware Collaborative Routing Protocol Using Bio-Inspired Algorithms for Heterogeneous Wireless Sensor Networks

Mohammed F. Alomari [1], Jaafar S. Alrubaye [2], Abdul Hadi M. Alaidi [3,*], and Haider TH. Salim ALRikabi [4]

[1] Department of Computer Technical Engineering, Imam Al-Kadhim University College (IKC), 64001, Dhi Qar, Iraq
[2] Department of Computer Science, College of Education for Pure Sciences, University of Wasit, Wasit, Iraq
[3] Department of Computer Science, College of Computer Science and Information Technology, University of Wasit, Wasit, Iraq
[4] Department of Electrical Engineering, College of Engineering, University of Wasit, Wasit, Iraq
Email: mohamed.fadhil@iku.edu.iq (M.F.A.); jsadiq@uowasit.edu.iq (J.S.A.); alaidi@uowasit.edu.iq (A.H.M.A.); hdhiyab@uowasit.edu.iq (H.T.S.A.)
*Corresponding author

***Abstract*—Heterogeneous Wireless Sensor Networks (HWSNs) technology is crucial for the operation of several Internet of Things (IoT), A Mobile Ad-hoc Networks (MANETs), and Vehicular Ad-hoc Networks (VANETs) focused on smart-city applications. Effective performance, particularly in energy consumption reduction and delay minimization, constitutes major challenge factors in this domain. Previous research underscores clustering's value in enhancing network energy efficiency by significantly decreasing communication energy use. However, the dynamic and resource-constrained nature of HWSNs, coupled with issues such as improper Cluster Head (CH) selection, mobility-induced instability, and uneven energy distribution, exacerbates these challenges. Existing CH selection methods consider only energy parameters and ignore crucial parameters such as mobility, node velocity, and communication stability, leading to increased energy consumption, delay, and reduced network lifetimes. To thwart these limitations, this research proposes a novel method—Meta-Heuristic Algorithms based Collaborative Dynamically Clustered Routing Protocol (MHA-CDCRP). This protocol integrates a Collaborative Dynamically Clustered Routing Protocol (CDCRP) with a hybrid optimization technique, i.e., the Meta-Heuristic Genetic Whale Optimization (MHGWO), which blends Genetic Algorithms (GA) and the Whale Optimization Algorithm (WOA). The proposed framework guarantees stable communication, fair energy consumption, and minimum delays via adaptive Cluster Head (CH) selection based on node distance, velocity, remaining energy, and packet delivery ratio. The performance analysis with Network Simulator 2 (NS2) demonstrates considerable enhancement in energy efficiency, packet delivery ratio, throughput, and less overhead over current solutions. This holistic solution is envisioned to improve the sustainability and scalability of HWSNs for large-scale smart applications.**

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I. Introduction

Wireless Sensor Networks (WSNs) have now become the cornerstone technology for various applications, such as environmental monitoring, disaster warning systems, health care services, military activities, and agricultural operations among many others [1]. WSNs are spatially distributed sensor networks with sensor nodes which sense the conditions and forward the data to a base station (BS). Despite all these advantages, conventional WSNs face several challenges: limited energy availability, restricted communication range, and processing constraints, which may result in non-efficiencies and reduced network longevity. To alleviate the constraints of conventional Wireless Sensor Networks (WSNs), Heterogeneous Wireless Sensor Networks (HWSNs) are designed. Unlike traditional WSNs, which are composed of sensor nodes that are homogeneous in type and capability, HWSNs are networks with nodes that have different energy capacities, processing capabilities, transmission ranges, and sensing capabilities. While this heterogeneity increases the network's potential to effectively sustain a variety of applications, it also brings challenges related to energy balancing, communication stability, and protocol design. Of all HWSN operations, wireless transmission is the most energy-consuming contributor, and hence the development of energy-efficient routing protocols is an open research issue.

To addressing these issues, researchers have developed clustering-based approaches where sensor nodes are organized into predefined clusters systematically, with every cluster assigned a Cluster Head (CH) [2]. The CH acts as a mediator between the sensor nodes and the base station, which significantly reduces energy consumption by minimizing redundant transmissions. However, the selection of a good CH is a challenging task, because improper selection can lead to unbalanced use of energy, inefficient communication, and instability in the network [3]. Recent advancements in meta-heuristic algorithms have given promising solutions for the optimization of Cluster Head selection and enhance energy efficiency. Strategies in the meta-heuristic classification, like Genetic Algorithms (GA) and Whale Optimization Algorithm (WOA), are widely used to solve optimization problems in large-scale, dynamic environments. The integration of those algorithms with clustering methods is potentially advantageous to reduce energy consumption, routing delays, and minimize communication overhead for overall network performance improvement [4, 5].

This work is focused on the design of a novel Meta-Heuristic Algorithms-based Collaborative Dynamically Clustered Routing Protocol (MHA-CDCRP) for energy-efficient HWSNs, primarily for smart city applications. The proposed protocol employs the combined use of GA and WOA to achieve efficient CH selection as well as clustering, eliminating the issues of congestion, network delay, and routing overhead. Further, the dynamically clustered routing process is developed on the basis of the nodes' estimated residual energy, enabling energy-efficient operations such as data transmission, node joining, and node leaving [6]. Fig. 1 presents the HWSN network architecture.

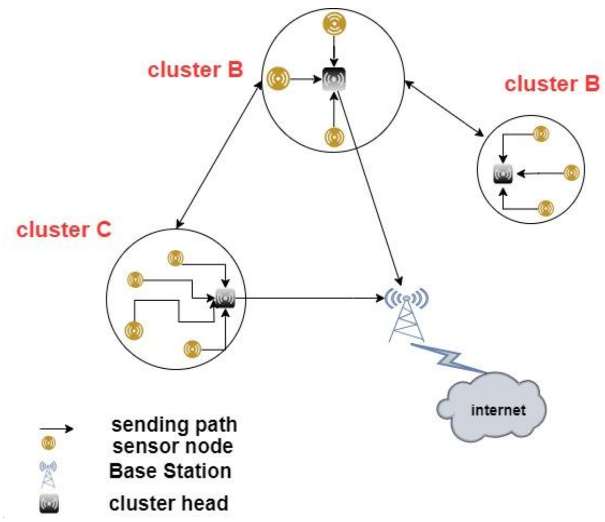


Fig. 1. HWSN network architecture.

By integrating clustering approaches with meta-heuristic optimization in a sequential manner, the proposed protocol is devised to alleviate key issues in HWSNs including limited energy, constrained environments, and limited operation times. These improvements play an imperative role in enabling HWSNs to achieve the demands of IoT-driven large-scale environments and also new-generation smart applications [7]. Here the new concept is proposed namely Meta-Heuristic Algorithms based Collaborative Dynamically Clustered Routing Protocol for Energy Aware Heterogeneous Wireless Sensor Networks. For establishing clustering and efficient routing, a Collaborative Dynamically Clustered Routing Protocol is designed which relies on the highest expected residual energy that minimizes the energy consumption. Conversely, a Meta-Heuristic Algorithms is utilized to minimize the delay and routing overhead which is the hybrid optimization method comprises Genetic Algorithm and Whale Optimization Algorithm (WAO).

A. Research Motivations

Effective use of power is most essential for attaining successful sensor localization in Heterogeneous Wireless Sensor Networks. Clustering, being a prominent approach, facilitates competent data aggregation while ensuring the saving of power. This approach acts by dividing the network into a base station (BS), clusters, cluster heads (CHs), and sensor nodes. Main advantages of clustering are less communication delay, reduction in overhead, equalization in load, and increased fault tolerance. Yet, issues like inefficient sensor placement and poor cluster head selection in current frameworks have led to inferior connectivity and network performance.

Existing methods of power consumption maximization in HWSNs [8–14] have been successful but often do not yield adequate efficiency and network lifetime levels. As a result, the proposed scheme considers a dynamic CH selection process with significant parameters like node distance, speed, residual energy, packet delivery ratio, mobility, and correlation intensity. This comprehensive parameter set enables improved CH communication, with seamless processes such as node handovers among clusters. The suggested approach also arranges node-to-node distances, CH-to-node distances, and BS-to-node distances to preclude connectivity issues and network congestion. With dynamic CH mobility monitoring, the approach enables efficient and stable communication in high-density networks, significantly enhancing the reliability and performance of HWSNs.

