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RESEARCH ARTICLE

ORQET: An Adaptive Relay Selection and Energy-Efficient Routing Strategy for Wireless Sensor Networks

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Abstract – Wireless Sensor Networks (WSNs) and Internet of Things (IoT) environments are the most popular paradigms of technology, and their most frequent use is in the field of healthcare, industrial automation, and smart agriculture. Nevertheless, there are certain challenges with this technology, including high power consumption, redundancy of transfers, over-delays and ratios of packet delivery. No inherent balance has been provided by standard clustering and relay choice methodology between the competing elements; energy efficiency, scale and safe information passing need to protect time-sensitive data in unstable environments. It is anticipated that the algorithm of Optimisation with Relay Quantisation and Efficient Selection with Transmission (ORQET) under the framework of Data Aggregation and Energy-Efficient Routing Optimiser (DAERO) will be developed. This network topology is changed to select cluster heads and relays in which the remaining energy and the data measures of the link quality, as well as the correlation of data to the minimality of the energy, could be considered globally, and trusted routing could be delivered. DAERO provides a continuous improvement of the cluster head relay selection plans that are oriented to the goals of decreasing additional transmissions, optimise sensor energy prices and increasing the reliability of packet transmission. Simulation experiments show that the ORQET-DAERO architecture, where ORQET transmits suitably depending on the correlation of data between packets and DAERO makes up on the outputs of ORQET depending on the correlations to execute multi-objectives of energy balance, redundancy transmission and reliability reach, can outperform throughput, higher than a 99 percent packet delivery ratio, delay, and most importantly, energy depletion rate, compared with competing frameworks. The article shows that the suggested framework can address the significant challenges of the WSNs and IoT in the area of scalable, energy-aware, mission-critical communications.

Index Terms – Wireless Sensor Networks, IoT, ORQET, Energy Efficiency, Clustering, Relay Selection, Improving Network Efficiency.

1. INTRODUCTION

The data on energy efficiency of wireless sensor networks (WSNs) and the Internet of things (IoT) has been extensively aggregated and clustered to improve the efficiency and life time of networks. [1]. The methods of improving energy consumption optimisation of data aggregation methods in IoT were deliberated upon, and the focus Ire on the impacts of effective methods of data dissemination techniques in an endeavour to reduce power consumption. In this light, [2] developed an energy optimisation model grounded on machine learning in WSNs, which reinforces the advantages of AI-based solutions to realise the optimal data transmission efficiency.

Similarly, [3] had an in-depth review of data aggregation techniques in precision farming and introduced an overview of the most appropriate agnostic techniques, which were energy-efficient but possessed the appropriate accuracy. Additionally, [4] introduced the principle of PCA and Q-learning to optimise clusterisation in an Internet of Things network that characterises the value of reinforcement learning in optimisation of performance. [5] proposed a near-optimal hybrid Particle Swarm Optimisation (PSO)-based clustering protocol in WSNs, which suggested a cluster head selection algorithm and power distribution.

The algorithms of optimisation are also commonly employed in order to guarantee that the highest data aggregation effectiveness is achieved. [6]. And [7] optimised the industrial internet of things with powerful optimisation models by means of quality and efficient data collection hybrid models. [8]. The deep learning method was also used to refine the data collection in the cluster-based IoT and was suggested to optimise the routing and energy efficiency with the help of neural networks. [9]. Discuss clustering algorithms in WSNs

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to arrive at a snapshot of the approach used to achieve the optimum network topology. [10]. Develop an IoT-based healthcare framework that will allow consolidating the data with a particular focus on the secure and efficient exchange of health-related data. [11]. Systematically reviewed the approaches used in aggregation in WSNs in terms of energy efficiency, reliability and security.

Energy efficiency is also still the most common area of research in WSNs. [12]. And [13] examined the optimisation of both WSNs and data centres in terms of energy use with a concentration on clustering solutions that provide a more improved power efficiency. A grid-based clustering system of WSN was to be conducted experimentally to introduce feasibility, so that unnecessary transmission of data could be reduced in order to increase the energy efficiency of the system. [15]. Suggested an energy-efficient data aggregation protocol to ensure that the remaining energy in the network nodes is used to redistribute more energy in the network.

Data aggregation techniques have discussed how machine learning (ML) and metaheuristic mechanisms (like swarm algorithms) can be used to aid in the accurate decision-making and allocation of resources. [16]. Combined machine learning property with Particle Swarm Optimisation (PSO) to create an aggregating and predictive model that provides better information quality and costs less in terms of energy. [17]. Developed an energy-sensitive clustering-based routing algorithm with the Capuchin Search Algorithm and fuzzy logic to enhance clustering functions. In [18] applied K-means clustering WSN lifetime with the best cluster head, using the Einstein weighted average of aggregation. In addition, [19] presented a critical analysis of the objectives of clustering in wireless sensor networks (WSN) and that there are major issues and opportunities in the future of data aggregation. Lastly, [20] added ML to mobile data collectors to improve the Quality of Service (QoS) of massive and microscopic WSNs to provide an objective and scalable framework with an orientation towards network performance enhancement. On balance, these articles suggest the overall positive improvement of data aggregation methods with the help of metaheuristic methods founded on optimisation, machine learning and energy-sensitive clustering to increase other aspects of the creation of the IoT and WSN networks.

1.1. Contribution

The fundamental contributions of this study are (i) presented an approach termed Optimization with Relay Quantization and Efficient Selection for Transmission (ORQET) that adaptively selects cluster-heads and relaying nodes based on a combination of the quality of connections, remaining energy, and relationships between data to achieve energy-aware routing and maximize system lifetime; (ii) extended the ORQET framework to include the Data Aggregation and Energy-Efficient Routing Optimizer (DAERO), which conserves the energy consumed by eliminating redundant transmissions and balances the distribution of energy consumed by the nodes while simultaneously maintaining an adaptive routing role through a multi-objective optimization process; and (iii) presented a suite of simulations comparing ORQET with DAERO to several benchmark protocols such as HMAC, PSO, Hybrid PSO, and CCOA indicating the superior performance of ORQET and DAERO for established metrics of network performance in terms of throughput, energy-consumption, transmission delay, packet delivery ratio, and packet loss. Overall, the framework presented is suitable to be scalable, secure, and manageable practical implementations in mission-critical IoT and WSN applications for healthcare monitoring, smart agriculture, machinery automation, and environmental sensing.

