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ENHANCED CSMA/CA PROTOCOL-BASED OPTIMAL ROBUST DYNAMIC QUERY-DRIVEN CLUSTERING FOR IMPROVED QoS IN HETEROGENEOUS WSNs

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ABSTRACT
Heterogeneous Wireless Sensor Networks (HWSN) are basically decentralized and distributed systems that playing a crucial role in numerous Internet of Things (IoT) applications, enabling efficient monitoring and data collection. However, these networks often suffer from high latency, routing overheads, and energy consumption. To meet these challenges effectively, This article proposes an enhanced CSMA/CA protocol based on an Optimal Robust Dynamic Query-Driven Clustering Protocol (ECODQC) model. The enhanced model includes two key components: the improved CSMA/CA protocol, which reduces network collisions, lowering delay and overhead during communication, and the Optimal Robust Dynamic Query-Driven Clustering (ODQC) protocol, which efficiently reduces energy consumption among sensors. In the first phase, the modified CSMA/CA protocol focuses on analyzing communication delays, defining dynamic data transmission, and evaluating data delivery beyond predefined times. In the second phase, the ODQC protocol addresses optimal load balancing and the dynamic process of cluster head selection, aiming to reduce energy consumption during sensor communication. The proposed techniques demonstrate superiority over conventional protocols and are recommended for enhancing the overall quality of service in decentralized, distributed HWSN-based IoT networks. The ECODQC model is compared against existing methods using the NS2 simulation platform in two scenarios: the varying numbers of nodes and varying speeds. The performance parameters of this proposed model are analyzed in terms of energy efficiency, cluster head efficiency, data success rate, computational delay, and node throughput. The Results demonstrate that ECODQC proves to be superior compared to existing techniques in terms of energy efficiency of 432.23 J, low latency of 85.23 ms, and increased throughput of 813.77 Kbits/s. With these observations, the possibility of using ECODQC with a high level of applicability in real-time IoT scenarios is evident
.***Keywords:*** *MAC layer, CSMA/CA, Sensor Networks, Clustering, Quality of Service, Energy Efficiency*

1. Introduction

The general requirement of any network model is that it has to transfer the information from one place to another using a suitable path (Tushar et al., 2020). In the case of the Heterogeneous Wireless Sensor Networks (HWSN) network, selecting the best path for data transmission is highly essential to balance the load and attain maximum efficiency (Pal et al., 2024). Additionally, several methods are introduced in HWSN to prolong the network's lifetime (Guedmani & Ould Zmirli, 2024). The recent advancement in wireless communication is that it gets incorporated with the Internet of Things (IoT) so that this technology can be widely utilized, which includes big data-driven applications (Pandey et al., 2025). The HWSN-based IoT environment is rapidly developed (Shafique et al., 2024); hence, it can handle high-speed data transmission according to the allocated time period, and it provides a way for the development of a huge number of innovative devices with the help of cloud stations (Alsharif et al., 2024), (Chaurasiya, Biswas, et al., 2023). The structure of the HWSN-based IoT environment is illustrated in Fig.1.

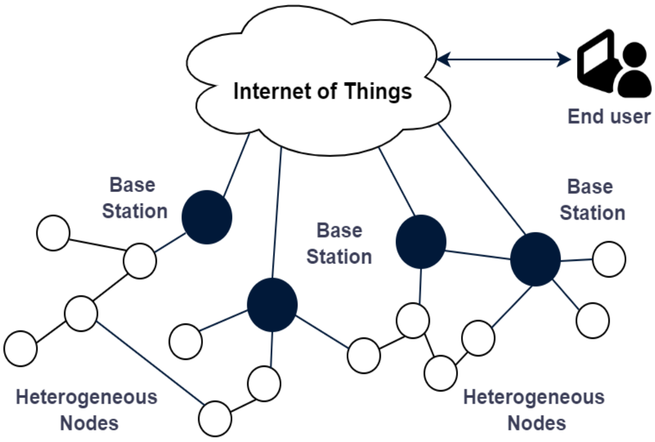

Fig. 1. HWSN-based IoT environment

In HWSN, energy utilization of sensors plays a major role in attaining maximum lifetime, as it concentrates on cooperative data processing (Chaurasiya, Mondal, et al., 2023). Hence, with sensors maintaining limited energy, non-cooperative transmission consumes more power (Alsaqour et al., 2022), which can affect the network performance (Jubair, Hassan, Aman, & Sallehudin, 2021). Thus, in most cases, a cooperative form of communication is carried out that performs certain activities like data management, collection, and grouping, thereby reducing the power utilization of the individual sensor, an area of focus for researchers (Krishnamurthi et al., 2020). In earlier studies, several CH selection processes maintained sensor trustworthiness through the trust calculation process (Fan & Xin, 2025), (Fang et al., 2020). In any densely populated area, sensors are grouped into clusters utilizing various innovative methods (Jubair, Hassan, Aman, Sallehudin, et al., 2021). Generally, data points with similar attributes are combined to form the clusters. Subsequently, the entire network is analyzed, and the collected data is evaluated; this process is defined as aggregation (Vo et al., 2024). This method is introduced to increase network lifetime via a statistical analysis of data, which makes it more compact. The clustered network consists of two sensor types: The Cluster Head (CH) and the sensors present in its coverage area are turned into its Cluster Member (CM) (Babu & Geethanjali, 2024; Jubair et al., 2024). Furthermore, the clustered network structure for the HWSN network is illustrated in Fig. 2.

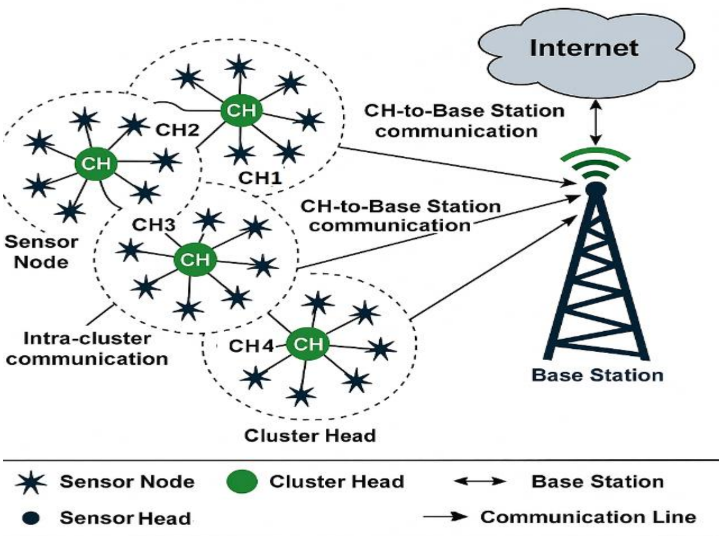

Fig. 2. HWSN clustered architecture.

Some optimization-based clustering processes are introduced in the HWSN-based IoT network to reduce both the delay and power utilization of the heterogeneous sensors (Gupta et al., 2021). Such meta-heuristic algorithms include artificial bee colony (ABC) (Sood & Sharma, 2022b) and evolutionary algorithms (Xie et al., 2020), the Monarchy Butterfly Optimization Algorithm (MBOA) (Prakash & Pandey, 2023),(Yue et al., 2024), which perform optimal CH selection, resulting in extraordinary performance. Recently, CH selections have been performed in a manner that provides trust-based secure selection, which greatly aids in increasing HWSN network performance in an IoT environment (Mengistu et al., 2024). Despite the significant progress in HWSN clustering protocols and MAC layer improvements, various limitations still exist (Alomari et al., 2022) (Famitafreshi et al., 2021). Current methods fail to jointly optimize both energy efficiency and communication latency concurrently in the face of dynamic and constrained resources (Malik et al., 2021). Traditional clustering models (Al-Sulaifanie et al., 2022), for instance, usually employ static cluster head selection, resulting in submaximal consumption of energy and even node premature failures. Moreover, current MAC protocols suffer from high collision probabilities and longer transmission latency due to inefficient backoff policies, especially for dense sensor placements. These limitations become vital in the context of applications enabled by the IoT, where timely and accurate delivery of data assumes importance. To overcome these limitations, we propose in this paper a novel Enhanced CSMA/CA Protocol-Based Optimal Robust Dynamic Query-Driven Clustering (ECODQC) paradigm combining a double-layer backoff mechanism with a novel, energy-aware clustering algorithm dramatically increasing the throughput, stability, and energy efficiency of HWSNs. The major contributions of this research are described as follows:

i. To Design a new Enhanced CSMA/CA protocol that is specifically developed for the minimization of network collisions and reduction of latency in HWSNs. This design uses a dual back-off mechanism, namely, Main Back-off and Secondary Backoff, to handle variable delays effectively, which reduces access collisions and improves packet transmission efficiency.
ii. To Develop CSMA/CA protocol-based optimal robust dynamic query-driven clustering mechanism, namely ECODQC, which selects CHs dynamically to balance the load and optimize energy utilization. This approach enhances QoS and network lifetime in IoT-enabled HWSNs by integrating energy-efficient clustering.
iii. To practically prove the feasibility of the implementation of the ECODQC approach in realistic scenarios of HWSN and highlight its adaptability and dependability for IoT-based applications.
iv. To Extensive NS2 simulations were conducted in order to validate the proposed model of ECODQC and confirm that it offers improvement in energy efficiency, throughput, computation delay, data success rate, and network lifetime in contrast with existing methods.