B. Contribution of the Research

1) Design of an Energy-Efficient Routing Protocol: is specifically designed to enhance energy efficiency, latency minimization, and overhead reduction in HWSNs.
2) 2-Combination of Collaboration and Optimization Techniques:

The MHA-CDCRP consists of two key components:

- The Collaborative Dynamically Clustered Routing Protocol (CDCRP) highlights dynamic clustering and the choice of an optimal Cluster Head (CH) as fundamentals in reducing energy consumption and providing efficient energy balance throughout the network.
- The Meta-Heuristic Genetic Whale Optimization (MHGWO) combines the Whale Optimization Algorithm with Genetic Algorithms for optimizing CH selection and routing mechanisms.

3) Dynamic CH Selection and Network Stability:

The proposed protocol uses advanced parameters such as residual energy, mobility, and packet delivery ratio to improve stability in CH and also smooth node transfer in clusters. By this approach, connectivity issues are mitigated, traffic congestion reduced, and communication efficiency achieved, particularly in high-density networks.

4) Comprehensive Performance Evaluation:

The protocol's performance is evaluated with the help of Network Simulator 2 (NS2), and its performance is compared to conventional methods. The main performance metrics considered for measurement are energy efficiency, packet delivery ratio, end-to-end delay, routing overhead, and throughput, thereby revealing the considerable enhancements obtained by the MHA-CDCRP scheme.

II. Related Works

In the domain of biological sciences, bio-inspired methods based on biological phenomena have been utilized within the clustering process, providing a potential method to construct clusters in terms of devices' energy allocation as well as the inter-cluster spatial interactions and the nodes forming them. Bio-inspired approaches provide a flexible platform for load balancing in this environment, which can be combined with clustering mechanisms to provide enhanced energy efficiency. Some of the most used biologically inspired optimization algorithms include Genetic Algorithms, Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Wolf Search Algorithm (WSA), and Social Spider Algorithm (SSA). Machine learning can also be utilized to optimize energy consumption in security systems, with artificial intelligence approaches helping with the detection of threats. Each one of these technologies supplements others for enhancing both energy efficiency and cybersecurity in sophisticated systems [15, 16].

Recent studies in clustering protocols have shown a trend towards hybrid optimization techniques. Bhushan *et al.* [8] proposed a hybrid clustering protocol in order to optimize the number of CHs by using inter-cluster and intra-cluster distances. Although it improves energy efficiency, its computational complexity is quite high. Likewise, Dogra *et al.* [9] employed the Sailfish Optimizer for CH selection and routing with the minimum number of inactive sensor nodes at the cost of adding system complexity.

In dealing with mobility and energy efficiency, Singh *et al.* [12] used a variant of Genetic Algorithm for CH selection, which was aimed at energy consumption. But the throughput suffered as the parameters were not optimized to a greater extent. Gong *et al.* [17] proposed a fuzzy clustering scheme in which cluster size was dynamically changed according to the energy and communication cost. This scheme increased the network lifetime but required a high computational overhead in dense networks. Our proposed MHA-CDCRP method uses metaheuristics to dynamically select CHs and optimize routing paths with reduced computational overhead, making it suitable for dense and heterogeneous networks.

By hybridizing GA with WOA, the proposed MHA-CDCRP overcomes these limitations by balancing global exploration and local exploitation. Additionally, the inclusion of mobility-aware parameters, such as node speed and distance, enhances energy efficiency while maintaining scalability in dense and dynamic networks. Ramteke *et al.* [11] suggested an adaptive Particle Swarm Optimization (PSO) ensemble with genetic mutation-based routing to solve the load balancing problem by providing an efficient path for data transfer. This technique minimizes the load balancing problem but energy consumption is increased. Sood and Sharma [13] proposed a new Uniform Connectivity based clustering Protocol to improve the energy-efficient coverage in three-tier heterogeneous network. To increase the cluster head selection a rotation epoch conditions are introduced. However, it reduces the computational complexity but affects the latency and reliability of the system. Furthermore, a model suggested to reduce the packet loss and delay in packet deliver in the network, a neuro fuzzy based cluster formation and routing protocol is implemented. However, the energy efficiency problem is increased due to design of sensor nodes [18]. Alomari *et al*. [19] were presented a mobile clustering routing protocol to increase the life span and the throughput of the network. Further, the selection of cluster formation is processed. Although this method was precise and effective, it adds computational overhead [20]. A hybrid Bee Colony Optimization and Firefly Algorithm for CH selection in HWSNs were proposed in Ref. [21]. This approach enhanced load balancing and energy efficiency by considering node energy and proximity during CH selection. However, the reliance on multiple optimization layers increased algorithmic complexity, impacting real-time deployment.

In addition, an optimized genetic algorithm for cluster head election was proposed in Ref. [22], primarily aimed at reducing the energy consumption of HWSNs. The parameters which are considered for the process of CH selection are node density, distance and energy. The communication models which are concentrated in the process are inter-cluster communication and intra cluster communication. The drawback identified in this method is the energy dissipation is occurred during the process of nodes leaving the present cluster and joining to the new cluster. Hence, the mobility or node speed is not considered in CH parameter selection that leads to the increase of delay and energy consumption during communication. Using only these parameters the desired level of performance cannot be attained in HWSN network. After analyzing the earlier researched we found the achieving maximum energy efficiency using effective CH selection process is still in the open research area. Maximum of the earlier works failed to concentrate on the node mobility in HWSN network. On the other hand, energy consumption can occur during the process of node leaving and joining in the cluster as well effective distance analysis is also not performed. These are all the major drawbacks which are identified in the earlier researches of HWSN network. To overcome this in our research Meta-Heuristic Algorithms based Collaborative Dynamically Clustered Routing Protocol is proposed where the parameter chosen for CH selection process are more effective when compared with the earlier works. Several studies have reviewed the advantages of hybrid metaheuristic algorithms, offering both theoretical and experimental insights into how combining different optimization techniques can improve performance. Our approach employs hybrid MHAs (GA and WOA) to enhance load balancing and energy efficiency, reducing computational complexity by limiting the number of optimization layers. For example, a comprehensive review on hybrid metaheuristics highlights the performance enhancements achievable through hybridization, emphasizing its ability to leverage the complementary strengths of different methods [23]. Furthermore, empirical evidence from hybridizing GA with ACO has demonstrated significant performance improvements, a concept that parallels the rationale for combining GA with WOA in Ref. [24]. Furthermore, the benefits of hybridization, particularly with bio-inspired algorithms like WOA, have been extensively discussed, showing how such combinations can lead to more efficient and effective solutions in complex optimization problems [25]. Unlike earlier methods, which often neglect node mobility or rely on static parameters, our approach dynamically adapts to changes in the network topology. This reduces energy dissipation during cluster reformation and ensures efficient communication paths, even in highly dynamic environments.

III. OVERVIEW OF MHA-CDCRP PROTOCOL

Heterogeneous wireless sensor networks yield greater benefits in real-time applications than do homogeneous networks. The distinct and dynamic nature of HWSNs is in high need of efficient and flexible routing protocols that will realize reduced energy consumption and elongated network lifetime. This paper proposes an advanced method of enhancing HSWNs using modern optimization techniques.

Mainly, it forms a mobility model and divides nodes according to various parameters, one of which is the geographically located positions with energies and communication ranges. The routing protocol used in this paper is the Cluster-Based Dynamic Routing Protocol, which had shown the exchange of the data between clusters with assigned Cluster Heads (CHs) for between-cluster communications. To select CHs two advanced things are mentioned here: the MHGWO-GWO-MFO algorithm and the Enhanced Whale Optimization Algorithm. The refinements included choice of CHs, data aggregation, and routing algorithms.

The proposed MHA-enhanced CDCRP protocol is evaluated through performance analysis, considering variables such as node count and speed. Comparisons with existing approaches like Hybrid Genetic Algorithm Collaborative Dynamic Clustering Routing Protocol (HGA-CDCRP) and Distance and Energy Aware Stable Election Routing Protocol for Heterogeneous Wireless Sensor Network (DESEP-HWSN) demonstrate significant improvements in overhead reduction, energy efficiency, and routing optimization. Future research should focus on addressing real-world deployment challenges, including security and fault tolerance. Fig. 2 presents the structure of the proposed MHA-CDCRP Protocol.