1.2. Research Objectives

The primary goal of the research is to design and, where feasible, to develop an ORQET algorithm that enables the adaptive selection of the relay to eliminate duplication of data, energy, and improvements to the Wireless Sensor Networks (WSNs) and IoT systems. In addition, the optimisation component (DAERO) will be introduced to optimise data aggregation efficiencies by removing data transmission redundancies and streamlining energy consumption expended by the nodes. Providing a routing pattern that is not only secure, but also scaled and reliable, in addition to facilitating the potential throughput, minimal transmission delays and maximum percentage of packet delivery. To accomplish these major objectives, the performance of the ORQET with DAERO will be compared with the other existing performance measures of the developed performance metrics of the established clustering and routing protocols, where simulation is the performance metric. Monitoring of these simulations will be carried out using various significant metrics: throughput, energy use, delays, ratio of packet delivery and ratio of packet loss. Finally, demonstrate the usefulness of the model and how it would be used in a mission-critical system, such as in healthcare monitoring, industrial automation and environmental monitoring.

1.3. Organisation

The article is simply written and rational. The Abstract presents the problem, states the importance of the problem, and the contributions, outputs of the proposed model. The paper is organised in the following way: Section 1, Introduction, introduces the problem, its importance, and outlines the purpose and contributions made by the study. Section 2 Background Study provides the literature review of the available literature and enumerates the existing gaps in the research. Section 3 Materials and Methods expound the proposed ORQET and DAERO systems, algorithms, equations and architecture scheme. Section 4 Results and Discussion begin the performance analysis, and compares the methods provided to the existing methods. Section 5 Conclusion presents a conclusion on the contribution, implication and recommendation on the potential research for the future.

2. BACKGROUND STUDY

Salam et al. (2023) [21] these authors have investigated cluster-based data collection in aerial sensor networks in the IoT setting. The authors proposed the optimal solution to enable data collection and communication through the use of clustering mechanisms. The research targeted minimising energy expenditure and network lifetime enhancement in aerial sensor networks. The research identified the need for intelligent data collection towards increasing IoT-based observation system scalability and dependability.

Venkateswaran et al. (2024) [22] A Firefly-Artificial Bee Colony hybrid optimisation algorithm was applied in the research to optimise data acquisition of IoT-based agriculture systems. Aggregation and processing were enhanced in efficiency, using Bio-inspired optimisation algorithms in the paper. The structure was optimised for energy consumption as well as proposed for precision agriculture. Intelligent algorithms utilised during processing in massive IoT networks were emphasised in the paper.

Osamy et al. (2022) [23] The authors illustrated the new applications of Artificial Intelligence (AI) techniques to resolve data gathering, aggregating, and trading issues in wireless sensor networks. They addressed various AI-driven solutions to maximise network efficiency and information effectiveness. They determined the predominance of AI-driven solutions in optimising sensor data processing and decision-making. The review revealed new insights into the current trends and limitations of AI-capable wireless networks.

Sridhar & Pankajavalli (2023) [24] the authors proposed an adaptive data fusion mechanism with enhanced hop selection in wireless sensor networks. The researchers proposed a Voronoi-based cooperation strategy with energy-conscious dual-path routing. Their method improved network performance by conserving power and data reliability during transmission. Their method would be capable of extending the lifespan of networks, as has been proven by their research.

Khan et al. (2023) [25], the above research highlighted an IoT-facilitated Advanced Metering Infrastructure (AMI) smart grid networks with minimal resources, a Quality-Of-Service (QoS)-centred data aggregation scheme. Optimisation for maximum accuracy of data, reduction of delay in transmission, and network efficiency has been achieved by the authors. Their result illustrated the manner in which correct modes of processing data must be adopted to provide reliability to the communication of smart grids. Sall & Bansode (2021) [26], the authors of this paper, achieve secure data transmission and acquisition in cluster-based wireless sensor networks through the Hash-based Message Authentication Code (HMAC) protocol. The authors suggested a cryptographic approach towards data security without compromising the network performance. Data integrity, authentication, and confidentiality issues were solved by the authors in this paper. The research laid importance on secure communication protocols in wireless sensor networks.

Jabbar and Kareem (2024) [27], The proposed CCOA-DC compression and NMF in data aggregation in WSNs; the processes comprised the aggregation using a cluster optimization, yet the high computational cost in large networks, and the gap in research is the implementation of suggested protocol in real-time, the results have indicated the pleasant performance of the proposed protocol in terms of accuracy and energy usage in data aggregation.

Krishnasamy et al., (2020) [28], The angled heuristic clustering is created to guarantee the introduction of the data aggregation of the WSN into the research and secure it using the angular clustering and encryption, the proposed approach does not provide the opportunity to manage the dynamic topology change, the gap between the adaptive security of the mobile nodes, the findings reveal the high degree of security and reliability of the data aggregation.

Chythany et al., (2020) [29], Ready to cluster-based routing and data aggregation WSNs in the format of cluster formation and inter/inter-cluster communication; energy imbalance constraint, the received results suggest the average enhancement of the network life.

Khan et al., (2024) [30], Data aggregation of IoT healthcare data, has been suggested with the use of redundancy elimination which is energy-efficient; limited by the scaling problem, difference between real-time networks on a large scale, results in data, and energy savings.

Darabkh et al., (2023) [31], The parameter adjusting of PSO to mobile sink and PSO to WSNs by introducing power-aware cluster protocol; the shortcoming of the parameter adjustment is that it is not dynamic and the experiment findings indicate that life of the network and optimal use of energy.