With the expanding dependence on IoT systems to support vital national requirements of precision agriculture, disaster resilience, and intelligent infrastructure development, optimal communication in HWSNs has taken a strategic importance. The ECODQC model proposed in this paper directly supports these aims through facilitating energy-efficient and delay-tolerant communication. The study hence aligns with national initiatives aimed at sustainable development, digital transformation, and effective public service delivery through technology.

This article is organized as follows: Section 2 presents the analysis of earlier cluster-based sensor models and identifying their drawbacks. Section 3 covers preliminaries and foundational concepts, and the proposed ECODQC model is elaborated on regarding its network structure and clustering process. In Section 4, the performance of ECODQC is compared and analyzed with earlier methods; finally, Section 5 provides the conclusion of the paper, which includes its limitations and future research directions.

2. Literature Review

This section describes the most common enhancements of CSMA/CA protocols and the development of dynamic clustering methodologies, highlighting their novelty and improvements over existing methods. We first provide an overview of traditional approaches and then review the most current techniques. In (Priyadarshini & Sivakumar, 2021), the work employs AVL tree rotation clustering and MCDS-MI techniques to achieve load balancing and improve network lifetime. This approach delivers a 50% reduction in network size, a 60% increase in network lifetime, and a 47.76% reduction in residual energy consumption. In (Mehra et al., 2020), the authors proposed fuzzy-based CH selection, considering residual energy, proximity to the sink, and local node density. FBECS calculates an eligibility index to select the CH, promoting load balancing and also offering improved stability, longer network lifespan, and enhanced data forwarding to the sink. In (Wang et al., 2019), the work proposes an efficient inter-cluster communication mechanism among nodes which consists of three key components: a novel layer scheme for self-organizing local nodes, a multi-hop path selection algorithm to choose relay nodes for data forwarding to CH and a secure communication mechanism to protect source node privacy within the cluster. This approach considers residual node energy in relay node selection, leading to improved network lifetime and data transmission efficiency.

In (Saoud et al., 2023), the authors presents an emerging WSN routing protocol that minimizes energy usage and maximizes the life of the network by choosing cluster heads from the sensor node energies using the Firefly Algorithm. The proposed strategy represents more efficient energy usage and packet delivery to the base station to maximize the life of the WSN. In (Karunanithy & Velusamy, 2020), the wok focuses on optimizing water and fertilizer delivery in agriculture utilizing residual energy-based CH selection and Unmanned Aerial Vehicles for wide-area data collection. Tested in sugarcane fields, the system automates irrigation and fertigation, achieving substantial water savings, of only 25.08% compared to existing methods. The work of (Fanian et al., 2021) introduce a parameter selection-shuffled frog leaping algorithm (PS-SFLA), a technique that uses the shuffled frog leaping model to select these parameters, with three versions for progressive evaluation. PS-SFLA, significantly improves network lifetime by tailoring fuzzy input parameters to specific applications and purposes.

The study of (Karunanithy & Velusamy, 2020) presents CTEEDG, a Cluster-Tree efficient data collection process, integrating WSN and the IoT to enhance network lifetime and throughput. It utilizes fuzzy logic for CH election and establishes efficient inter-cluster communication topology. In (Yarinezhad & Hashemi, 2019), the author presents an approximation algorithm with a 1.1 approximation ratio to address the load-balanced clustering problem in WSN. The algorithm, designed for large-scale WSNs, employs a virtual grid infrastructure and provides practical solutions. It also introduces a routing algorithm that optimizes power utilization and balance. In (García-Nájera et al., 2021), the authors addresses the multi-objective problem of CH selection, considering distance, delay, and residual energy. It employs three multi-objective evolutionary algorithms and evaluates their performance and trade-offs. The assessment of the solutions' effectiveness in terms of lowering power utilization is conducted with the objective of improving the lifetime of the network.

In (Maheshwari et al., 2021), the work tackles energy constraints in WSN by applying Butterfly Optimization for optimal cluster head selection and Ant Optimization for route optimization to the base station. The proposed methodology surpasses traditional approaches in alive nodes, achieving 200 alive nodes at 1500 iterations. In (Guleria et al., 2021), the authors present the Enhanced Clustering model for tracking events in WSNs, especially in habitat monitoring. Mobile nodes select CHs based on placement and energy levels, and relay nodes, selected by velocity and location, assist in data transmission to the BS via sensor data fusion. This method reduces overall power utilization by leveraging fixed and mobile nodes. In study of (Sood & Sharma, 2022), introduce the Enhanced-Threshold model, a clustering protocol for efficient coverage in HWSN. LUET reduces isolated nodes by considering node energy and proximity to lines of uniformity. This approach accomplishes superior performance in network lifetime, power efficiency, death rate, isolated nodes, and throughput.

In (Malisetti & Pamula, 2020), the study tackles the energy consumption challenge in WSN by proposing a CH selection based on the optimization of the quasi-oppositional butterfly. This scheme outperforms existing methods in terms of energy efficiency and network lifetime, offering significant improvements. The study by (Gong et al., 2022), is introduce Query-Driven Clustering (QDC) for enhancing WSN's energy efficiency. QDC employs network partitioning, low-energy centralized sub-network maintenance, query-driven clustering, and energy-efficient load-balanced routing. In (Santhosh & Prasad, 2023), the authors introduce EOR-iABC, an energy-efficient routing scheme for cluster-based WSN. EOR-iABC uses an improved artificial bee colony algorithm to select energy-efficient cluster heads, minimizing energy consumption and prolonging network lifetime.

After analyzing all existing methods, certain drawbacks are identified. Table 1 provides a concise overview of prior research contributions and limitations. The key requirements for the current HWSN IoT networks are increasing network stability, enhancing the CH selection process, enabling effective power utilization, and prioritizing packet forwarding. To address these needs, the ECODQC model is proposed, which is elaborated in the next section.

Table 1 - Comparative Analysis of Existing Techniques from the Literature

Ref	Proposed Method	Major Contributions	Limitations
(Priyadarshini & Sivakumar, 2021)	Minimum Connected Dominating Set with Multi-hop Information (MCDS-MI) and Bi-Partite Graph (BG)	Introduces a hybrid CH selection mechanism MCDS-MI + BG to minimize CH count and energy use.	Does not consider security or privacy mechanisms in routing or CH election
(Mehra et al., 2020)	Fuzzy-Based Enhanced Cluster Head Selection (FBECS) algorithm	Implements fuzzy logic (Mamdani method) to handle uncertainties and improve CH selection efficiency.	Mobility and dynamic topology conditions are not evaluated; all nodes and BS are assumed static.
(Wang et al., 2019)	Energy Efficient Intra-Cluster Scheme (EEICS)	Develops a secure data transmission approach using random numbers known only by nodes and cluster head	Computational complexity due to the secure communication method
(Saoud et al., 2023)	new clustering-based routing protocol optimized by the Firefly Algorithm (FFA).	Utilizes the Firefly optimization algorithm to effectively select CHs	Does not address security issues in data transmission.
(Karunanithy & Velusamy, 2020)	Efficient Scalable Data Collection Scheme (ESDCS)	Introduces waiting-time-based CH selection to uniformly balance energy consumption.	UAV path optimization complexity could introduce computational overhead
(Fanian et al., 2021)	Shuffled Frog Leaping Algorithm (SFLA)	Introduces an adaptive fuzzy input parameter selection method based on SFLA	Assumes static nodes without mobility considerations.
(Karunanithy & Velusamy, 2020)	Cluster-Tree based Energy Efficient Data Gathering (CTEEDG) protocol	Develops a fuzzy logic-based CH selection to achieve uniform distribution and balanced energy consumption.	Security mechanisms and data integrity aspects are not incorporated.
(Yarinezhad & Hashemi, 2019)	RFPT (Routing algorithm based on an FPT-approximation algorithm)	Introduces an FPT-approximation algorithm with a precise approximation ratio (1.1).	Does not address security, reliability under failures, or real-time delay and latency explicitly.
(García-Nájera et al., 2021)	multi-objective cluster head selection problem	Performs a comprehensive multi-objective optimization analysis to clearly identify and quantify objective conflicts in the CH selection problem.	Does not evaluate scenarios with node mobility; static networks are assumed.
(Maheshwari et al., 2021)	Energy-efficient Cluster-based Routing Protocol	Applies BOA to optimize CH selection based on multiple parameters	Does not consider node mobility; assumes static sensor nodes and static BS placement.
(Guleria et al., 2021)	An Enhanced Energy Proficient Clustering (EEPC) algorithm	Novel relay node selection using enhanced PSO based on velocity, location, and fitness values.	Algorithm complexity is O(n), which may become costly in very large-scale WSNs.