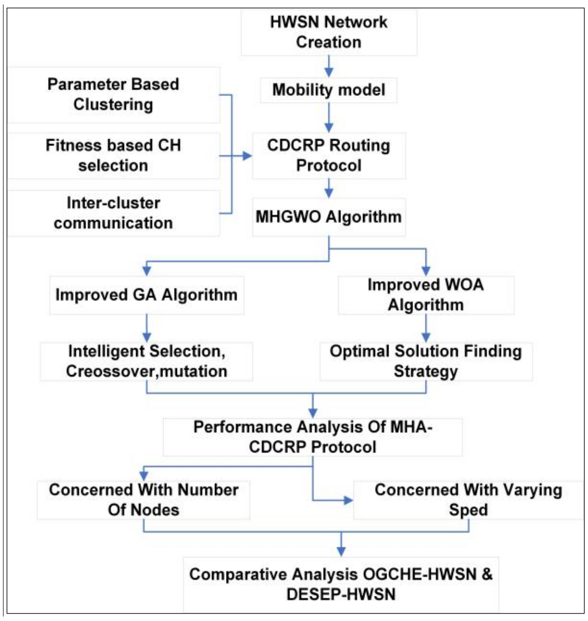


Fig. 2. Flow diagram of the MHA-CDCRP protocol.

Traditional multi-hop communication in HWSNs can lead to increased traffic, network congestion, delays, and overhead, ultimately impacting power consumption. Energy and Quality of Service (QoS) optimization require continuous, dynamic adjustments to task assignment and scheduling in response to network fluctuations, vehicle dynamics, and energy availability.

Several research works have focused on energy-efficient clustering and routing strategies in WSNs for specific application scenarios. For instance, energy harvesting has been shown to contribute significantly to prolonging network lifetime, as demonstrated in Ref. [26]. Although applicable in some scenarios, this will entail extra hardware, which can add to the cost of deployment.

Energy efficiency through data flow optimization in static networks was addressed [27] . However, this scheme is not adapted to dynamic network topologies, where node mobility and re-clustering events are prominent energy dissipation causes.

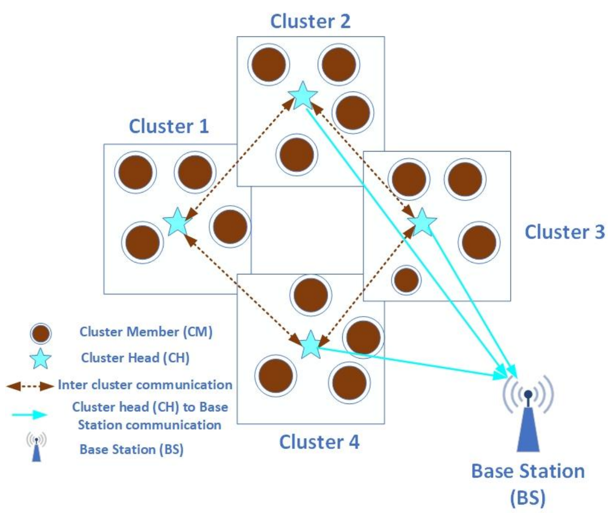


Fig. 3. Architecture of network model.

Cooperative routing mechanisms have been proposed to address unique challenges such as high energy consumption and low communication reliability, as suggested in Ref. [28]. Although it has enjoyed success in the underwater environment, the applicability of this to the terrestrial WSNs is rather limited due to the differences in the communication models and energy dynamics.

To address these challenges, a clustering-based routing protocol is introduced, incorporating CHs, Cluster Members (CMs), and a Base Station (BS). Communication within this network involves inter-cluster, intra-cluster, and data transmission between CHs and the BS. CHs are responsible for data collection from CMs, aggregation, and subsequent transmission to the BS. Fig. 3 illustrates the architecture of the network model.

A. Collaborative Dynamic Clustering Routing Protocol (CDCRP)

In order to create a best network to work effectively with dynamic topologies in our research we developed an effective routing protocol namely Collaborative Dynamic Clustering Routing Protocol for HWSN. In CDCRP protocol, selection of CH is the complicated task. The parameters which are taken for CH selection are node distance, speed, residual energy, packet delivery ratio, and mobility and correlation intensity. According to these parameters the fittest node to become a CH is calculated.

During the process of communication in the rhombus shape HWSN network which is intersected into several clusters. All the nodes in the clusters are interconnected and they are accountable to the CH. If any nodes detect information it passes those data to all the nodes which are in its coverage area which affects the communication efficiency. In the earlier cluster based researches in HWSN the neighbor nodes of CH is maintained periodically which creates routing overhead at the time of data transmission. Periodically message transmission for neighbor identification is not an effective model for HWSN. So in our CDCRP routing protocol, multiple dynamic CH selection is performed where the neighbor identification is also carried out which the help of the CH. Concerning with certain parameters like node distance, speed, residual energy, constancy factor, and packet delivery ratio and correlation intensity, CH is chosen. During the process of transmission is any nodes receives a message it transfer it directly to the CH then followed by the inter cluster transmission will takes place and at the end it reaches the destination. This method greatly reduces the network overhead, delay and energy consumption. The work flow diagram for CDCRP routing protocol is shown in Fig. 4.

Mobility clustering adapts to changes in node power levels, moving, and network topology, thereby balancing energy usage across the network. This contrasts with static clustering, which fixes group configurations and often leads to uneven energy drain between nodes. Dynamic clustering in MHA-CDCRP reduces reaggregation overhead and extends network lifetime by ensuring clusters remain energy efficient and responsive to network conditions.

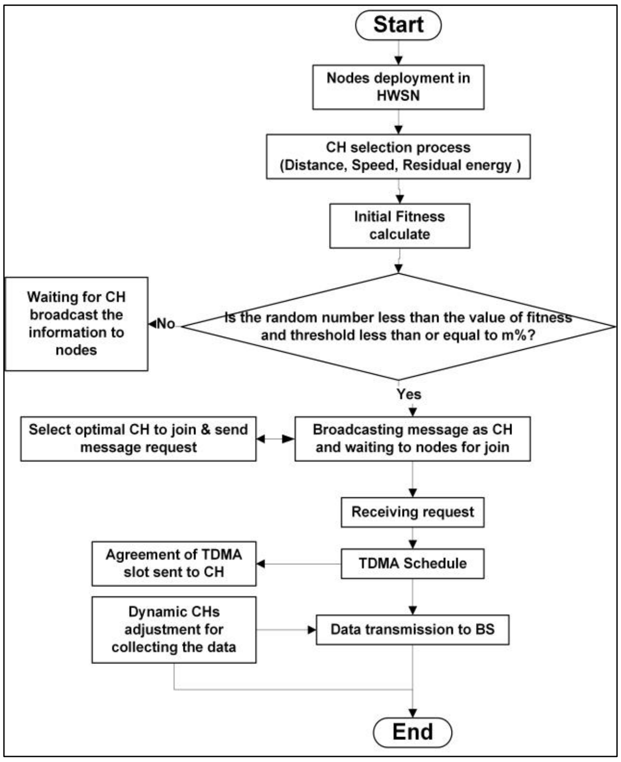


Fig. 4. Flowchart of the CDCRP protocol.