Sahoo et al., (2024) [32], Intelligent clustering in uncertainty with the assistance of fuzzy logic has a positive influence on the life of the network; but the cost of calculations is high, lightweight real time clustering is not compared with it, and the outcomes of this clustering are the improved lifetime of the network and the stable operation. Al-Heeti et al., (2024) [33], Heterogeneous WSNs aggregation was designed, with the energy-efficiency factor; sparseness of dense networks, the absence of consensus between scalable heterogeneous aggregation, data was demonstrated to conserve energy and the findings were stationary collection of data.

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Senthil et al., (2022) [34], Cluster-based routing proposal with hybrid PSO to design energy-efficient IoT networks; lack of sensitivity and mobility of PSO is its weakness in the network, lack of robust dynamic routing, the findings indicate that the network has a longer life and consumes less power.

Rajaram Jatothu and colleagues (2022) [35] proposed some significant elements of the Internet of Things (IoT) data aggregation, based on heuristic methods, under machine learning, clustering. In some way, this may allow them to focus on scalability and reliability, since the management of resources in driving infrastructures is fluid. Their additional point, therefore, was that the impact of a combined hindsight/experience heuristic method and machine learning, without doubt, will increase as IoT develops.

Manigandan and Saranya (2025) [36] build upon Rajaram Jatothu et al.'s (2022) study, and proposed Secretary Bird Optimisation with Differential Evolution (SBODE) for WSNs, and a Trust Energy Aware Clustering Routing (TREAC) Protocol. This hybrid approach improved energy-aware routing and security in communications. The authors showed improved performance using the hybrid approach as compared to existing clustering routing protocols.

Mehrjoo and Khunjush (2018) [37] optimally noted that they had designed an IRFD-driven data aggregation tree using semi-rural WSNs, while allowing for a mechanism of equalising node energy levels/discharge rates with less communication overhead; another recommendation made was the lifetime of the network through distributed workloads.

In 2020, Xiao et al. (2020) [38] suggested a hyper-local energy-efficient clustering routing protocol for underwater WSN; note was the utilisation of genetic algorithms of evolutionary genetics, which could reduce redundancies through merging data. Later, they trialled that protocol and noted energy savings in difficult conditions underwater.

In a recent work in 2023, Sharada et al. [39] proposed a method by which they found a routing protocol for WSNs based on adaptive ant colony optimisation (ACO) distributed clustering; the approach focused on minimising power consumption and maximising network life. They noted better performance compared to fixed clustering methods.

While Fischlin et al. (2018) [40] commented on vulnerable hash functions, especially HMAC and HKDF, and proposed possible ways to mitigate trust, this was significant because it focused on secure communications in WSN and IoT. On one hand, Jain et al. (2022) [41] studied it forms and changes with respect to Particle Swarm Optimisation (PSO) and on the other hand, observed hybrid types to the accuracy and speed of convergence i.e., algorithms. Authors studied PSO-based studies to clustering or routing on WSN. Kamboj (2016) [42] presented an example of a hybrid PSO-GWO (Grey Wolf Optimiser) algorithm and looked at the unit commitment problem, where hybrid methods offer both better search and better accuracy. These simulations will have their legacy to WSN, specifically in adapting to energy-efficient optimisation.

Sugumaran et al. (2025) [43] studied a blockchain-based data aggregation schema and its features of security, tampering-proof data transmissions, and risk awareness in MANET. Also, mobile distributed networks have increased with trust and security.

Jabbar and Kareem (2024) [44] introduced CCOA-DC, which is an optimisation process based on clustering and non-negative matrix factorisation (NMF) for WSN data. In addition to low communication cost, saving energy was also a concern at a high level of aggregation to large networks.

Fischlin et al. (2018)[45] analysed how Hash-based Message Authentication Code (HMAC) and (HKDF) can be used securely with immunisations to protect against malicious back doors. The vaccination approach presented to defend systems with high security sensitivities provided WSN and IoT communication safety, resulting in secure data transmission.

2.1. Problem Identification

Over the years, data aggregation and clustering methods applicable to IoT and WSN data have improved; nevertheless, there remain issues. Energy efficiency still presents a challenge to achieve, especially in resource-constrained and larger environments. Existing heuristic (and hybrid) optimisation and clustering algorithms have difficulty combining and optimising energy efficiency, security, and accuracy of data efficiently. In addition, ensuring safe delivery of data in heterogeneous and mobile networks (including MANETs, underwater WSNs) is becoming increasingly difficult. Combinations of AI, blockchain and bio-inspired algorithms show promise; however, they currently require experimentation to be scaled or shown they be flexible enough to increase the lifetime and performance of networks.

3. MATERIALS AND METHODS

Optimization with Relay Quantization and Efficient Selection for Transmission Algorithm (ORQET) is an optimisation technique created to assist in aggregation of data and performance of relay node selection in the context of transmitting data packets between nodes and gateways in a wireless sensor network (WSN) or the Internet of Things (IoT) or networks. It can offer energy-saving clustering, and offer selection and a decision of the most effective relay nodes to alternate roles to help a more successful transition to a longer survival time and a more consistent data transmission. It employs a data aggregation algorithm and relay selection that is conditional on the current network properties (remaining energy and link quality) to limit the

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overhead costs of sending and receiving node packets in each direction. The simulations verify that ORQET is energy efficient, and can offer enormous bandwidth to the network and deliver more precise data than conventional clustering and relay elevation methodologies, and can be utilised to practical scenarios like environmental measurements and industrial control. Once the ORQET is developed, the ORQET performance could be tested with the assistance of DAERO. When routing decision was conducted in the WSN case and in the IoT case, routing using the ORQET framework, intimacy has been optimised by developing an adaptive optimiser, DAERO, to assist in adaptive routing, intelligent aggregation of information, predictive relay choice and energy-efficient clustering. DAERO to the solution of redundancy of data in the sense of energy sustenance of WSN and IoT, and hence optimisation of the energy consumption of the capability of the nodes. DAERO, further, is less risky and more reliable based on the utilised procedures, regarding the procedure of the WSN and IoT routing, and energy-saving.