(Sood & Sharma, 2022)	LUET protocol (Lines-of-Uniformity based Enhanced Threshold)	LoU-based CH selection mechanism enhances coverage and reduces isolated nodes.	cluster head election depends on centralized computation, which limits scalability
(Malisetti & Pamula, 2020)	Quasi-Oppositional Butterfly Optimization Algorithm (QOBOA)	Introduced QOBOA for CH selection to improve energy efficiency and network lifetime.	Centralized execution at the base station limits scalability and adaptability in large-scale
(Gong et al., 2022)	Query-Driven Clustering (QDC) protocol	Introduces an estimation-based scheme to maintain network information at low energy consumption and high scalability.	Potential computational overhead of centralized clustering and estimation mechanisms under very large-scale networks.
(Santhosh & Prasad, 2023)	Energy Optimization Routing Improved Artificial Bee Colony (EOR-iABC) method	Uses iABC algorithm, enhanced by GEM and Cauchy operators, to perform global and local searches dynamically for selecting CHs.	Lacks mechanisms for security and privacy in data transmission.

3. Preliminaries and Foundations

3.1 Network Structure

The ECODQC approach, as developed, has three distinct steps. During the first stage, energy-efficient clusters are created by leveraging the spatial correlation of data among neighboring nodes. The ECODQC approach, which stands for robust regression, is used for the purpose of identifying neighbor nodes that exhibit spatial correlation. Every non-CH node is linked to a CH node that has a significant amount of remaining energy and has a strong resemblance in data with the non-CH node. Following the establishment of clusters, the subsequent step involves the creation of a dependable backbone network structure connecting all the CH nodes for the purpose of communication with the stationary sink. The backbone enables the determination of the most energy-efficient path, having high-quality connection, from a CH to the sink. During phase three, intra-cluster and inter-cluster communication methods for data transmission were introduced. Instead of collecting all the sensed information from the nodes belonging to the cluster, each CH expects the sensed information of their corresponding member nodes. Next, each CH processes the task of data aggregation by taking the average of all the expected information and sends the aggregated information to the sink through the inter-cluster backbone connection.

3.2 Energy Model

The calculation of expended energy in the WSN is based on the reference of the functioning configuration sheet of Mi-caZ 2.4GHz IEEE 802.15.4 motes. The calculation of energy consumption for transmitting a quantity of data, measured in k bytes, is as follows:

$$E_{rx}(k) = P_{rx} \times T_{rx}(k) \tag{1}$$

Where $P_{rx} = volt \times Ampere$ represents the amount of energy expended (measured in Joule/sec) during the process of receiving a packet. In this equation, T_{rx} refers to the time of receiving k bytes of data. If the data transmission rate is $R\ kbps$, then the time duration of transmitting or receiving k bytes of data can be calculated as $\frac{\left(\frac{k}{1000}\right)}{R}$ seconds. The time required to transmit or receive k bytes of data may be determined by dividing the size of the data (k) by $\frac{\left(\frac{k}{1000}\right)}{R}$ seconds. Several packets are transmitted across the network throughout the clustering process, backbone formation, and data communication.

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3.3 Threshold Energy Computation

In general, the implementation of uniform cluster head rotation mitigates network energy depletion since cluster heads are tasked with data aggregation and relay. Thus, it is important to examine the stability of the node chosen as the CH in terms of its energy parameter, since it depletes the remaining energy at a high pace. The stability analysis of a sensor node's cluster head candidacy involves computing a threshold energy parameter in ECODQC. The threshold energy parameter refers to the minimum residual energy that a sensor node must possess in order to function as a dependable cluster head for the purpose of effectively disseminating data. According to the specifications of the employed energy model, the energy consumption rate of sensor nodes, denoted as 'ECP', is dependent on the square of the distance between the sources and sink nodes, as expressed in equation (2).

$$E_{CP} = \frac{d_{i,s}}{d_{i,k}+d_{k,s}} \tag{2}$$

Where the variables "i" and "k" are used to denote the inter-distance between the source and the cooperative intermediate node. This node is characterized by having a route length that is less than a specified value "m". The optimum consumption of sensor nodes occurs when the E_{CP} reaches its highest value at $k = 1$, where k represents the position of the node in the shortest routing route from i to s. The primary objective of this analysis is to establish a dependable shortest route between the sources and sink sensor nodes.

The model used for energy consumption in this research differentiates between two propagation environments for signal: free-space and multipath fading. Equation (3) defines the total energy $Erc\ (m, d)$ required to send a data packet of size m bits over a distance d. When the distance of the transmission is under a critical level d_t, the free-space model is relevant, and the consumption of energy grows quadratically with the distance. When $d < d_t$, the free-space model applies, and energy consumption scales quadratically with distance. Conversely, for $d \geq d_t$, the multipath fading model is invoked, where energy consumption increases to the fourth power of the distance. This two-tier formulation provides a more accurate representation of real-world transmission losses in heterogeneous wireless environments. The energy model as follows:

$$E_{rc}(m,d) = f(x) = \begin{cases} mE_{ec} + mf_{sd} * d^2, & if\ (d < d_t) \\ mE_{ec} + mt_{mp} * d^4, & if\ \left(d \geq d_t\right) \end{cases} \tag{3}$$

where, Eec denotes per-bit power consumption in the electronic circuitry, f_{sd} is the free-space path loss amplifier coefficient, and t_{mp} is the amplifier coefficient during multipath fading. To find the crossover between the two regimes of propagation, Equation (4) finds the d_t threshold distance as,

Threshold parameter,

$$d_t = \sqrt{\frac{f_{sd}}{t_{mp}}} \tag{4}$$

The energy consumption of the amplifier in HRFCHE (Amuthan & Arulmurugan, 2021), which facilitates long-distance transmission, is measured at 0.0018 pJ per bit per square meter. On the other hand, On the other hand, the energy used for the transmission of shorter degrees is f_{sd} ¼ 10=bit=m2. The variables E_{ec}, m, f_{sd}, and f_{mp} denote the energy, number of bits of data sent, frequency for establishing connection between source and destination, and transmission rate, respectively. In a similar vein, the transfer of data between the source and the sink may occur by either single-hop or multi-hop transmission, depending on whether they are within the shared communication range. The energy consumption associated with both single and multi-hop data transport in this method is comparable to that seen in LEACH. The determination of the threshold energy parameter in ECODQC is based on the probe parameters that are encapsulated inside the packets exchanged between the source and the sink. Additionally, Equation (5) defines the Threshold Energy Parameter (TEP) as E_{TEP}, which is employed to determine whether a node is eligible to serve as a cluster head in the framework of ECODQC. The TEP represents the overall energy expense of data processing as well as intra-cluster communication overhead. the calculation of the threshold energy parameter for each sensor node is performed using equation as follow,

$$E_{TEP} = mE_{elect} + m\left({}^{1}/_{C} - 1\right)E_{drain} \qquad (5)$$

Where m is the size of the data message (in bits), E_{elect} is the energy consumed by the node's electronics per bit for transmission, C represents the number of nodes in the current cluster, E_{drain} refers to the average energy loss associated with cluster-level responsibilities, such as data aggregation and routing coordination. Within the model of ECODQC, this equation enables the system to examine if a node possesses sufficient residual energy to assume more tasks such as acting as a cluster head or a relay node. The static energy cost in electronics is covered by the first term, mE_{elect} , while the second term, $m(\frac{1}{c} - 1)E_{drain}$, captures the dynamic drain in energy from the structure of the cluster, decreasing with larger clusters (as the overhead is distributed over more members).

This threshold is pivotal in facilitating an energy-balanced distribution of roles. Through the calculation of whether the given node is at or above TEP, the technique for the ECODQC prevents the allocation of essential roles to nodes with low energy, enhancing network stability, lifetime, and robustness against mobility. The equation depicts the balance between localized communication requirements and overall system fairness of energy

4. Proposed ECODQC Model

This method is developed to diminish the latency and energy utilization of the HWSN-based IoT environment. The major category of this method is the clustering process, privacy-based communication model, query-driven model, clustering through the query-driven model, and finally enhanced CSMA/CA protocol. The workflow of the proposed ECODQC model is illustrated in Fig. 3.

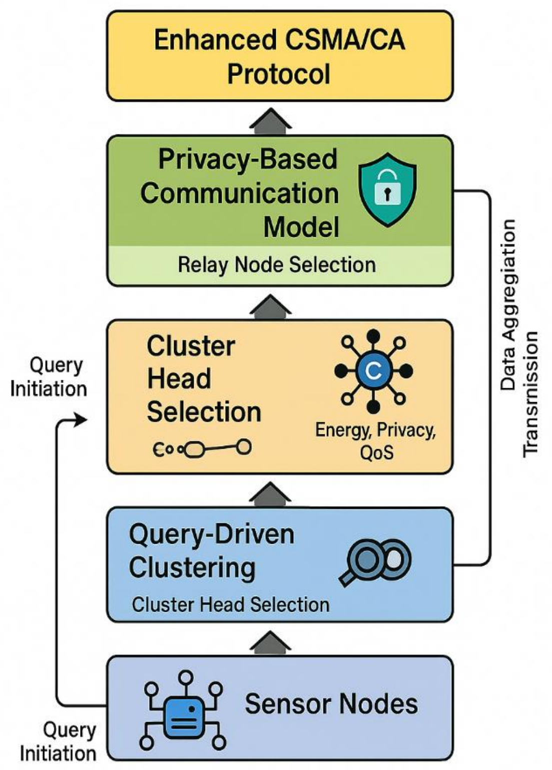

Fig. 3. ECODQC system model

4.1 Clustering Process

The foundation of the multi-hop route selection method lies in the cluster and layer stages. The first stage of this strategy involves the process of clustering, which is a significant field of study within WSN. The CH node identification in this study is done using a clustering technique based on energy distribution. Subsequently, the cluster creation process will be completed by the CH nodes, as previously outlined in our prior research. The network displays a non-uniform spatial distribution of nodes and varies energy consumption based on the locations of the nodes. Consequently, the distribution of the remaining energy across the network is unequal.