B. CH Selection Process

Initial stage basic parameters taken for CH selection are listed here. Node distance is denoted as that $Dis_{(N_1,N_2)}$ which represents the distance between two nodes N_1 and N_2. The attributes used for this are $\left(A_{N_1}, B_N\right)$ and $\left(A_{N_2}, B_{N_2}\right)$ correspondingly and it is derived mathematically in Eq. (1) [29].

$$Dis_{(N_1,N_2)} = \sqrt{(A_{N_1} - A_{N_2})^2 + (B_{N_1} - B_{N_2})^2} \quad (1)$$

Followed by that, the node speed is measured with the help of considering its threshold value and velocity. The mathematical expression for the calculation of Node Speed (NS) is given in Eq. (2).

$$NS_{node} = \frac{TH_{node} \times V_{node}}{time} \quad (2)$$

In Eq. (2), the terms TH_{node} and V_{node} implies the threshold value and velocity of the node which is selected at each instant of time during communication. Considerably the residual energy calculation is an important aspect to analysis the node performance. Therefore, the residual energy of the node is also considered in this calculation where its mathematical expression is given in Eqs. (3) and (4).

$$RE_{node} = IE_{node} - EC_{node} \quad (3)$$

$$EC_{node} = DT_{node} + DA_{node} \quad (4)$$

In Eqs. (3) and (4) the term RE_{node} implies the node residual energy, IE_{node} implies the initial energy, EC_{node} implies the node energy consumption, DT_{node} implies the energy gets utilized during data transmission and DA_{node} implies the energy gets utilized during data aggregation. Next, to understand the effectiveness of each node its packet delivery rate is considered and it is mathematically expressed in Eq. (5).

$$PDR_{node} = \frac{RP_{node}}{TP_{node}} \times 100 \quad (5)$$

In Eq. (5), the terms RP_{node} implies the node's received packets and TP_{node} implies the node's transmitted packets. In this situation using certain parameters like node speed NS_{node} , node individual delivery rate PDR_{node} and distance between any two nodes $Dis_{(N_1,N_2)}$ the correlation intensity is measured and it is mathematically expressed in Eq. (6) [30].

$$CI_{node} = \frac{NS_{node} . PDR_{node}}{Dis_{(N_1,N_2)}} \quad (6)$$

By considering from Eqs. (1) to (6), the initial fitness for each node is measured by considering the mathematical expression Eq. (7).

$$IF_{node} = \frac{(\alpha . RE_{node}) + (\beta . CI_{node})}{2} \quad (7)$$

In the second level of CH selection process, certain parameters are taken to find the best among the nodes which becomes CH; they are neighbor node proximity calculation and node queue level. The neighbor node proximity (PR_{nn}) is mentioned mathematically in Eq. (8).

$$PR_{nn} = \frac{1}{T_{nn}} \sum_{n=(1,2,..i)}^{T_{nn}-1} Dis_{(N_1,N_2)} \quad (8)$$

In Eq. (8), the terms T_{nn} implies the presence total neighbor in HWSN network, $Dis_{(N_1,N_2)}$ implies the distance between the current node and its possible neighbors. Followed by that the node queue level is measured and it is expressed in Eq. (9) [31].

$$QS_{node} = \frac{IQS_{node} - CQS_{node}}{FL} \quad (9)$$

In Eq. (9), the term QS_{node} implies the queue length of the node, IQS_{node} implies node's initial queue size, CQS_{node} implies the consumed queue size and FL implies the single frame length of node at each instant of time. In the proposed CH selection process with the help of the Eqs. (7)–(9) CH is chosen. The nodes which are present very nearer to the BS will transmit the data directly to BS so that it does not require any CH to transmit the data. The CH is created mainly to control the nodes which are present outer the coverage area of the BS. Once after the selection of CH, it can able to transmit its advertisement through broadcast messages within its coverage radius. The CH's overage radius is measured using the following mathematical expression in Eq. (10).

$$R_{CH} = \sum_{n=1}^{N} \left[\left(1 - C_{size} \times \frac{Dis_{(N,BS)} - Dis_{(CH,BS)}}{Dis_{(N,BS)}} \right) \times \frac{PE_{CH}}{RE_{CH}} \right] \quad (10)$$

In Eq. (10), the terms R_{CH} implies the CH radius, C_{size} implies the cluster size, $Dis_{(N,BS)}$ implies the distance between any node to the BS, $Dis_{(CH,BS)}$ implies the distance between the current CH to the BS, PE_{CH} implies the present CH efficiency and RE_{CH} implies the residual CH efficiency. The node will transmit the request message to the CH within certain coverage area which is mathematically given in Eq. (11).

$$R_{node} = \sqrt{(M.M)/(\pi . CH_{opt})} \quad (11)$$

In Eq. (11), the term R_{NN} implies the node radius, $(M \times M)$ implies the network coverage area and CH_{opt} implies the optimal CH count. The optimal CH count is measured using certain criteria and its math calculations are given as follows.

$$CH_{opt} = \left(\frac{\sqrt{T_{node}}}{\sqrt{2\pi}} \right) \left(\sqrt{\varepsilon_{fs} / \epsilon_{mp}} \right) \left(M / {Dis_{toBS}}^2 \right) \quad (12)$$

$$Dis_{(CM,CH)} = M / \left(\sqrt{2\pi CH_{opt}} \right) \quad (13)$$

$$Dis_{(CH,BS)} = 0.765 \left(\frac{M}{2} \right) \quad (14)$$

In Eqs. (12)–(14), the terms T_{node} implies the total number of nodes, $Dis_{(CM,CH)}$ implies the distance between the cluster member (CM) to CH and $Dis_{(CH,BS)}$ implies the distance between the CH to BS. By this way the effective CH is selected in the proposed CH selection process.

At this condition after the process of node localization and CH selection, all the elected CH maintains its own TDMA schedule to perform data transmission with the CM nodes and BS. In case is some area the CH coverage is absent at those condition a mobile Access Point (AP) is elected to collect the data from the outer coverage sensors. At the initial condition the AP transmit the "HELLO" packets to those nodes and check the ID where it belongs to the BS and wait for response. Once after getting the confirmation it transmit the data using the TDMA schedule [30]. Both AP's ad CHs maintains the TDMA schedule for data transmission. Once after collecting the data from the particular outer coverage sensors the data gets transmitted to the respected CH or the BS. Hence each network structure consists of multiple CHs, it is essential to create m slots of TDMA schedule. If some case the BS will present far away from the CH at that condition the APs collects the data from the respective CH and then transmit that to the BS.

Followed by this the CH consists for adjustable sensing range to improve its efficiency to control the HWSN network. So that it can able to overcome the data overlapping issues as the results the power utilization of CH gets reduced. Hence the network model is HWSN all the sensors nodes are mobile in nature so that at certain instant CHs also maintains a dynamic sensing range where it can able to cover dense cluster containing nodes and that can also present in the vicinity of other CHs. In order to optimize the power utilization the CH which contains more energy efficiency can able to collect more data from the densely populated area and it get transmitted to the BS simultaneously. Through this process the power utilization of the CHs can be reduced that helps to reduce the total transmission power utilization as the results the high connectivity can be achieved with minimum deployment cost [32]. According to certain parameters the CH sensing range is obtained they are, (i) sensors sensing range, (ii) CH and nearest CM node distance and (iii) CH and longest node distance. The measurement of CH sensing range is mathematically expressed in Eq. (15).

$$CH_{SR} = \left(1 - C_{size}\left(\frac{Dis_{max-CH} - Dis_{(CH,CM)}}{Dis_{max-CH} - Dis_{min-CH}}\right)\right) \quad (15)$$

In Eq. (15), the term CH_{SR} implies the sensing range of the CH, CH_{size} implies the cluster size, Dis_{max-CH} implies the maximum coverage distance of the CH, Dis_{min-CH} implies the minimum coverage distance of the CH, $Dis_{(CH,CM)}$ and implies the current distance of the CM and the CH. According to this network structure it is stated that the CH which is closest to the BS consists of minimum number CM nodes and the CH which is present farthest to the BS which consists of longest coverage area when can able to maintain maximum number of sensors.

C. *Bio-Inspired Meta-Heuristic–Genetic Whale Optimization Algorithm (MHGWO)*

MHGWO algorithm is the combination of two effective optimization models like Genetic Algorithm and Whale Optimization Algorithm. In our hybrid optimization process, optimization is performed in two levels; they are initial optimal path selection and best optimal solution finding. In the MHGWO algorithm, GA is used for initial optimal path selection and WOA algorithm is used for best optimal solution finding process.

In the proposed MHGWO process, the GA algorithm is used to find the initial best path selection for the nodes that leads to perform effective inter and intra cluster communication in HWSN. The proposed MHGWO algorithm combines the strengths of the Genetic Algorithm and the Whale Optimization Algorithm to overcome their respective weaknesses. While GA is good at maintaining diversity and exploring the search space globally, it often suffers from premature convergence. On the other hand, WOA is good at exploitation by improving solutions in the local neighborhood, but it could lack the diversity needed for global optimization. By hybridizing these algorithms, MHGWO successfully combines the exploration ability of GA and the exploitation efficiency of WOA, hence forming a balanced search mechanism. The combination ensures a solid convergence to optimal or near-optimal solutions and avoids the problems of local optima stagnation. Empirical results demonstrate that MHGWO has better performance in terms of convergence speed, solution quality, and robustness compared with independent GA, WOA, and other state-of-the-art algorithms. A hybrid algorithm combining WOA with another optimization technique, showcasing the advantages in solving engineering problems [21]. In addition, the studies [23–33] have discussed the combination of heuristic algorithms.