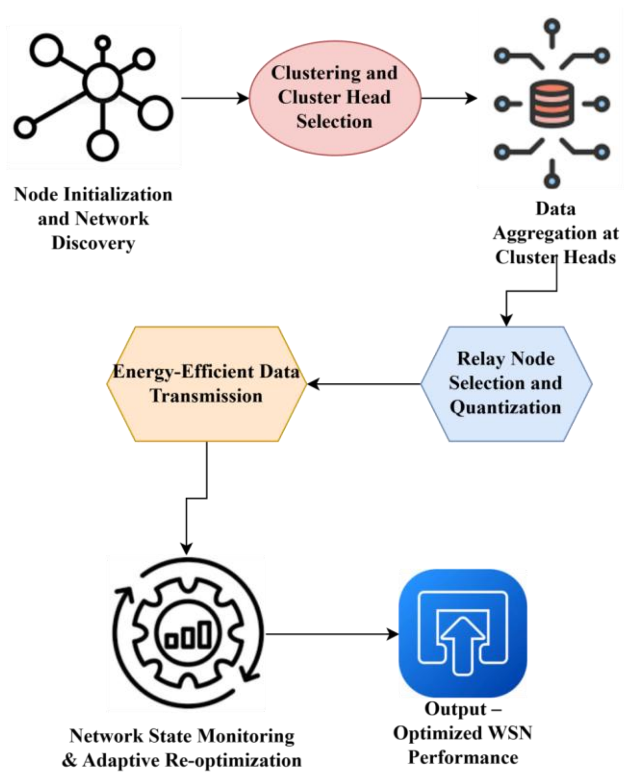

Figure 1 Overall Architecture

Figure 1 gives us a protocol that can be refined to enable a Wireless Sensor Network (WSN) to route its data in such a manner that it can be used to minimise the energy usage by the network. The protocol will start with Clustering and Cluster Head Selection, where sensor nodes will cluster and choose cluster heads in a way that optimally serves the most efficient communication. The Relay Node Selection policy and the Quantisation policy say what relay nodes would most effectively transmit forward, and would also offer more useful quantisation to the transmission of data. Energy-efficient data Transmission is the other element of the protocol that attempts to preserve and conserve the amount of energy consumed by forwarding data. Performance Optimisation and final Data output finally completes the protocol and fills in the circulatory loop of protocol and resource consumption, and leaves behind a low-power adaptive communication system to continue with the rest of the trial protocol.

3.1. This Eliminates Relay Quantisation and Efficient Selection to Transmission Algorithm Optimisation

Cluster networks also prove more effective in gathering and transferring information to other optimisations, the conservation of energy and the reliability of the transmission. The ORQET design (Algorithm 1) will solve these problems by relying on very brilliant data aggregation techniques and on the best selections of relay nodes. The algorithm can be implemented in a two-dimensional model where the algorithm uses the best possible data of the cluster nodes at the same time to eliminate redundancy, thus transmission overhead, as well as the resultant optimum fit relay nodes upon which to broadcast the data gathered in a bid to maximise on the life of the network as much as possible and still relay the data.

In picking the relay nodes, ORQET takes into account the mixed algorithm approach of optimisation clustering, heuristic algorithm and machine learning. The clustering algorithm initially supposes a rigid neighbour to cluster sensor nodes and relies on equal amounts of energy expended and information to insert an order, which is actualised in the stabilisation of the cluster to encourage the requisite trustworthy multiplier of energy. A suitable relay node selection of all clusters will then be dynamically learned over real parameter values of all the remaining energy, connection quality, and data balancing of the nodes. This will do away with a scenario of making one node useless in the effort to expand the network due to the load.

The other notable strength of ORQET is that it is capable of reacting to the changes in the network environment. This will consume resources as opposed to the rest of the clustering or relay selection algorithms that are available in the industry, and will make any number of pre-determined decisions. ORQET can then take action in real-time with real-time information and optimisation of algorithms rather than deterministic clustering and relay decision-making. This allows ORQET to make an on-the-fly decision at a given time. This and the connotation of energy savings further contribute to the potential of optimum data and low latency of relay.

The other desirable aspect of ORQET is security. The lightweight encryption is triggered on the algorithmically

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encrypted and fair authentication schemes in a way that the data cannot be manipulated or unjustly attacked during transmission. Better still, ORQET will support relaying of already occupied relaying nodes to relay the data accordingly and therefore as much as possible maintain the integrity and confidentiality of passing data. This has been particularly demonstrated in the vast networks of IoT and WSN, where an enormous amount of data transfer will be a potential loss and straining of packet transfer.

The ORQET uses clustering to reduce the bandwidth of similar data it sends before sending an Ion order, with the aim of reducing the majority of the overhead of communications. It allows it to be applied in those applications where real-time aggregation and real-time communication of data is needed, as in environmental monitoring, agricultural monitoring and industrial controls.

In a general sense in the performance comparisons that could have been made, it could be made that ORQET could outperform the traditional performance of clustering and selection of relay nodes in the sense that the outcome of the simulation displayed a wide spread of energy saving, network throughput enhancement and information accuracy, all of which are required by WSN. The asymmetric energy injected into the whole network was minimised by the selection of relay nodes using intelligence, and risk of the risk of a node in the first life cycle failing in the network was minimised to a minimum. The decision regarding the relay nodes extended the time span of the WSN.