It is obviously good to select CH nodes from areas of high-energy distribution, primarily due to network coverage Strategically locating nodes within the region of high-energy distribution has a significant positive effect on network performance. Based on the above-stated study, we propose incorporating the concept of energy core into WSN. The selection of CH node involves determining the energy concentration area within the network. Thus, the entire cluster can be formed after selecting the location of CH node. The CH nodes disseminate a specific subset of information concerning the cluster to the network. The information provided merely comprises geographical dimensions, coordinates, and the ID of the CH node. The membership of the cluster determination for the remaining nodes in the network is based on the assessment of the strength of the received broadcast information. Simultaneously, a reply is forwarded to the CH node. The message includes not just node's remaining energy information and distance information to CH. This communication is meant for the process's next step. A random number is further sent by each sensor node and CH to ensure safe transfer of data across the cluster.

The CH node stores the values of $r\ N\ i$ and $ID\ N\ i$. It should be noted that the node chooses of $r\ N\ i$ on its own and then sends the result to the CH node before the data connection. The purpose of this study is to collect sensor data stored within the network area's target node. The relay nodes within the multi-hop route blend the data packet originating from the source node with a randomly generated number, and then broadcast this combined information to the succeeding node in the sequence. After the relay node transmits the data packet to the next relay node, the packet is removed from the relay nodes.

The header of message serves as a unique identification for the message, allowing for the categorization and classification of the information received. This study primarily encompasses three distinct categories of information: broadcast, feedback, and data information. The information of the header refers to the distinctive identifier of a node inside a network, often referred to as the node's ID. The variability of this information differs between nodes within the cluster. The next two pieces of information pertain to the node's position inside the network, as determined by the coordinate system. Reducing the computational load on the CH node is the information tail's ultimate goal. The previously sent broadcast information contains the positional data of the CH node. As a result, by analyzing the broadcast data that each CH node sends out, nearby nodes can calculate the distance to the CH node. The CH node is the only location where distance data is collected, and it acts as the only point of reference for the method's subsequent step. Every node is allocated to a particular local cluster after the cluster construction and CH node selection processes are finished. This method has the advantage of improving local node management efficiency.

The privacy of the node is rather great since the whole cluster is seen as a single node from the perspective of the base station. Indeed, apart from the role elucidated in the preceding section, the role of the CH node encompasses other functions. The main goal of this section is to establish an appropriate layer by using the cluster's feedback information and accounting for the energy and distance information at the CH node. The fact that there are differences in the intervals between each layer is worth mentioning. The cluster head node first measures the distance between it and the farthest node in its immediate vicinity. It then sets this value as the cluster's maximum distance. Subsequently, the calculation of the cluster's node count performed based on the identification number. Ultimately, the CH node begins to arrange itself in a hierarchical manner based on the quantity of nodes and the maximum distance value. The selection of the CH node is based on the concentration point of the network energy. It is evident that the quantity of nodes exhibiting equidistant proximity to the base station is much more as compared to the CH node.

4.2 Privacy-Based Communication Model

Following this is the transmission of data. The consideration of the path selection issue is crucial in the context of data transmission. The con. The active cluster path selection technique is used in this research. A node looks for a neighboring node that is within one hop's transmission range before sending data packets to the CH node. All nodes within this range have their layer IDs and corresponding distances collected by the source node. The nodes begin the process of choosing the best relay nodes after all required preparations are finished.

The chosen relay node shares a common feature, which is that its ID number is either less than or equal to the ID number of the source node. The packet of data is sent to the CH node during the relay transmission process. There are some rules that should be followed when choosing relay nodes. Let's move on to introducing them in the next section:

Only the nodes that have the same ID layer as the source node exist if they are in the communication range of the source node, and the candidate node is chosen as the relay node. Only if the relay nodes in the subsequent layer have yet to be discovered are the data packets sent back to the source node and queued. The subsequent sub-cluster is to reach after the queued data has been delivered. The process of selecting the path is complete when the CH node is one hop close to the relay node's transmission range. Direct transmission to the CH node is provided by the relay nodes. Based on the temporal and spatial monitoring data, a correlation has been observed. Consequently, a linear fitting approach is used, using a time series data compression technique, to achieve data compression and minimize the amount of data packets transferred inside the network.

i. In scenarios where the relay node candidate of the source node has numerous layers, it is desirable to prefer the choice of nodes in the innermost layer.
ii. In scenarios where all nodes are located in the next layer, it is absolutely necessary to give priority to the choice of nodes that are close to the source node.

Once the multi-hop route has been established, the source nodes start the transmission of the desired data to the CH node using the designated communication channel. It should be noted that the channels connecting the nodes are accessible to potential attackers. The anonymity of the source data is safeguarded by integrating the actual data with a randomly generated number during the first phase of the system. Moreover, the ECODQC supports relay node selection with a lightweight privacy-enhancing mechanism that injects random number encoding into the payload while forwarding in multi-hop mode. Dynamic relay path selection coupled with randomized encoding diminishes the probability of repeating patterns in transmissions, with little chance of traffic analysis or passive listening in return. ECODQC does not follow the fixed-path relay approach, instead dynamically updating the path of packets as well as the embedded identifiers, leaving it more difficult for adversaries to deduce the relationship between the sources and destinations or individual identities of the nodes.

4.3 Query-Driven Model

The Quasi-Oppositional Butterfly Optimization Algorithm (QOBOA) incorporates opposition-based learning in order to improve the algorithm's performance in terms of convergence and optimality of the solution. In order to obtain a solution of superior quality, a population diametrically opposed to the current population is created and simultaneously analyzed. A value chosen at random between the variable's mirror point and the search space's midpoint is the query-driven value of a potential solution. The process that follows yields the quasi-opposite population.

$$x_{i,j}^{q} = rand(a,b) \tag{6}$$

$$a = \frac{x_{ij}^{min} + x_{ij}^{max}}{2} \tag{7}$$

$$b = x_{ij}^{min} + x_{ij}^{max} - x_{ij} \tag{8}$$

Where x_{ij} is the j^{th} variable of i^{th} candidate solution $x_{ij}^{min}, x_{ij}^{max}$ are the minimum and maximum of $x_{ij}, x_{i,j}^{q}$ is quasi opposite value of x_{ij}.

The integration of the Butterfly Optimization Algorithm into ECODQC enables global and more robust search in the clustering solution space, minimizing the chances of converging prematurely towards the local optima. The opposition-based learning strategy compares the existing candidate with its quasi-opposite, thereby supporting fast convergence in the initial iterations and also preserving diversity in the population. This behavior is particularly useful in dynamic WSN scenarios wherein the topology and query distribution frequently alter. Although QOBOA imposes a marginal computational overhead in the form of increased numbers of fitness evaluations, the overhead occurs only in the sink node, in which the resource limitation is less severe than in the sensor nodes. These acceptable response times are sustained by the use of population size limitation, termination by fitness threshold, and adaptive parameter adjustment. As illustrated in the experiments carried out, the increased computational cost is justified in terms of considerable improvement in the quality of the obtained clusters, energy balancing, and efficiency in delivering the data, proving it suitable for real-time, query-aware optimization in resource-constrained WSN scenarios.

4.4 Clustering Through Query-Driven Model

The algorithm functioning relies on a centrally managed Quasi Oppositional Butterfly Optimization Algorithm (QOBOA) mechanism, which is implemented either at the sink or the BS. The BS serves as a high-energy node in this context. The suggested clustering algorithm, based on QOBOA, functions in a series of rounds. Each round starts with a setup phase, during which the construction of clusters takes place. The steady-state phase is characterized by the use of identical procedures as outlined in reference. Upon the beginning of each phase, every node transmits data on the present energy status and the positions of the base stations. The nodes with energy levels above the mean remain CHs for the duration of this round in order to guarantee the selection of CHs with an appropriate energy level. The proposed quasi opposition-based BOA clustering technique, which has the potential to minimize the fitness function as outlined below, is used by the next Base Station to select the best cluster heads.

$$\text{Fitness Function} = \varepsilon_1 \times f_1 + \varepsilon_2 \times f_2 + \varepsilon_3 \times f_3 \tag{9}$$

Where $\varepsilon_1 + \varepsilon_2 + \varepsilon_3 = 1$ and $0 < \varepsilon_1, \varepsilon_2, \varepsilon_3 < 1$

$$f_1 = \sum_{R=1}^{m} \frac{1}{l_j} \left(\sum_{j=1}^{l_j} dist\left(S_j, CH_R\right) \right) \tag{10}$$

$$f_2 = \frac{1}{\sum_{f=1}^{m} E(CH_j)} \tag{11}$$

$$f_3 = \frac{\sum_{j=1}^{m} dist(CH_j, BS)}{N} \tag{12}$$

The variable *f1* represents the intra-cluster nodal distance between nodes and their respective Cluster Heads, whereas *lj* represents the set of nodes that belong to Cluster *CHk*. The function *f2* is defined as the reciprocal of the total power of the cluster chiefs as well as their candidates within the current round. The function *f3* denotes the ratio between the average sink distance and the total number of nodes present in the network. The user defines the values of the weigh $\varepsilon_1, \varepsilon_2, \varepsilon_3$, which are used for the purpose of managing three goal functions. The aforementioned fitness function aims to minimize the intra-cluster distance between nodes and their respective cluster heads, quantified by *f1*. This optimization contributes to enhancing the energy efficiency of the network, as represented by *f2*, while also minimizing the average sink distance, *f3*. The following is a list of the stages involved in the QOBOA-based clustering method.