1) Population Initialization: At the initial condition, the population declaration in done randomly where the chromosomes are generated in a random manner. The primary stage chromosomes are denoted as P_{cs} which maintain the nodes information such as its categories CH, CM or DN (Dead Nodes). Hence the number of nodes in the network is predefined so that the number of CH which is needed to cover the entire network can be easily defined. The secondary stage chromosomes are denoted as S_{cs} which maintains the routing information of the nodes which is present in P_{cs}.
2) GA process and conditions: The process which is involved in this section is illustrated in Fig. 5. This GA process consist various steps behind it. They are selection, crossover, mutation and fitness calculation and as well it is performed using the chromosomes and it occurs for the maximum number of iteration. The results obtained from GA provide the initial best path among the nodes. So the initial optimal condition is activated to CH, CM and BS. At this condition the power utilization among the nodes are analysed to find the optimality of nodes which is performed using the objective functions f_a and f_b . The math expressions to address the process of the objective functions are given below.

$$f_a = \frac{Dis_{Intra\_C}}{Dis_{Inter\_C}} \quad (16)$$

$$f_b = \frac{RE_{CM}}{RE_{CH}} \quad (17)$$

In Eqs. (16) and (17), the terms Dis_{Intra_C} implies the intra cluster distance, Dis_{Inter_C} implies the inter cluster distance, RE_{CM} implies the CM residual energy and RE_{CH} implies the CH residual energy.

3) Fitness Calculation Process: Fitness function is calculated using the objective functions like Dis_{Inter_C} and Dis_{Intra_C} and as well its math expression is given as described.

$$Dis_{Inter\_C} = \sum_{a,b} Dis\ (CH_{a,b}) \quad (18)$$

$$Dis_{Intra\_C} = \frac{1}{CH_{count}} \sum_{a} \sum_{b \in C_1} Dis\ (CM_{b,} CH_a) \quad (19)$$

From Eqs. (18) and (19), the term $Dis\ (CH_{a,b})$ implies the distance between any two CHs and $Dis\ (CM_{b,} CH_a)$ implies the distance between CM and its respective CH. Using this process the initial path selection is performed in the proposed work.

WOA algorithm is the highly intelligent optimization model which analysis the social behaviour and hunting strategy of whales. The strategy mainly consists of two processes such as upward-spirals and double-loops. The math model consists of three main processes namely prey encircling, spiral bubble-net feeding process, and prey search. At the initial stage, prey encircling process gets performed using that the optimal solution for position identification is performed. The math expression for this better candidate selection process is expressed in Eqs. (20) and (21).

$$\vec{D} = \left|\vec{C}.\vec{X}.(t) - \vec{X}(t)\right| \tag{20}$$

$$\vec{X}(t+1) = \vec{X}.(t) - \vec{A}.\vec{D} \tag{21}$$

In Eqs. (20) and (21), the term $\vec{C}$ and $\vec{A}$ implies the coefficient vectors, $\vec{X}$ implies the vector position of the best optimal solution and as well its value get updates at each instant of time. The mathematical expression for the coefficient vectors are measured as below.

$$\vec{C} = 2\vec{r} \tag{22}$$

$$\vec{A} = 2\vec{a}.\vec{r}\text{-}\vec{a} \tag{23}$$

In Eqs. (22) and (23), the term $\vec{r}$ implies the vector which the range of [0, 1], and $\vec{a}$ implies the iteration source which gets linearly decreased as of 2 to 0. The optimal candidate can be achieved by adjusting the coefficient vectors. Followed by that the process of spiral bubble-net feeding process gets initiated and its math expressions are given in Eqs. (24) and (25).

$$\mathrm{X}'(t+1) = \mathrm{D}'.e^{bl}.\cos(2\pi l) + \mathrm{X}'\mathrm{x}(t) \tag{24}$$

$$\mathrm{D}' = |\mathrm{X}'\mathrm{x}(t) - \mathrm{X}'(t)| \tag{25}$$

In Eqs. (24) and (25), the terms D' implies the optimal solution of first stage, b implies the logarithmic spiral with this constant value, l implies the variable in the form of random number which ranges from [–1, 1]. In general the whale creates a spiral-shaped path with certain form which is expressed in equation below.

$$\vec{X}(t+1) = \begin{cases} \vec{X}.(t) - \vec{A}.\vec{D}, & if\ p < 0.5 \\ \vec{D'}.e^{bl}.\cos(2\pi l) + \vec{X}.(t), & if\ p \geq 0.5 \end{cases} \tag{26}$$

In Eq. (26), the term p implies the random value which ranges from [0, 1]. Finally, the process of prey search is preceded. The math expression of the global prey search is mentioned as below in Eq. (27) and (28) where the value of $\vec{A}$ is random and it has to be more than 1.

$$\vec{D} = \left|\vec{C}.\ \vec{X}_{rand} - \vec{X}\right| \tag{27}$$

$$\vec{X}(t+1) = \vec{X}_{rand} - \vec{A}.\vec{D} \tag{28}$$

With the help of this math analysis the general best solution can be obtained and it is most suitable for WSN. Hence our network model is HWSN is needs further improved. For that purpose Obstacle Avoidance based WOA (OAWOA) is developed. At the end of calculating the above three random movements, the idea of OAWOA is initiated. The Pseudo code for the process of OAWOA is given below. Here the initial whale population $\vec{X}$ gets analyzed according to the mobile sensors which is present in the network and as mentioned $\vec{X}$ implies the best optimal solution. According to the mobility of the sensors its randomness needs (the random movement patterns of mobile sensor nodes within the network. Sensor nodes may move unpredictably due to environmental factors or the design of the system, which can lead to changes in the network topology) to get concentrated, particularly the obstacle points (locations or areas within the network environment that impede or obstruct the movement of sensor nodes).

Algorithm 1. Pseudo code for the process of OAWOA

1. Calculation of number of movements using $X_i(i = 1,2,\ldots,n)$
2. Fitness calculation **for** each candidate $\vec{X}$
3. $\vec{X}*$ implies the best optimal solution
4. **If** the time is greater than T_{max} then the general process of WOA such as prey encircling, spiral bubble-net feeding process, and prey search gets updated which is denoted from the Eqs. (20) to (28).
5. Search space of the candidate are analysis to find **if** any candidates crossed its region.
6. Measure the final fitness for every candidate then update the $\vec{X}*$ value
7. Find the best $\vec{X}*$ the best optimal solution

To address scalability concerns, we have conducted a thorough analysis of the computational complexity of the hybrid MHGWO algorithm. The complexity is broken down as follows:

1. Time Complexity: The time complexity of the hybrid MHGWO algorithm is primarily influenced by the number of iterations T and the size of the population N. For each iteration, the computational cost involves evaluating the fitness function for each individual in the population. Thus, the overall time complexity for the algorithm is O (T. N), where (T) represents the number of iterations and (N) is the number of candidate solutions in the population. The complexity of the fitness evaluation depends on the specific problem and can be denoted as O (f), leading to a total time complexity of O (T. N. f).

2. Scalability Considerations: The scalability of the algorithm is a critical factor for large networks. As the network size increases, both (N) and (T) may grow, leading to increased computational cost. Specifically, for larger networks, the time complexity grows linearly with the size of the population and the number of iterations, which can become prohibitive in practice.

3. Heuristic Approximations: In large-scale networks, exact solutions may not always be necessary. By implementing heuristic approximations or simplified versions of the algorithm, we can achieve near-optimal solutions with reduced computational complexity. For example, using a reduced population size or fewer iterations can significantly decrease computation without sacrificing significant performance.

Dynamic clustering is used by the CDCRP framework to arrange nodes according to network structure and energy efficiency. With Cluster Heads (CHs) facilitating data aggregation within the cluster and communication between the clusters, these clusters form the basis of the routing protocol. Energy consumption is reduced, redundant transmissions are minimized, and efficient data delivery to sink nodes is ensured due to this interaction.