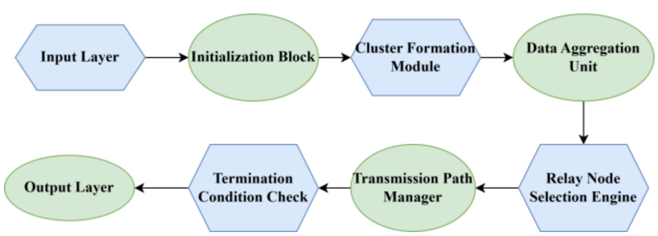

Figure 2 Relay Quantisation and Efficient Selection of Transmission Algorithm Optimisation

Figure 2, Data within a WSN carries a smart routing architecture which comprises a modular architecture. It begins with the components of the Input Layer, then the Initialisation Block and then it ultimately is the Cluster Formation Module. One of the components of this module Data Aggregation Unit, normalises and aggregates the node data of many other nodes. Second is the Routing and Scheduling Module that builds on the Cluster Formation and Data Aggregation Module and introduces the Relay Node Selection Engine and Transmission Path Manager, which operates the data of the Communications Layer and then sends it to the Data Manager. Termination Conditions are considered, and the outputs are forwarded to the output Layer.

$$E_{tx}(l,d) = l \times E_{elec} + l \times \epsilon \times d^n \qquad (1)$$

Equation (1) captures the energy expenditure in sending a data packet of length l through a distance d. The initial term, $l \times E_{elec}$, represents the energy spent on processing and transmission by electronic circuits, and the second term, $l \times \epsilon \times d^n$, is the propagation distance loss of transmission, as well as other environmental losses, with ϵ being the coefficient of energy dissipation and n is the path loss exponent.

$$E_{rx}(l) = l \times E_{elec} \qquad (2)$$

Equation (2) presents the energy cost of receiving a data packet of length l. The expression $l \times E_{elec}$ is for electronic circuitry, the energy cost of processing received data. There is no distance-related energy loss in reception, and hence it depends only on the electronic energy cost per bit.

$$DAR = \frac{D_{before}}{D_{after}} \qquad (3)$$

Equation (3) yields the Data Aggregation Ratio (DAR), representing data aggregation efficiency for minimising the size of data to be transmitted. Here, D_{before} represents the total raw data size before the data aggregation process, and D_{after} represents the size of data aggregation after the aggregation process. High DAR indicates more efficiency of the aggregation process with fewer transmission overhead and energy utilisation for wireless sensor networks.

$$E_{CH} = \sum_{i=1}^{N}\left(E_{rx}(l) + DAR(l) + E_{tx}(l, d_{BS})\right) \qquad (4)$$

Equation (4) expresses the total energy consumption E_{CH} of a CH in a WSN. It consists of the energy expended on receiving data from N cluster members ($E_{rx}(l)$), the energy spent on data aggregation ($DAR(l)$), and the energy spent on transmitting the aggregated data to the base station ($E_{tx}(l, d_{BS})$).

$$C_r = \alpha \times \frac{E_{residual}(r)}{E_{initial}(r)} + \beta \times \frac{1}{d(r,CH)} + \gamma \times QL(r) \qquad (5)$$

Equation (5) defines the clustering coefficient C_r for a sensor node r in a WSN. It considers multiple factors: the ratio of the residual energy $E_{residual}(r)$ to the initial energy $E_{initial}(r)$, the inverse of the distance $d(r, CH)$ between the node and the cluster head, and the quality of the link $QL(r)$. The parameters α, β, and γThe weight parameters are used to scale the influence of these factors on the cluster decision.

$$T_{net} = \frac{E_{total}}{\sum_{i=1}^{N} E_i} \qquad (6)$$

Equation (6) is the Network Lifetime (T_{net}), and it is obtained as the quotient of the total energy available in the network (E_{total}) and the summation of energy dissipated by all the sensor nodes ($\sum_{i=1}^{N} E_i$). This equation is used to analyse the sustainability of a wireless sensor network, where the larger T_{net} implies a longer duration of network working and better energy usage.

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$$D_i = \frac{P}{B} + \frac{d_i}{S} \quad (7)$$

Equation (7) is the data transmission delay (D), and P is the processing time, B is the bandwidth, d is the receiver distance, and S is the signal propagation speed. Equation (7) helps in network performance analysis by considering both processing and transmission delays for efficient data aggregation and timely delivery in clustered networks.

Input:

N ← Set of sensor nodes

BS ← Base Station

BEGIN

Step 1: Initialisation

For each node i in N do

Initialise energy E_i, communication range, and position

Discover neighbouring nodes and store neighbor info (energy, distance, link quality)

End For

Step 2: Cluster Formation

For each node i in N do

Compute clustering metric C_i based on residual energy, distance to BS, and connectivity

End For

Select Cluster Heads (CHs) with the highest C_i values

Assign non-CH nodes to the nearest CH, minimising transmission cost

Step 3: Data Aggregation at CHs

For each CH do

Collect data from cluster members

Perform data aggregation (e.g., compression, averaging)

Apply redundancy reduction to minimise data size

End For

Step 4: Relay Node Selection

For each CH do

Identify relay candidates from CH or neighbours with:

- High residual energy

- Strong link quality

- Shortest path to BS

If multiple candidates have similar scores then

Apply relay quantisation metric to select the optimal relay node

End If

Authenticate the selected relay node for secure forwarding

End For

Step 5: Data Transmission

For each CH do

If the relay node is selected then

Transmit aggregated data to the relay node

Relay node forwards data to BS

Else

Transmit data directly to BS

End If

End For

Step 6: Termination

If percentage of dead nodes > threshold or network lifetime expired then

Terminate algorithm

Else

Go to Step 3

End If

END

Output:

Optimized data transmission with energy-efficient clustering and relay selection

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Algorithm 1 Optimisation with Relay Quantisation and Efficient Selection for Transmission (ORQET)

The ORQET algorithm is robust and aggressive in quality communication strategy, and has a distinct architecture, and the energy requirement is minimal since it uses clusters and speed during the process of selecting relay nodes. The remaining energy determines the CH, and they are dependent on the distance to the base station (BS), implying that they do not overlook the two. Cluster and inter-cluster information aggregation is performed, and the exchange of information between clusters is performed in the most optimal way possible, which is guided by a quantisation measure which is defined based on energy consumption, link quality and distance. This plan is directed at the minimisation of unneeded data transmissions, data balancing, network lifetime and provision of data in the proper and secure way to its ultimate destination terminal in a fashion that is both intended and not hazardous.