Step 1 : Initialization of network parameters such as the quantity and size of nodes within a sensor network.

Step 2 : The initialization of energy parameters consists of the initial energy E_o of the sensing nodes, the energy required to operate the transmitter and receiver E_{elec} ,and the aggregation and amplification of energy ε_{fs} , ε_{mp}.

Step 3 : Initialization of the population size, maximum iterations, sensor modality *c*, switch probability *p*, and power exponent *a* for the optimization.

Step 4 : Disperse the sensor nodes in the sensing field at random.

Step 5 : The initial population of CHs is created by making a selection among the network's existing nodes

Step 6 : Every node's fitness is assessed after the first population is generated in order to provide excellent results since the best nodes are selected to be the cluster heads. Equations (10) to (12) illustrate the distance between the related nodes of the CH and energy parameters that are included in the fitness function.

Step 7 : Determining the optimal option for the population.

Step 8 : Employ global and local search strategies of quasi-oppositional based butterfly optimization, using switching probability across populations to update the candidate solutions in case the stopping conditions are not met. Once more, calculate each solution's fitness.

Step 9 : Update the current population with the assistance of the new generation if its fitness is lower than that of the initial population; if not, it must be maintained at the same level as the previous population until the completion of the subsequent iteration.

Step 10 : The best nodes are chosen as CHs from the population relevant to that round if the stopping criteria are satisfied.
Step 11 : Based on the distance between the sensor node and the CH, a node is assigned to each CH after they have been selected.
Step 12 : Following this, communication between the nodes and the CHs is started. The last correspondence between the CH and the BS has been completed.
Step 13 : Finally, the parameters and their ultimate computation are then finished.

The basis of selecting high-energy density zones as a criterion for selecting CHs stems from maximizing the stability and longevity of the network. Nodes in high-residual energy regions are statistically less probable to experience premature depletion, minimizing the occurrence of CH re-election and its corresponding overhead. Furthermore, choosing CHs in energy-concentrated regions will optimize the chances of CH formation with balanced loads of communications, preventing the localized depletion in the lifetime of a single node. This also maximizes the dependability of inter-cluster communication since CHs with larger energy resources are in a good position to perform data aggregation and forwarding without affecting the network lifetime. Dynamically assessing the energy's spatial distribution, ECODQCs ensure CH selection remains adaptive according to real-time scenarios and evades the drawbacks of fixed or proximity-dependent methods prevalent in past techniques.

4.5 Enhanced CSMA/CA Protocol

To enhance the performance of CSMA/CA, this paper introduces a modified version of CSMA/CA. This update effectively addresses the issue of access collisions due to the limited bandwidth efficiency, resulting in a reduction in the average delay for packet delivery. The proposed approach employs a Main Back-off (MB) and Secondary Backoff (SB) technique to introduce variable delays in the nodes for an irregular number of backoff periods. In the standard CSMA/CA, the maximum delay value, referred to as *Backoff*, is provided as:

$$\text{Backoff} = 2^{macmaxBE} \tag{13}$$

In the modified unslotted CSMA/CA protocol, nodes choose MB and SB values in a random manner. The MB value is selected from between the ranges of 10% to 50% of the *Backoff* duration, while the SB value represents the residual delay after the *Backoff* period. The computation of MB and SB is as follows:

$$MB = (\text{Backoff} * \text{BP})/100 \tag{14}$$

$$SB = Backoff - MB \tag{15}$$

Where the variable BP represents the *Backoff* Percentage, which denotes the actual percentage value of the *backoff* delay. The possible values for BP are 10, 20, 30, 40, and 50. When a node has a packet to transmit, it sets the initial values of the factors as follows: $NB = 0$ and *Backoff* = $2^{macmaxBE}$. The node selects the BP in a random manner. The node thereafter enters a state of waiting, during which it undergoes an irregular number of backoff periods. These backoff periods are picked from a range of values *(0, MB)*, as determined by the calculation described in (1). When the node has finished calculating the random value of the MB delay, it performs the first Clear Channel Assessment, abbreviated as CCA1, to determine the channel state. If the channel is found to be devoid of any other transmissions, the node proceeds to transmit its packet to the coordinator. In accordance with (14), if the node does not get a response, it proceeds to wait for a variable number of back-off periods, denoted by SB, within the range of *(0, SB)*. After the arbitrary length of SB delay has been completed, the node performs the second

Clear Channel Assessment, designated as CCA2, for data transmission. In the event that the channel is determined to be unoccupied, the node proceeds to send its packet to the coordinator. In the event that the node is already engaged, it proceeds to repeat the *backoff* procedure by incrementing the NB value by one. If the value of NB reaches its maximum limit beyond the threshold of macMaxCSMABackoffs, the transmission is stopped due to a failure in channel access.

The use of arbitrary selection of *MB* and *SB* values significantly decreases the probability of several nodes selecting the same irregular *MB* value, as well as the *SB* value. Consequently, this reduction in the risk of access collision greatly minimizes the occurrence of access conflicts. Based on the prescribed methodology, the nodes perform *CCA* at the primary back-off level without the need to pause until the completion of the full irregular back-off delay. Hence, the implementation of this CSMA/CA protocol results in a decrease in the transmission delay of packets.

5. Simulation Environments

The network performance of the ECODQC approach has been evaluated through an extensive implementation using the NS2 software. The performance of ECODQC is calculated in the presence of an enhanced CSMA/CA protocol and an ODQC clustering protocol. At the end of this simulation, the results are compared with baseline works, such as the Quasi Oppositional Butterfly Optimization Algorithm (QOBOA) (Karunanithy & Velusamy, 2020), the Energy-efficient Query-Driven Clustering protocol (EQDCP) (Gong et al., 2022), and the Energy Optimization Routing using Improved Artificial Bee Colony algorithm (EORIAB) (Santhosh & Prasad, 2023). The network coverage dimension is 1000m*1000m where the nodes are moving at a speed of 5Km/hr to 50Km/hr. The other essential parameters involved in this research are given in Table 2.

Table 2 - Parameter table

Matrices	Values
Simulator	NS2
Time	200 ms
No of Nodes	Hundred Nodes
CH Nodes	Ten Nodes
CM Nodes	Ninety Nodes
CH Sensing Radius	50m
CM Sensing Radius	10m
CH Initial Power	100 Joules
CM Initial Power	10 Joules
Antenna Type	Omni-directional
UMTS Threshold	-94 dBm
Queue Length	50
Node Speed	5Km/hr to 50Km/hr
Power for Data Sensing	0.100 Joules
Power for Data Transmitting	0.500 Joules
Power for Data Receiving	0.050 Joules
Idle Power	0.040 Joules
Data Rate	256 to 512 Kbps
DATA Traffic	Constant Bit Rate

5.1 Results Concerned with Number of Nodes

In this section, the simulation outcomes are evaluated in terms of the number of nodes, and the results are explained graphically for methods such as QOBOA, EQDCP, EORIAB, and the Proposed ECODQC. Performance is evaluated using parameters such as energy efficiency, CM efficiency, success rate in data, nodes computational delay, and nodes throughput level.

5.1.1. Energy Efficiency Calculation

In the case of HWSN, the energy level of each sensor is varied according to its utility. The efficiency of the sensors is analyzed in the localization area. In general, the static nodes consume more power than the heterogeneous nodes; hence, the static nodes are assigned more loads. At the time of simulation, the initial energy allocated to each node is 10 joules. Fig. 4 presents the graph of energy efficiency, which demonstrates that the proposed ECODQC achieves better efficiency than the baseline methods, such as QOBOA, EQDCP, and EORIAB.

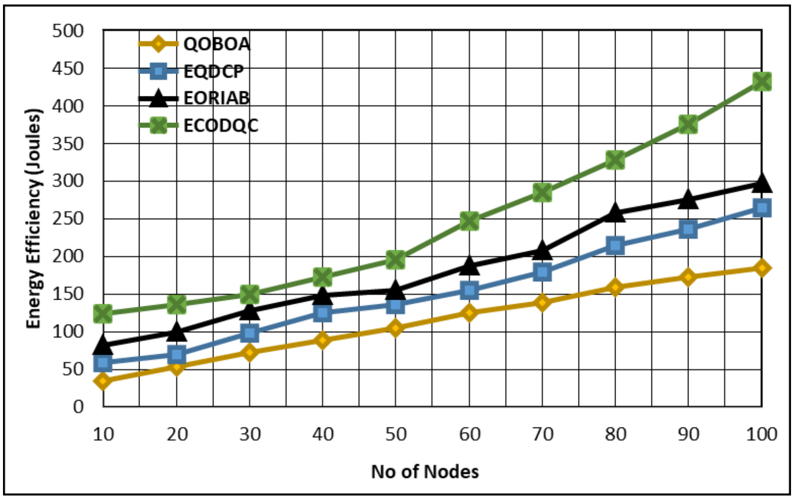

Fig.4. Energy efficiency calculation

5.1.2. CH Efficiency Calculation

The energy level of CH varies from one another according to its communication process, but the primary goal of this research is to increase the lifetime of CH. From the final observation, as shown in Fig. 5, the performance of the proposed ECODQC is superior to that of baseline works, such as QOBOA, EQDCP, and EORIAB.