These strategies will ensure that the hybrid MHGWO algorithm remains scalable and computationally feasible for large-scale networks, making it suitable for practical deployment in real-world scenarios.

IV. Experiment Setup

The simulation of the proposed MHA-CDCRP routing protocol is performed in the Network Simulator 2 (NS-2). To evaluate the performance of the proposed MHA-CDCRP approach we used NS-2 simulation. The simulation parameters and methods used in this study are thoroughly discussed, and the proposed protocol is compared with the existing protocols An Optimized Genetic Algorithm for Cluster Head Election in IoT-Based HWSNs (OGCHE-HWSN) [34] and DESEP-HWSN [35]. The simulation is conducted on a computer system equipped with an Intel Core i7-8700T processor running at 2.3 GHz. The operating system used is Windows 11, and the computer has 16 GB of RAM. A total of 100 nodes are randomly distributed across a monitoring zone of 100 × 100 m^2, taking into account the total energy of the network, which is 70 Jules. The proposed protocol involves four Mobile Stations (MSs), with two sinks located inside the networks and two sinks located outside the networks. Additionally, there are four MSs located outside the networks with Automatic Speech Recognition (ASR), and four MSs with two sinks within the networks and two sinks outside the networks, also with ASR. The radius for the mobility of the sinks outside the networks is 70 m, measured from the exact center of the networks. Throughout the network, the radius is 50 m. The performance analysis is performed using two scenarios they are varying number of nodes and varying speed. Basically, NS2 is one among the event driven simulator with the front end language (Object-oriented Tool Command Language-OTcL) and as well back end language (C++). Table I show the input simulation parameters which are employed in simulation process.

TABLE I. Input Simulation Parameters

Parameters	Values
Simulator	NS2
Time	500 ms
Network Coverage	200 m × 200 m
Threshold Distance	100m
Number of nodes	100 nodes
Packet Size	2000 bits
Antenna Type	Omni-directional Antenna
UMTS Threshold	−94 dBm
Queue Type	DropTail
Initial Power	0.5 J
Transmission Power	0.500 J
Receiving Power	0.050 J

A. Simulation Setup

(1) Node Distribution: Nodes are distributed randomly to simulate a real-world scenario in which sensor nodes are most of the time deployed in an ad hoc way over the target area. This allows the examination of protocol performance under realistic conditions by varying node densities and network topologies.

(2) Energy Considerations: Each node is assigned an initial energy reserve of 0.5 J. The energy efficiency of the protocol is considered, as the Wireless Sensor Networks (WSNs) are subject to the limitations brought about by finite energy resources, especially in applications like remote monitoring and telerehabilitation systems.

(3) Routing Protocol Parameters: The MHA-CDCRP approach integrates a hybrid genetic-whale optimization mechanism in order to dynamically select CHs that ensure minimum energy consumption and maximum throughput, as well as the network lifetime. The routing protocol parameters, including the threshold distance for data forwarding and the energy consumption models, are optimized by its objective of minimal delay and energy usage.

(4) Mobility Model: The mobility of nodes is modeled on a random waypoint model in which the speeds of the nodes vary between 6 km/h and 30 km/h. The impact of node mobility on the end-to-end delay and energy efficiency of the network is evaluated to prove the robustness of the proposed protocol in dynamic environments.

B. Performance Metrics

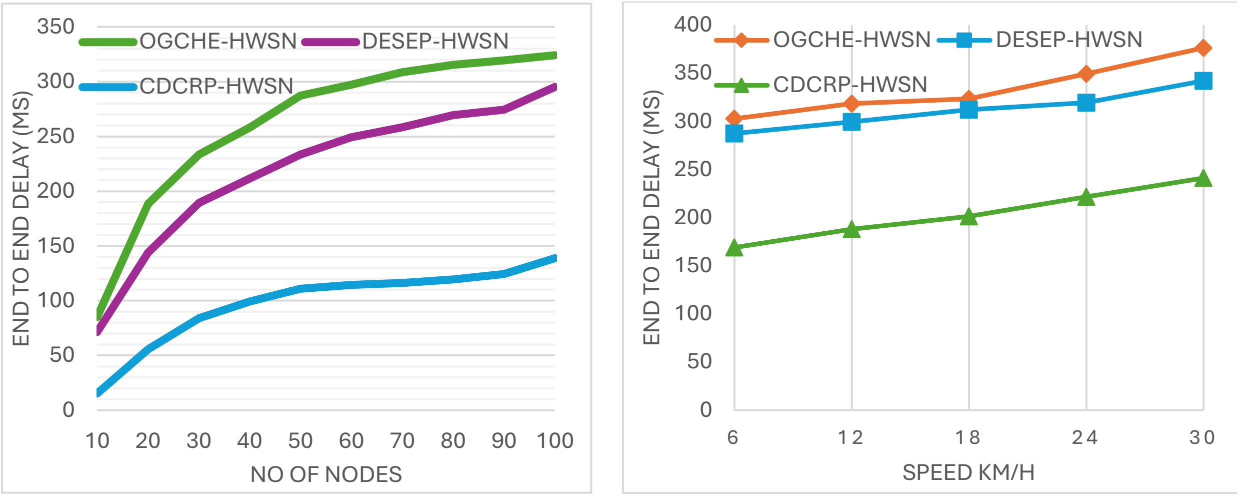
These metrics are used to evaluate the performance of the MHA-CDCRP protocol:

- End-to-End Delay: The average time a packet takes to travel from the source to its destination.
- Energy Consumption: The total energy consumed by the network is a function of the number of nodes.
- Throughput: The rate at which data is successfully delivered across the network.
- Routing Overhead: The amount of control traffic required to maintain network topology and routing information.

C. Performance Analysis

In this section, the simulation results are measured concerned with the number of nodes and varying speed of 6 km/h to 30 km/h, the results are described in the graphical manner for the two exiting methods OGCHE-HWSN, DESEP-HWSN and proposed CDCRP-HWSN approach. The performance of three Hierarchical Wireless Sensor Network (HWSN) protocols OGCHE-HWSN, DESEP-HWSN, and CDCRP-HWSN was evaluated in terms of end-to-end delay under varying numbers of nodes and different speeds. Fig. 5 illustrates these variations and provide insights into the scalability and robustness of these protocols.

Fig. 5 presents the end-to-end delay as a function of the number of nodes in the network. There is an increase in the latency in all protocols at the end and the beginning as the number of nodes increases. However, the magnitude of this increase varies gradually and somewhat significantly between protocols. OGCHE-HWSN shows the largest latency at all node numbers from end to end, starting at 100 ms with 10 nodes and increasing to approximately 325 ms with 100 nodes. We note that the DESEP-HWSN methodology performs slightly better than OGCHE-HWSN, but its latency still increases significantly, from approximately 90 ms at 10 nodes to 300 ms at 100 nodes. In contrast, CDCRP-HWSN shows superior scalability, maintaining a much lower latency that increases modestly from approximately 50 ms at 10 nodes to 120 ms at 100 nodes. This shows that CDCRP-HWSN is significantly more efficient at handling larger, wide-area networks, making it a more scalable solution for environments with a large number of nodes.



(a) (b)

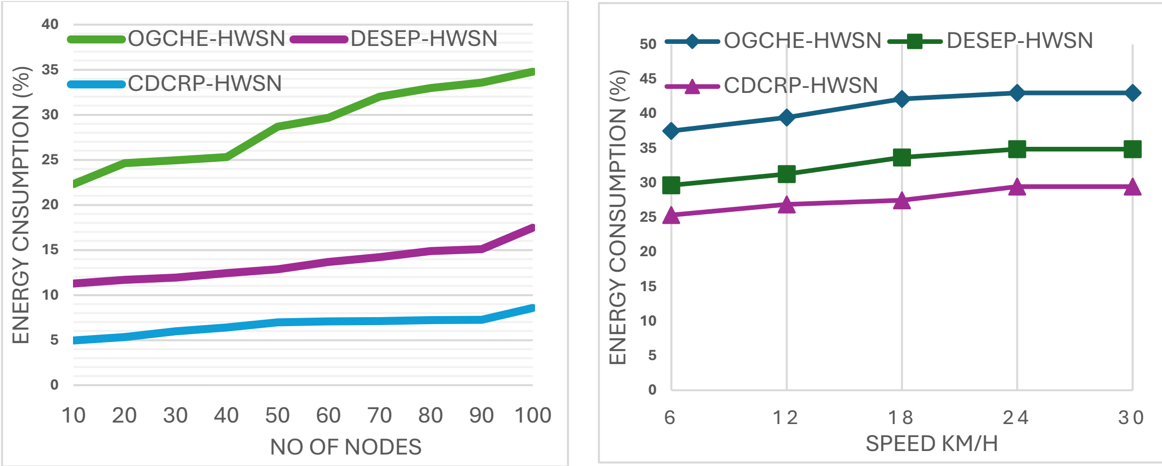
Fig. 5. End to end delay *vs* no. of (a) nodes and (b) speed.