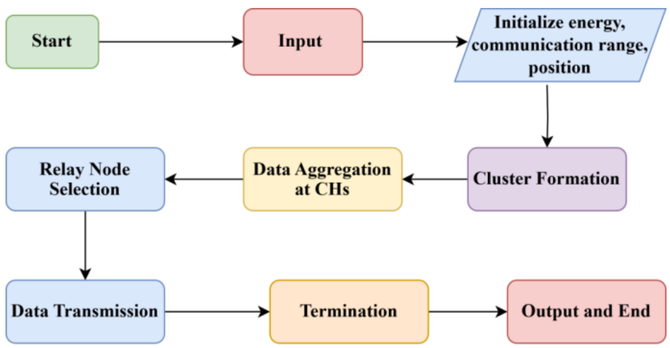

Figure 3 Optimisation with Relay Quantisation and Efficient Selection to Transmit the Flow Chart

Figure 3 displays the workflow of the WSN routing protocols. The initial one would involve the generation of parameters, i.e., Node Energies vs. Transmission Range and Position, Node Clustering and Relay Node Selected, and then the CH gains and summative data. Once the aggregation is done, the CH communicates it to the sink and the round of communication is complete leading to the presentation of data.

3.2. Energy efficient Data Aggregation and Routing Optimiser.

A further, further layer of optimisation layer over performance and energy consumption efficiency of data transmission on ORQET is proposed, and is simply called DAERO (Algorithm 2). DAERO has a little resemblance here in its objective of attaining energy efficiency through the smart clustering of nodes and the selection of a relay node to reduce redundant transmissions. DAERO will differentiate between CHs and the relay node based on the remaining energy of the nodes, and the interrelationship with their neighbours and data correlation analysis.

$$R_{data} = \frac{1}{M} \sum_{j=1}^{M} \frac{S_{raw}(j) - S_{agg}(j)}{S_{raw}(j)} \quad (8)$$

Equation (8), where, $S_{raw}(j)$ is the raw data size from the node group j, $S_{agg}(j)$ is aggregated (compressed) data after fusion, M is the number of clusters. It measures how much repeated or correlated data is being transmitted unnecessarily. DAERO reduces $R_{data}$by aggregating similar data at CHs. A lower R_{data} means more effective aggregation.

$$PDR = \frac{P_{received}}{P_{sent}} \times 100\% \quad (9)$$

Equation (9), where, P_{sent} is the total number of packets sent, $P_{received}$ is the total number of packets received at the base station. It indicates the reliability of the network: how many packets are successfully delivered compared to how many were sent. A high Packet Delivery Ratio (PDR) (close to 100%) is desirable and indicates low packet loss.

The optimisation will be accomplished using a multi-objective fitness function that considers energy consumption, delay, data redundancy, and reliability. The fitness function is defined as (Equation 10):

$$min\, F = \alpha_1 \cdot E_{CH} + \alpha_2 \cdot R_{data} + \alpha_3 \cdot D_i - \alpha_4 \cdot PDR \quad (10)$$

Equation (10), where, E_{CH} Is the total amount of energy taken, R_{data} is the redundancy from correlated data, L_{delay} is the end-to-end lag, and PDR. The weighting factors α_1 to $\alpha_4$re-adjusted dynamically based on the network conditions. DAERO utilizes adaptive optimisation mechanisms to periodically update CH and relay roles to foster prolonged network lifetime, high reliability, and low communication overhead in WSN/IoT scenarios.

DAERO enhances ORQET to the extent that it can cluster and preempt energy in a manner that will not cause overloading of a single node, extending the life of a certain network. The clustering of correlated data at a small number of CHs, especially, causes fewer packets to be sent by the same node, which is observed in massive bandwidth savings as well as in the overall number of packets entering the network because only a small number of nodes transmit along longer routes. DAERO helps in the selection of relay nodes that generate energy-efficient multi-hop paths and communicate among themselves either through a relay node inside the network or directly to the hub that controls the network. DAERO, in both cases, lets you or the network enjoy savings of costs in long-distance communication that are measurable. DAERO is carrying out field cycles of the energy state of each node, and is able to change routing decisions, and even clustering in case it is needed, based on energy state and topology change. This ultimately guarantees performance based on total packets sent, and delays that is caused by delivery as well as issues in larger, more distributed networks. So, perhaps, DAERO can become a highly desired mechanism under time-constrained or resource/battery-constrained IoT scenarios, such as smart agriculture or environmental sensing and monitoring, or even health care.

Input:

N ← Set of sensor nodes with their residual energy, positions, and data profiles

Current CHs and relay nodes from ORQET

Network parameters: energy thresholds, delay tolerance, data correlation metrics

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BEGIN

Step 1: Collect Network State

For each node i in N do

Measure residual energy E_residual(i)

Assess connectivity and link quality QL(i)

Evaluate data correlation with neighboring nodes, Data_corr(i)

End For

Step 2: Compute Clustering Fitness for each node i

For each node i in N do

Calculate clustering coefficient C_i:

End For

Step 3: Select Optimal CHs

Choose nodes with the highest C_i values as CHs, ensuring coverage and load balance

Step 4: Evaluate Relay Node Candidates for each CH

For each CH, do

Identify relay candidates from neighbouring nodes

For each candidate node r do

Compute relay fitness R_r:

End For

Apply quantisation if multiple candidates have close R_r scores

Select the relay node with the highest R_r

End For

Step 5: DAR Optimization

For each cluster do

Calculate DAR

Adjust data aggregation parameters to maximize DAR, reducing redundant transmissions

End For

Step 6: Multi-Objective Fitness Evaluation

For each CH and relay pair, do

Evaluate fitness function:

Select cluster and relay assignments minimising F

End For

Step 7: Update Network Assignments

Assign new CHs and relay nodes based on fitness evaluation

Update routing tables and transmission schedules accordingly

Step 8: Adaptive Re-optimisation Loop

Periodically or when network conditions change:

Repeat Steps 1 to 7 to maintain optimal performance

END

Output:

Optimised cluster head and relay node assignments

Minimised data redundancy and energy consumption

Improved reliability and network lifetime

Algorithm 2 Data Aggregation and Energy-efficient Routing Optimiser (DAERO)

The DAERO algorithm is based on the optimisation of the routing and data aggregation process on the grounds of energy residual, the quality of links, and the property of the data correlation of the CHs and the relays. DAER computes a clustering fitness and a relay fitness to trade off (communication) paths and energy. The DAERO algorithm will attempt to maximise the Data Aggregation Redundancy (DAR) to avoid the cost of duplication information and the costs of transmissions. This is determined with the help of the fitness role among the various goals that determine the optimum selection of the CH-relay pair that improves the stability and life cycle of the system and the adaptive re-learn process is used so that the network can be maintained topical with fluctuation or change in conditions.