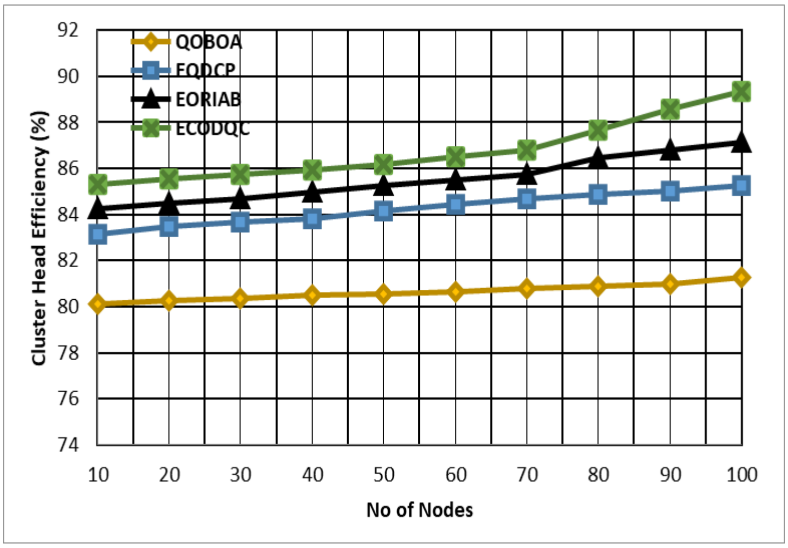

Fig. 5. CH efficiency calculation

5.1.3. CM Efficiency Calculation

The energy level of the nodes varies according to their communication, and attaining maximum efficiency is the primary goal of the proposed ECODQC. From Fig. 6, it is shown that the cluster member efficiency obtained by the ECODQC approach is significantly better than that of the baseline works.

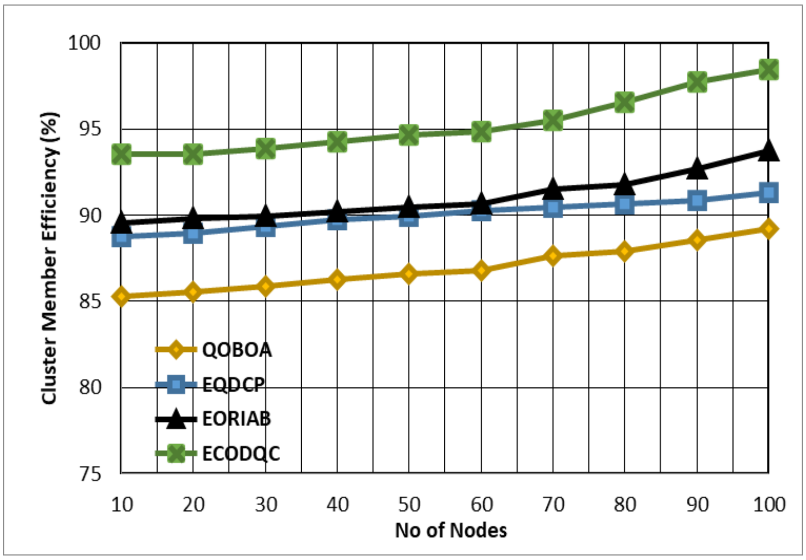

Fig.6. CH efficiency calculation

5.1.4. Rate (DSR) Calculation

The data success rate is defined as the ratio of the total sum of the packets that were successfully communicated and received to the total sum of the packets that were generated from the source, which is termed the data success rate. Fig. 7 implies the graph of DSR of the proposed ECODQC and baseline techniques such as QOBOA, EQDCP, and EORIAB. This analysis proves the superiority of ECODQC over the others for 100ms of simulation time, respectively.

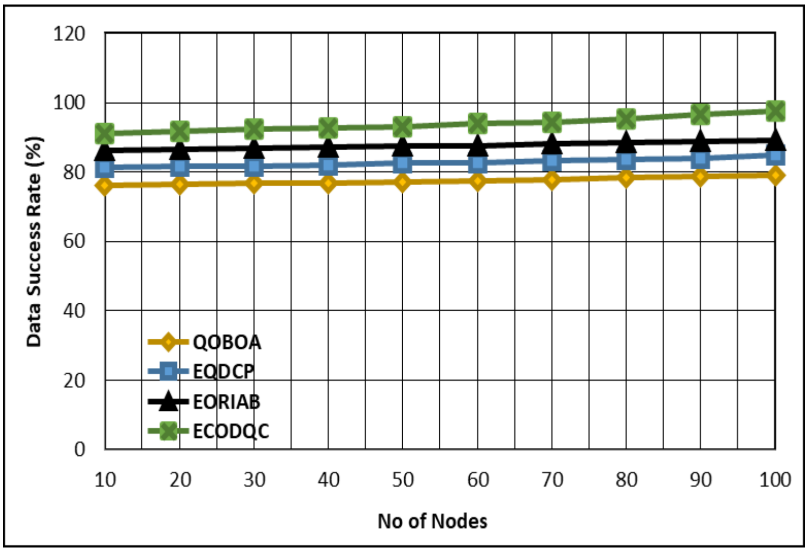

Fig 7. Data success rate calculation

5.1.5. Nodes Throughput Level Calculation

The throughput level of the network is the measurement of the total volume of data effectively generated until the end of the simulation run time. The sensors are heterogeneous, and at some time, they may move out of the coverage area and reach the neighboring cluster. As a result, the data transmitted by a particular sensor can be received by more than one CH. At the final stage, all the information is forwarded to the destination. Fig. 8 illustrates the throughput calculation of the proposed ECODQC and the baseline works. From the results obtained, it is proven that the throughput level of this method is higher than that of the baseline works.

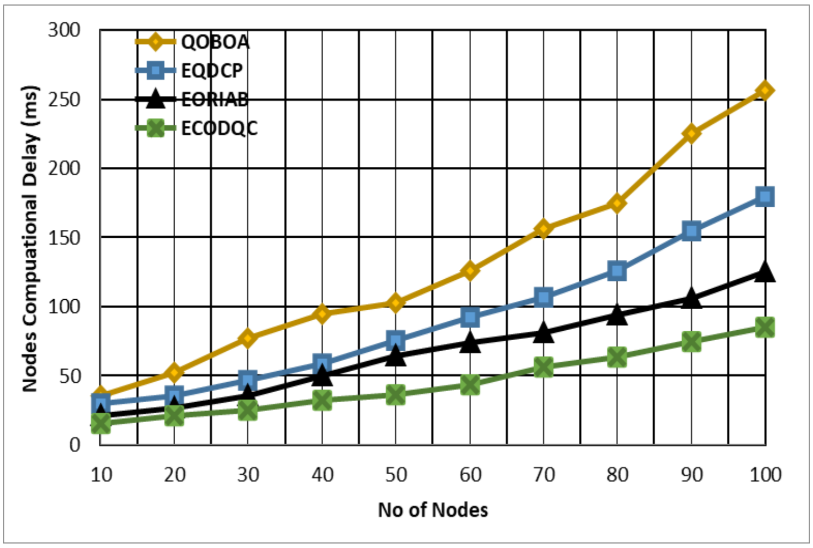

Fig. 8. Throughput level calculation

5.1.6. Nodes Computational Delay Calculation

It is the measure of the time duration utilized for any packets to reach their targeted destination from the transmitted source. The sensed data gets transmitted to the CH and from there to the base station. Fig. 9 shows the end-to-end delay calculation of the proposed ECODQC, and it produced a lower delay than the baseline works QOBOA, EQDCP, and EORIAB.