In addition, the end-to-end delay is studied as a function of node speed, measured in kilometers per hour (km/h). As expected, increasing speed results in higher delays for all three protocols. OGCHE-HWSN and DESEP-HWSN show similar performance, with OGCHE-HWSN showing slightly higher delays. At 6 km/h, both protocols have delays of around 300 ms, which increase to around 375 ms and 350 ms, respectively, at 30 km/h. On the other hand, CDCRP-HWSN consistently maintains the lowest delays, starting at around 200 ms at 6 km/h and rising to 275 ms at 30 km/h. This steady increase and overall lower delay suggest that CDCRP-HWSN is more robust in mobile environments, handling higher speeds with less performance degradation than OGCHE-HWSN and DESEP-HWSN.

Comparative analysis confirms the efficiency and robustness of CDCRP-HWSN, especially in scenarios requiring low latency and high reliability, such as telerehabilitation systems. Given the critical importance of timely data transmission in telerehabilitation sessions, CDCRP-HWSN's ability to maintain lower and more stable end-to-end delays makes it the preferred protocol. The results indicate that CDCRP-HWSN can enhance the overall quality of service in telerehabilitation, ensuring that optimal performance remains even as the network expands or when nodes are in motion. Conversely, OGCHE-HWSN and DESEP-HWSN, with their higher latency, may be less suitable for such applications, especially in larger or more dynamic network environments. Fig. 6 shows the percentage of energy consumption relative to the number of nodes for three different Hierarchical Wireless Sensor Network (HWSN) protocols: OGCHE, DESEP, and CDCRP. This metric is critical in evaluating the efficiency and sustainability of these protocols, especially in resource-constrained environments such as wireless sensor networks. The OGCHE-HWSN protocol consistently exhibits the highest energy consumption across all node counts. Starting from an energy consumption of approximately 25% with 10 nodes, it steadily increases, reaching approximately 35% as the number of nodes increases to 100. This suggests that the OGCHE-HWSN may not be the most efficient choice for networks where energy conservation is critical.

In contrast, the DESEP HWSN protocol exhibits moderate power consumption. It starts at around 15% with 10 nodes and gradually increases to around 22% with 100 nodes. Although this represents an improvement over the OGCHE-HWSN, it still indicates that there is room for improvement, especially in larger networks. The CDCRP HWSN protocol exhibits the lowest power consumption among the three protocols. Starting at about 5% of the power consumption with 10 nodes, it only increases slightly too about 10% when the number of nodes reaches 100. This consistently low power consumption highlights the superior efficiency of the CDCRP HWSN protocol in managing power resources, making it highly suitable for enterprises.

A clear trend is observed in all three protocols: energy consumption increases with the number of nodes. However, the rate of increase varies widely. The OGCHE-HWSN shows the steepest rise, followed by the DESEP HWSN, with the CDCRP HWSN having the most gradual increase. This indicates that CDCRP HWSN scales more effectively in terms of energy efficiency than the other two protocols. In conclusion, CDCRP-HWSN not only reduces end-to-end delay but also excels in energy efficiency, making it the optimal choice among the three analyzed protocols. Its ability to maintain low power consumption across an increasing number of nodes underscores its potential for large-scale, power-constrained wireless sensor network applications. The OGCHE-HWSN, with its high energy consumption, may be less suited for such scenarios, while the DESEP HWSN offers a middle ground but still falls short of the efficiency demonstrated by CDCRP HWSN.



(a) (b)

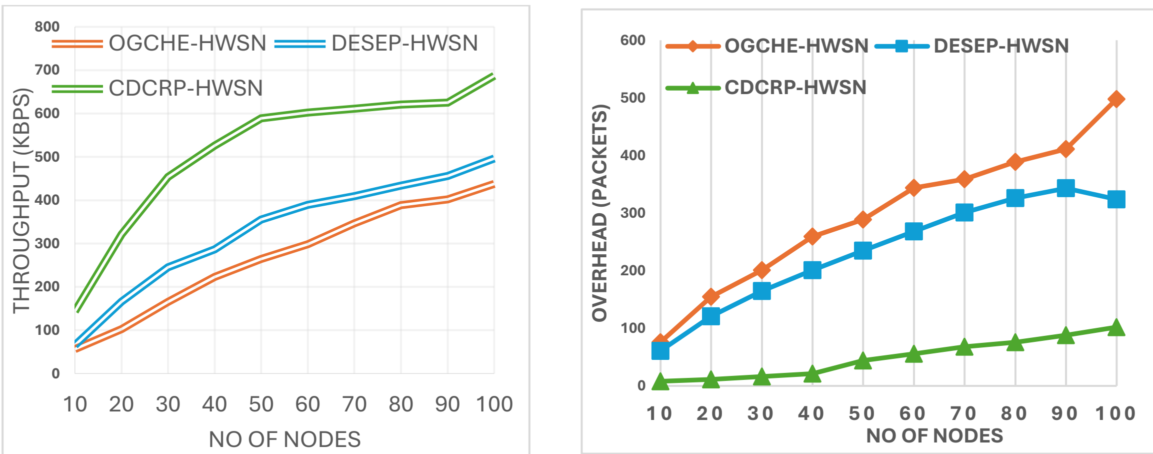
Fig. 6. Energy consumption *vs* no. of (a) nodes and (b) speed.

The OGCHE-HWSN protocol demonstrated moderate throughput, gradually increasing with the number of nodes. It reached approximately 600 Kbps with 100 nodes, indicating its ability to accommodate increasing node densities without significant performance degradation. However, its efficiency was somewhat limited compared to the other protocols.

In contrast, DESEP-HWSN achieved the highest throughput among the three protocols. Starting at around 700 Kbps, it steadily increased to approximately 800 Kbps with 100 nodes. This consistent high performance highlights DESEP-HWSN's suitability for applications demanding high data transfer rates.

CDCRP-HWSN exhibited a balanced performance, falling between OGCHE-HWSN and DESEP-HWSN. While not achieving the peak throughput of DESEP-HWSN, CDCRP-HWSN offered reasonable throughput while maintaining stability, making it a viable option for various applications.

To evaluate routing effectiveness, the total number of data packets transmitted across the network was analyzed. Fig. 7 visually depicts the routing cost, demonstrating that CDCRP-HWSN generated the lowest routing cost compared to OGCHE-HWSN and DESEP-HWSN. This lower cost signifies more efficient resource utilization within the CDCRP-HWSN network, minimizing congestion and improving overall performance.



(a) (b)

Fig. 7. Network (a) throughput and (b) routing overhead *vs* number of nodes.

This study underscores the critical importance of selecting the appropriate protocol based on the specific requirements and performance objectives of the HWSN. While DESEP-HWSN excels in throughput, CDCRP-

HWSN offers a compelling balance between performance and resource efficiency. The choice of protocol will ultimately depend on the critical factors for the particular application, such as data rate demands, energy constraints, and the need for efficient resource management.