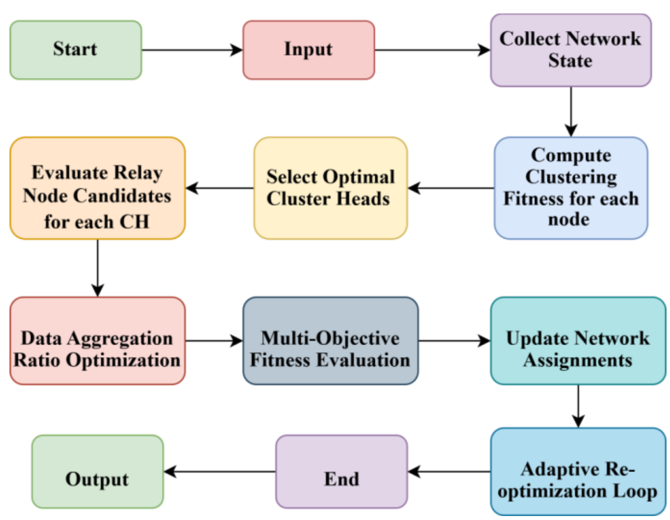

Figure 4 Data Aggregation and Energy-Saving Routing Optimiser Flow Chart

Figure 4 represents a dynamic multi-objective routing algorithm of WSNs, and it uses a cluster-based routing

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algorithm. The collection of the network state and estimation of the clustering fitness is the first step of this flowchart. The next step before the CH is the selection of its CH and also measuring the corresponding relay node candidates. The algorithm then contrasts the efficiency of the data aggregation and applies a multi-objective fitness function, again repeating the adaptive re-optimisation until the final stage or an output stage is approached, which is the last opportunity to make decisions limited by design.

4. RESULTS AND DISCUSSION

In this part, the proposed ORQET with the DAERO framework performance is discussed through comparison to other routing protocols. It will concentrate on the parameters of the simulated environment, the parameters of the parameters and the analysis of the results to demonstrate the effectiveness, consistency and the suitability of the suggested method of energy-constrained Wireless Sensor Networks (WSNs). Cluster heads (CHs) will be selected on the basis of energy left, distance to the base station and connectivity. The sensor nodes send data to CHs who then allocate tasks to jointly aggregate the data and reduce Data Aggregation Redundancy (DAR). The selection of relay nodes can also be based on their fitness score, which considers their energy, link quality and their distance to the CH. Information is relayed between the CH and the base station, or one of the relay nodes that were selected in advance. Every time the data are transmitted the energy of the nodes are also updated and, in case the state of the network has been altered, the algorithm will also optimize and re-select CHs, clusters and relay nodes.

4.1. Simulation Parameters

Provide a complete WSN in the simulation with the sensor nodes randomly located with a fixed initial energy. The selection of cluster heads (CHs) is based on their remaining energy, distance to base station and their connectivity. CHs receive the data of sensor nodes and DAR is avoided by collaboratively aggregating the data. Relay nodes may be chosen depending on the fitness score concerning the remaining energy, the quality of links and their distance to the CH. The CHs will subsequently be transmitting data to either the base station or one of the chosen relay nodes. Every time a transmission takes place, the node's energy is updated, and the algorithm optimises and re-optimises the CHs, clusters, and relay nodes in case of a network change of state.

4.2. Performance Comparison

4.2.1. Throughput

Throughput is a measurement of the amount of data that was transmitted successfully in one second (bits/sec) along the network. Thus, higher throughput results in higher performance in transmitting or transmitting data across WSN(s).

Table 2 Throughput Value Comparison Table

Packet Size (bits)	HMAC [40]	PSO [5]	Hybrid PSO [42]	CCOA [27]	ORQET with DAERO (Proposed)
1000	1.19	2.01	2.10	2.11	2.38
2000	1.89	2.13	2.29	2.58	3.69
3000	2.25	2.47	2.94	3.01	4.72
4000	2.85	3.00	3.09	3.49	5.99
5000	3.49	4.05	4.62	4.89	7.03

Table 2 compares throughput and various packet sizes of HMAC, PSO, Hybrid PSO, CCOA and proposed ORQET versus DAERO. Any of the algorithms is observed to increase throughput with increased packet size up to 5000bits. ORQET and DAERO gave the maximum throughput of each packet size used (7.03 bits/sec at 5000 bits), thus ORQET and DAERO give the highest efficiency. CCOA was the one with the next highest throughput, which was followed by the Hybrid PSO, PSO and finally HMAC, which had the lowest throughput. This means that ORQET with DAERO tends to have the overall best management of its resources dedicated to its overall transmitting performance and to its packet management with regard to the sizes of packets that are common in WSN.

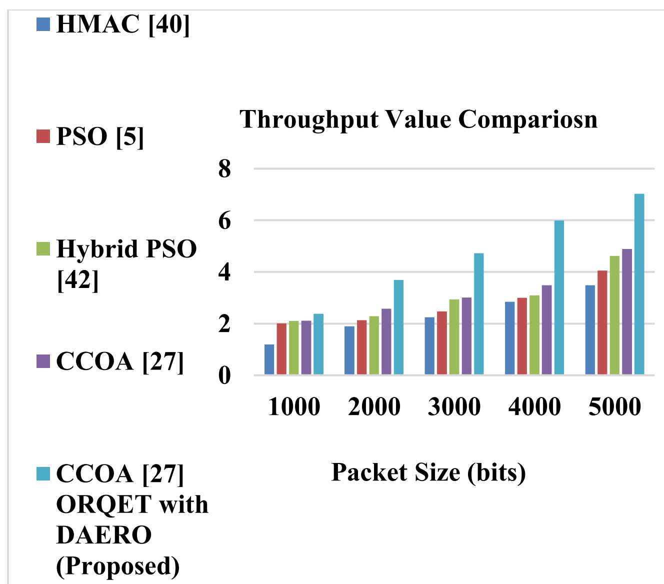

Figure 5Throughput Value Comparison Chart

Figure 5 shows the throughput performance of each of the five algorithms, once more versus packet size, (x) 1000-5000 bits and through (y) throughput. Test to test ORQET with

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DAERO produced the highest throughput at better scalability and total efficiency.