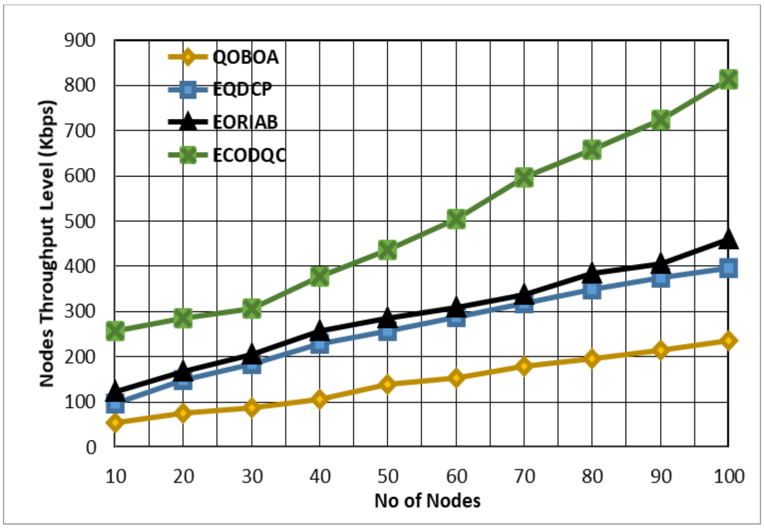

Fig. 9. End to end delay calculation

5.2. Results and Discussion Concerned with Number of Nodes

In this section, the simulation outcomes are described regarding the number of nodes in detail to analyze the performances of the previously proposed methods and the proposed scheme. The parameters considered in the measurement of the performances are energy efficiency, CH efficiency, CM efficiency, data success rate, nodes computational delay, and nodes throughput level. The simulation results presented in Table 3 and Table 4 validate the proposed model's ECODQC superiority over the comparative techniques QOBOA, EQDCP, and EORIAB in all the parameters considered. In particular, ECODQC achieves an energy efficiency of 432.23 Joules at 100 nodes, which is 135.49 Joules over EORIAB. This improvement is attributed to ECODQC’s adaptive CH selection mechanism, which considers both residual energy and spatial correlation unlike QOBOA static selection or EQDCP threshold-dependent clustering. However, in terms of CH efficiency, ECODQC achieved a leading value of 89.34%, surpassing QOBOA (81.25%), EQDCP (85.24%), and EORIAB (87.13%). Additionally, the ECODQC cluster member efficiency achieves 98.47%, outperforming EORIAB (93.74%) and EQDCP (91.28%).

This fact to its capacity to ensure intra-cluster communication under steady conditions despite increasing node density, due to its hierarchical clustering at the layer level and adaptive backoff mechanism at the MAC level. Those results reinforce the model presented in [40] that optimization algorithms enhance clustering robustness, and further elaborate by proving that combining MAC-layer tuning (as with ECODQC) achieves synergic QoS improvements. Additionally, the data success rate (DSR) is significantly enhanced to 97.55%, which is a vital factor for applications in real-time IoT. The results show that the reduction of computational delay is 85.23 ms in the case of ECODQC compared to 125.47 ms for EORIAB and 256.17 ms for QOBOA. Finally, in terms of node throughput, ECODQC exhibited the highest performance, achieving a throughput of 813.77 Kbps. The dramatic reduction is an affirmation that MAC and clustering co-optimization (not present in earlier approaches) directly affects latency

Table 3 - Measurement of the parameters such as energy efficiency, CH efficiency, and CM efficiency concerned with number of nodes

No of Node	QOBOA	EQDCP	EORIAB	ECODQC	QOBOA	EQDCP	EORIAB	ECODQC	QOBOA	EQDCP	EORIAB	ECODQC
	Energy efficiency (Joules)				Cluster head efficiency (%)				Cluster member efficiency (%)			
10	35.17	59.22	81.28	124.37	80.14	83.16	84.27	85.29	85.29	88.74	89.55	93.54
20	54.21	70.45	99.63	135.81	80.24	83.49	84.49	85.54	85.56	88.94	89.78	93.56
30	72.58	97.52	127.82	149.75	80.38	83.68	84.67	85.76	85.84	89.34	89.95	93.85
40	89.37	124.78	147.85	172.36	80.49	83.82	84.96	85.92	86.24	89.75	90.18	94.28
50	104.67	135.69	154.96	195.69	80.56	84.16	85.26	86.19	86.58	89.95	90.47	94.67
60	124.65	154.32	187.52	247.14	80.64	84.45	85.52	86.52	86.79	90.26	90.68	94.83
70	138.97	179.64	207.89	285.32	80.79	84.69	85.74	86.79	87.65	90.48	91.48	95.48
80	158.63	214.79	257.84	327.96	80.87	84.87	86.46	87.64	87.92	90.67	91.79	96.58
90	171.92	235.97	274.89	374.81	80.96	85.01	86.79	88.56	88.56	90.86	92.67	97.73
100	185.24	265.16	296.74	432.23	81.25	85.24	87.13	89.34	89.24	91.28	93.74	98.47

Table 4 - Measurement of the parameters such as data success rate, nodes computational delay, and nodes throughput level concerned with the number of nodes

No of Node	QOBOA	EQDCP	EORIAB	ECODQC	QOBOA	EQDCP	EORIAB	ECODQC	QOBOA	EQDCP	EORIAB	ECODQC
	Data success rate (%)				Nodes computation delay (ms)				Nodes throughput level (Kbps)			
10	76.23	81.49	86.28	91.24	35.14	29.79	21.47	15.29	55.17	96.24	121.74	256.79
20	76.58	81.64	86.67	91.64	52.31	35.65	26.53	20.98	74.15	149.32	168.32	285.32
30	76.79	81.79	86.94	92.46	76.84	46.32	35.69	24.68	86.34	184.95	204.89	305.89
40	76.81	81.93	87.19	92.79	94.58	58.89	49.65	32.59	105.97	227.89	256.94	376.25
50	77.24	82.49	87.54	93.18	102.98	75.64	64.25	36.49	138.94	256.94	284.61	435.64
60	77.48	82.69	87.62	93.85	125.78	92.56	73.56	43.87	154.23	287.64	308.47	504.87
70	77.71	83.17	88.23	94.37	156.32	106.52	81.25	56.29	179.68	317.84	336.94	596.32
80	78.34	83.65	88.49	95.46	174.58	125.98	93.58	63.25	195.63	349.16	384.56	657.94
90	78.68	84.06	88.74	96.75	224.85	154.85	105.63	74.56	214.56	374.82	405.63	723.65
100	79.17	84.76	89.11	97.55	256.17	179.34	125.47	85.23	235.17	396.17	458.72	813.77

5.3. Results Concerned with Varying Speed

The implementation outcomes are measured concerning varying speeds from 5Km/Hr to 50Km/Hr, and the results are given for methods like QOBOA, EQDCP, EORIAB, and the

Proposed ECODQC. The parameters used in performance evaluation are data success rate, data failure rate, energy efficiency, and energy consumption.

5.3.1 Data Success Rate (DSR) Calculation

The Fig. 10 implies the graph of DSR with respect to varying speeds from 5Km/Hr to 50Km/Hr, and it is proven here that the ECODQC achieves better performance than the earlier approaches, such as QOBOA, EQDCP, and EORIAB. In general, an increase in speed decreases the success data rate of the nodes; however, the variation is comparatively very low and negligible for the proposed ECODQC.

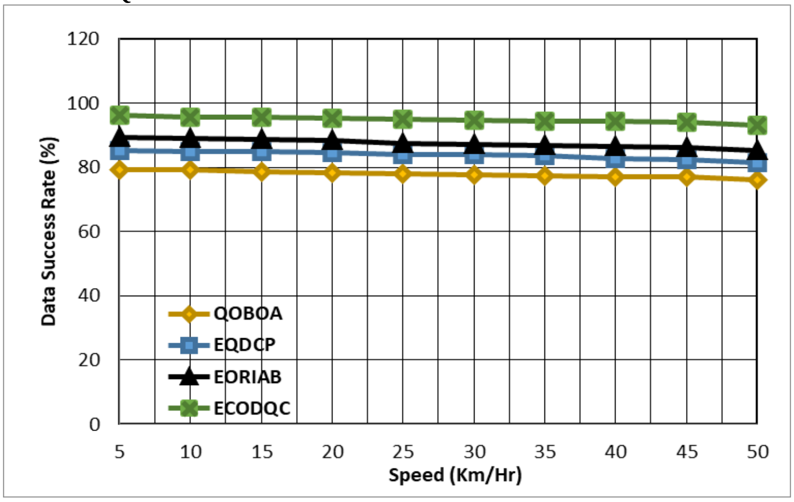

Fig. 10. Data success rate calculation

5.3.2. Data Failure Rate (DFR) Calculation

It is the measure of the total number of packets that are lost at the time of communication among the HWSN network. The malfunctions of faulty nodes are significantly reduced in the proposed ECODQC; as a result, the failure rate obtained by this method is lower than that of other works, as illustrated in Fig. 11.

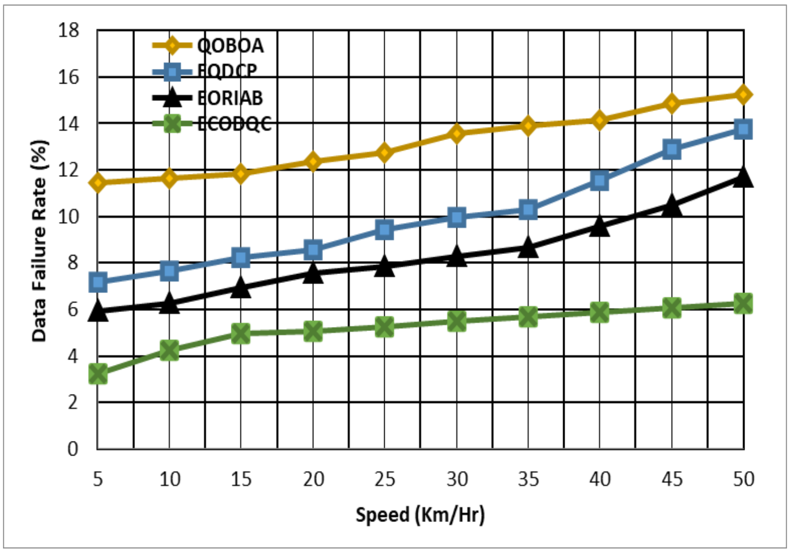

Fig. 11. Data failure rate calculation

5.3.3. Energy Efficiency Calculation

The figure of energy efficiency calculation related to the varying speed from 5Km/Hr to 50Km/Hr, and from that, as shown in Fig. 12, it is confirmed that ECODQC produced higher efficiency than the earlier approaches like QOBOA, EQDCP, and EORIAB.