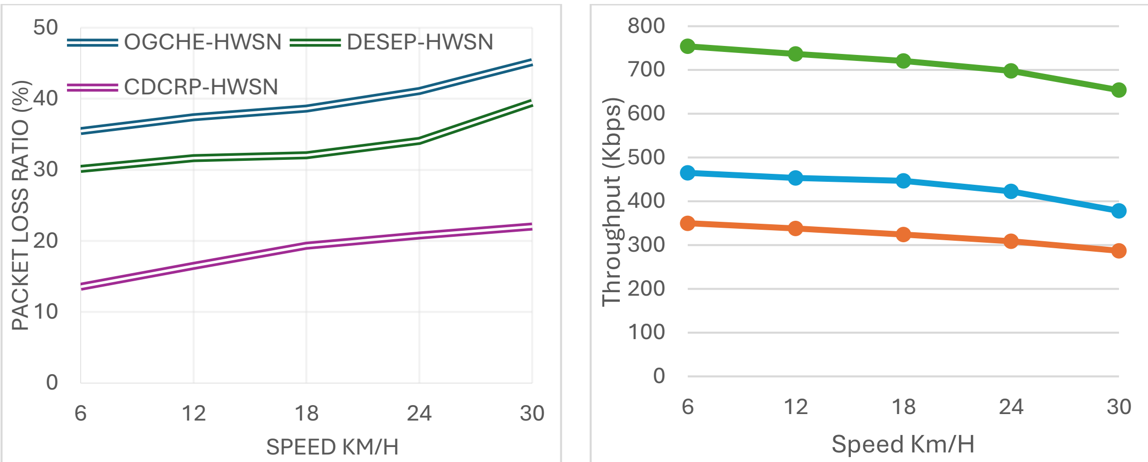
The MHA-CDCRP protocol demonstrates a clear advantage in terms of energy efficiency compared to OGCHE-HWSN and DESEP-HWSN. Our simulation results show that MHA-CDCRP consumes significantly less energy, particularly in larger networks. For instance, when 100 nodes are deployed, the energy consumption of MHA-CDCRP is approximately 10%, which is substantially lower than the 35% energy consumption of OGCHE-HWSN and 22% for DESEP-HWSN. This demonstrates MHA-CDCRP's potential to extend the operational lifetime of the network and reduce the energy burden, which is critical in resource-constrained environments such as telerehabilitation and remote monitoring.

This article evaluated three hierarchical Wireless Sensor Network (WSN) protocols: OGCHE-HWSN, DESEP-HWSN, and CDCRP-HWSN. Throughput was determined by assessing the maximum number of data packets transmitted from each node to its destination, considering both forwarded and lost packets. Fig. 8(a) demonstrates that CDCRP-HWSN achieved a higher throughput compared to OGCHE-HWSN and DESEP-HWSN. Specifically, CDCRP-HWSN's throughput increased from approximately 300 kbps to nearly 500 kbps with 100 nodes, showcasing its ability to maintain a good balance between data transmission rate and stability.

Each protocol exhibited distinct throughput trends. OGCHE-HWSN displayed reasonable throughput that gradually increased with the number of nodes, reaching around 600 Kbps with 100 nodes. DESEP-HWSN consistently achieved the highest throughput, starting at approximately 700 Kbps and increasing to over 800 Kbps with 100 nodes. These results highlight DESEP-HWSN's efficiency, making it a suitable choice for high-performance WSN applications. However, the moderate throughput of OGCHE-HWSN suggests a need for further optimization.

Furthermore, the network load, measured in packets, was examined as the number of nodes increased (Fig. 8(b)). OGCHE-HWSN exhibited moderate load, increasing to approximately 600 packets with 100 nodes. DESEP-HWSN maintained stability, starting at approximately 500 packets and remaining efficient with increasing node numbers. CDCRP-HWSN demonstrated a balanced approach, starting at approximately 300 packets and reaching around 400 packets with 100 nodes.

This comparative analysis reveals DESEP-HWSN's effectiveness in reducing overhead, making it suitable for resource-constrained environments. CDCRP-HWSN strikes a balance between efficiency and stability, providing reasonable throughput with low routing overhead.



(a) (b)

Fig. 8. Represent the (a) Network throughput packet loss ratio, and (b) Network throughput *vs* speed.

The comparative analysis demonstrates the robustness of CDCRP-HWSN, especially in scenarios that require low latency and high real-time reliability, such as telerehabilitation systems. Given the critical importance of timely data transmission in telerehabilitation sessions, CDCRP-HWSN's ability to maintain lower and more stable end-to-end delays makes it the preferred protocol in this area. The results indicate that CDCRP-HWSN can enhance the overall quality of service in telerehabilitation, ensuring that optimal performance remains even as the network expands or when nodes are in motion. Conversely, both OGCHE-HWSN and DESEP-HWSN, with their high latency, may be less suitable for such applications, especially in larger or more dynamic network environments.

One of the major advances in MHA-CDCRP is the hybrid genetic-whale optimization mechanism, MHGWO. This integrated approach combines Genetic Algorithm with Whale Optimization Algorithm for dynamically deciding Cluster Heads in an attempt to reduce energy consumption and increase throughput for prolonging the network lifetime. The strategy presented herein is in direct comparison with the direct optimization approaches of OGCHE-HWSN and DESEP-HWSN that are not able to provide similar degrees of energy-efficient dynamic routing optimization. The superior performance of MHA-CDCRP is also improved by the significantly increased adaptability of the network to environmental condition changes through the hybrid optimization structure.

The proposed method is characterized by hybrid optimization using MHGWO that dynamically adjusts the choice of the network cluster head to balance energy expenditure with maximum throughput. It is this overall strategy and the fact that it can sustain performance under varying node densities and mobility rates that renders it a viable solution for future wireless sensor networks.

The experimental validation in diverse HWSN environments, such as urban, rural, and industrial environments, is to be carried out to determine performance in realistic environments. Environmental Variability, Scalability and Network Size, Energy Efficiency, and Latency and Throughput will be the most important aspects of the experimental testing. Hardware limitations, i.e., low processing capability and energy in sensor nodes, can influence overall performance. To struggle these issues, energy-efficient algorithms and low-power hardware optimization techniques will be researched. Furthermore, network dynamics such as interference, mobility variations, and physical obstacles can influence communication reliability. Adaptive routing strategies and on-line parameter tuning can enhance robustness even more in these cases. These challenges will be a focal area of interest for future empirical studies and optimization.

V. Conclusion

This article considers the improvement of energy efficiency in hierarchical wireless sensor networks. For this purpose, we propose a meta-algorithm-based cooperative dynamically clustered routing protocol, MHA-CDCRP, which is the integration of two fundamental components: the cooperative dynamically clustered routing protocol, CDCRP, and meta-whale genetic optimization, MHGWO. The CDCRP will be designed to have an efficient cluster-based routing protocol while the MHGWO combines both the Genetic Algorithm, GA and Whale Optimization Algorithm, WOA, to provide hybrid optimization. The proposed approach significantly improves the energy efficiency of networks by effective minimization of energy consumption, latency, and overhead of operations in communication within HWSNs. The increased scalability and reduced latency involved with CDCRP make it highly suitable for high-performance WSN applications, especially those requiring reliable and timely data transmission, such as remote rehabilitation systems. The hybrid optimization offered by MHGWO enhances the performance of the protocol to ensure efficient energy management even in large or mobile node networks. This approach optimizes energy consumption while, at the same time, improving the overall network performance in terms of reduced end-to-end delay and related overhead. This characteristic renders it a very effective and powerful option for utilization in applications encompassing large-scale, energy-restricted wireless sensor networks. Further, features such as power consumption and latency minimization in their latest releases require consideration to enable a more comprehensive analysis and understanding of the optimization techniques applicable to heterogeneous wireless sensor networks in a broad assortment of applications. Lastly, security is a significant aspect that must be dealt with during real-world implementation. Heterogeneous wireless sensor networks are vulnerable to a variety of attacks like data tampering, malicious node attacks, and unauthorized access. Encryptions, authentication protocols, and anomaly detection systems must be implemented to provide confidentiality and integrity of data. Utilization of lightweight cryptographic primitives, along with effective key management practices, is also important in attaining security at low computational cost. Future research will aim at overcoming the above challenges for the efficient and effective deployment of the suggested methodology in practical scenarios.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Mohammed F. Alomari conceptualized the research, developed the problem statement, and assisted in developing the methodology. Jaafar S. Alrubaye conducted data analysis, carried out statistical tests, and interpreted results. Abdul Hadi M. Alaidi monitored the execution of the research, offered technical inputs, and assisted in writing the manuscript. Haider TH. Salim ALRikabi read the final draft, ensured the correctness of results, and assisted in revising the paper. All the authors have written, reviewed, and edited the manuscript and approved the final manuscript.

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