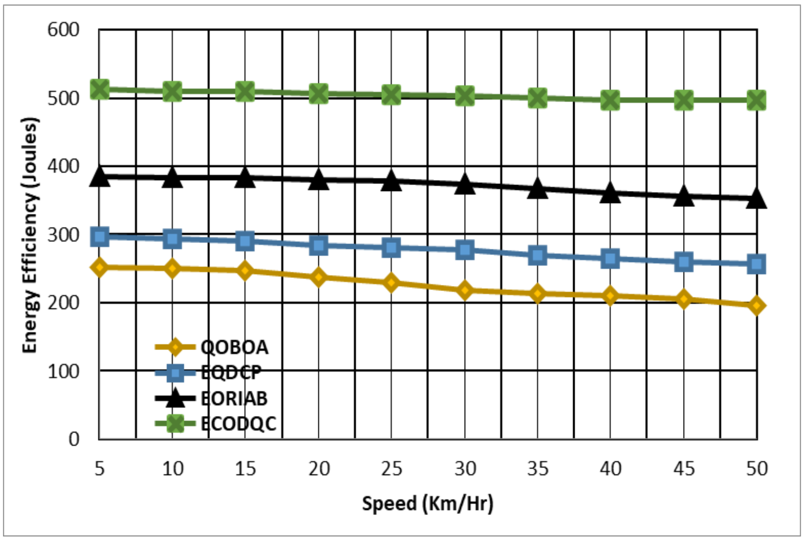

Fig. 12. Energy efficiency calculation

5.3.4. Energy Consumption Calculation

The energy consumption of the methods considered in this research concerning varying speed from 5Km/Hr to 50Km/Hr, and it is shown that the ECODQC produced lower power consumption than earlier approaches like QOBOA, EQDCP, and EORIAB as shown in Fig. 13.

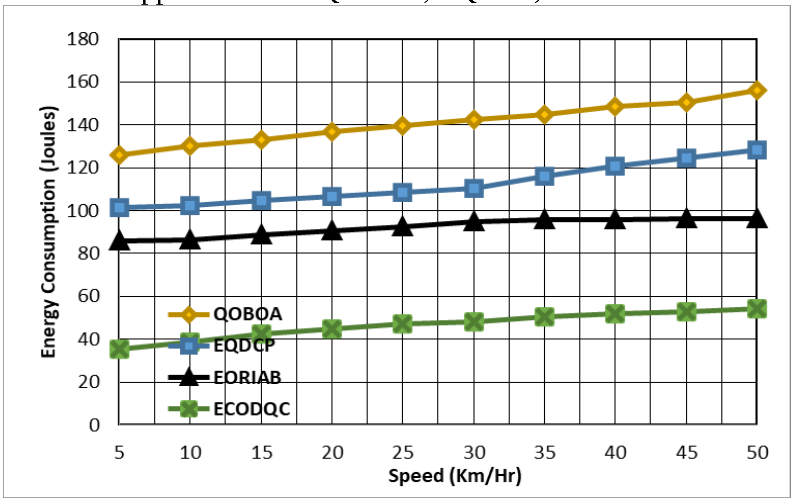

Fig. 13. Energy consumption calculation

5.4. Results and Discussion Concerned with Varying Speed

In this section, the simulation results are discussed related to the varying speed in an elaborate way to analysis the performance. The parameters used in performance evaluation are data success rate, data failure rate, energy efficiency, and energy consumption. The measurements of the calculated parameters are shown in Tables 5 and 6. In all the major performance metrics, ECODQC performed consistently above the baseline models. ECODQC's performance remained constant with a 6.28% data failure, and It had a 93.16 % data success rate, The ECODQC system recorded the highest energy efficiency of 496.28 Joules, with 54.28 Joules of power consumption compared with baselines. All these findings confirm the scalability, stability, and power-conscious design principles of ECODQC for dynamic WSN. In order to validate the statistical significance of the presented results, every scenario was simulated 20 times with varying random seeds, 95% confidence intervals for which were calculated. Paired t-tests also evaluated the performances of the other protocols compared to ECODQC and indicated statistically significant improvements in all the metrics ($p < 0.01$). Furthermore, the two-layer structure of ECODQC MAC-layer dual back-off collision control integrated with query-driven adaptive clustering is beneficial in the presence of heterogeneity and mobility. The combination improves long-duration network stability, reduces packet loss, and enhances responsiveness.

Table 5 - Measurement of the parameters such as data success rate and data failure rate concerned with varying speed

Speed (Km/Hr)	QOBOA	EQDCP	EORIAB	ECODQC	QOBOA	EQDCP	EORIAB	ECODQC
	Data Failure Rate (%)				Data Success Rate (%)			
5	11.47	7.18	5.94	3.24	79.33	85.16	89.14	96.14
10	11.65	7.64	6.24	4.25	79.15	84.97	88.97	95.68
15	11.82	8.24	6.94	4.98	78.64	84.76	88.64	95.46
20	12.36	8.56	7.56	5.05	78.28	84.52	88.32	95.12
25	12.74	9.45	7.84	5.26	77.82	84.05	87.56	94.89
30	13.56	9.94	8.27	5.49	77.58	83.94	87.25	94.61
35	13.89	10.28	8.67	5.68	77.34	83.54	86.74	94.47
40	14.15	11.56	9.56	5.89	77.18	82.81	86.31	94.21
45	14.85	12.89	10.48	6.05	77	82.45	86.05	94.06
50	15.24	13.74	11.71	6.28	76.14	81.49	85.28	93.16

Table 6 - Measurement of the parameters such as energy efficiency and energy consumption concerned with varying speed

Speed (Km/Hr)	QOBOA	EQDCP	EORIAB	ECODQC	QOBOA	EQDCP	EORIAB	ECODQC
	Energy efficiency (Joules)				Energy consumption (Joules)			
5	252.17	296.85	384.27	512.89	125.96	101.28	85.79	35.47
10	250.14	293.48	383.24	510.26	130.24	102.56	86.25	38.56
15	247.23	289.67	382.59	508.95	132.85	104.89	88.56	42.32
20	236.85	284.63	380.47	506.78	136.97	106.75	90.67	44.85
25	229.64	280.29	378.69	504.89	139.52	108.47	92.56	46.97
30	218.94	276.93	373.24	502.63	142.56	110.26	94.86	48.29
35	213.58	270.31	367.25	500.28	144.57	115.86	95.64	50.62
40	209.56	264.89	361.59	497.64	148.65	120.64	95.85	51.62
45	205.24	260.34	355.61	497.25	150.28	124.69	96.05	52.87

50	196.25	256.25	352.17	496.28	156.23	128.17	96.24	54.28

To ensure the performance gain observed in the scenarios is highly reliable and generalizable, every simulation scenario was run 20 times with independent random. For every measure of performance, the mean was computed, as well as the standard deviation, with the construction of 95% confidence intervals. To further compare ECODQC with every baseline model (QOBOA, EQDCP, and EORIAB), a paired t-test was performed. Findings showed statistically significant gains in energy efficiency, data success rate, and throughput ($p < 0.01$), proving the consistency of the performance gains of ECODQC and the fact that the gains are not due to random change. This supports the consistency of the proposed protocol under different operational conditions.

5. Conclusion

The ECODQC model has been introduced to achieve effective communication in an HWSN-based IoT environment by reducing delay and power utilization of nodes during data transmission. The main goals of this method is to reducing network collisions and latency through a dual-backoff CSMA/CA mechanism; enabling energy-efficient clustering via a query-driven strategy; enhancing QoS and data success rate. The novelty of the work focus in its CH selection process and the privacy-based communication model, which enhances data gathering and provides effective optimization during communication among the sensors. Extensive simulations of the proposed ECODQC were conducted using the NS2 simulator, demonstrating that it offers maximum efficiency and lifetime compared with baseline methods like QOBOA, EQDCP, and EORIAB. Both CH and CM node efficiency are enhanced, increasing the overall efficiency of the HWSN network. ECODQC demonstrates strong potential for real-world deployment toward various application domains. In smart agriculture, it supports efficient energy usage and long-range communication, while in industrial IoT, it meets the demands for low latency and reliable data delivery. The model also holds promise for smart city infrastructures, environmental monitoring, and disaster response systems. In future work, this proposed ECODQC will be implemented in a real-time test bed with the required hardware. Additionally, the integration of trust management mechanisms and lightweight cryptographic modules will be explored to enhance security and resilience against adversarial threats.

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