4.2.2. Energy Consumption

Energy consumption is the sum of the energy expended, which is bought by the network nodes. Once again, low values reflect high overall performance.

Table 3 Energy Consumption Value Comparison Table

Operating Time (Hrs)	HMAC [40]	PSO [5]	Hybrid PSO [42]	CCOA [27]	ORQET with DAERO (Proposed)
10	1.0	0.9	0.8	0.4	0.1
20	1.5	1.4	1.3	0.8	0.2
30	2.3	2.1	1.9	0.9	0.4
40	2.8	2.7	2.1	1.3	0.5
50	3.0	2.9	2.4	1.7	0.7

Table 3, The quantities of energy consumed by HMAC, PSO, Hybrid PSO, CCOA and the proposed ORQET with DAERO are given in Table 3 under the scaling operating times. Energy consumption rose with the operating time of all algorithms and ORQET with DAERO always had the lowest recorded energy consumption, meaning that it was more energy efficient as compared to all other options. Indicatively, HMAC used the highest energy consumption with Hybrid PSO and CCOA being comparatively energy-consuming.

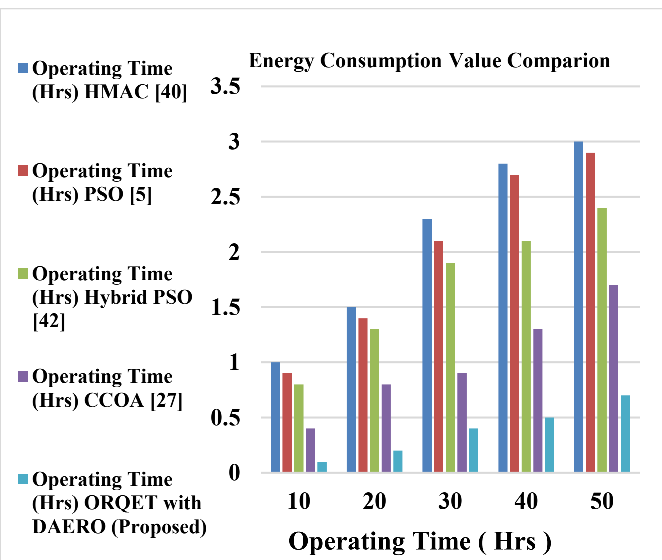

Figure 6 Energy Consumption Value Comparison Chart

Figure 6, The trends of the energy consumption with time are plotted in Figure 6, and they relate to the performance of the algorithms. Because smaller values have better results, ORQET with DAERO remains the lowest among all the times, and this proves that ORQET with DAERO works well in energy-limited settings of wireless sensor networks (WSNs).

4.2.3. Transmission Delay

Transmission delay measures how much time it takes a packet to reach its assigned destination, and in a rule of thumb, the lower the value, the more favourable it is.

Table 4 Transmission Delay Value Comparison

Number of packets	HMAC [40]	PSO [5]	Hybrid PSO [42]	CCOA [27]	ORQET with DAERO (Proposed)
50	5.0	4.5	4.0	3.2	2.0
100	4.8	4.2	3.7	3.0	1.8
150	4.5	3.9	3.4	2.8	1.5
200	4.3	3.7	3.1	2.5	1.3
250	4.0	3.5	2.8	2.2	1.0

Table 4 provides a summary of transmission delays of the algorithms using three packet sizes. The fastest algorithm was the proposed ORQET with DAERO since it was the algorithm with the lowest delay, and HMAC had the largest delays.

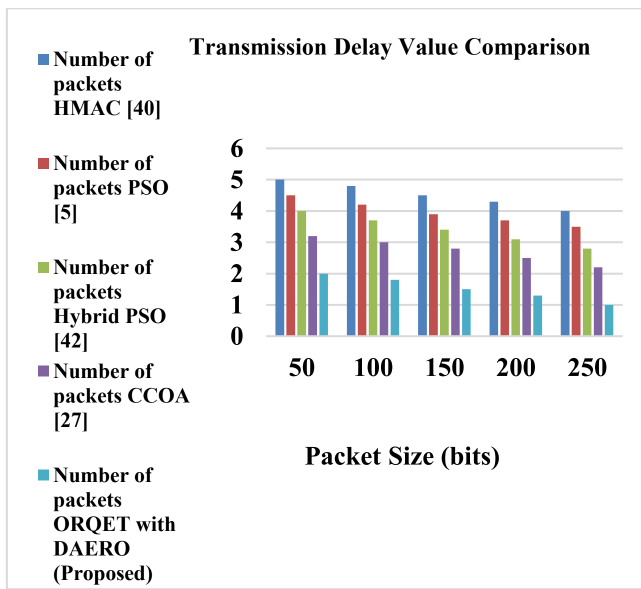

Figure 7 Transmission Delay Value Comparison Chart

In Figure 7, the trends of transmission delays are compared with the packet size. ORQET and the DAERO fast SAR exhibit the highest levels of performance among all three other ways of the packet size tested.

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4.2.4. Packet Delivery Ratio (PDR)

The ratio of packets delivered to their destination is the Packet Delivery Ratio (PDR). The larger the PDR, the more reliable the network.

Table 5 Packet Delivery Ratio Value Comparison Table

Number of packets	HMAC [40]	PSO [5]	Hybrid PSO [42]	CCOA [27]	ORQET with DAERO (Proposed)
50	95.84	95.89	96.00	97.10	98.72
100	96.18	96.21	96.22	97.75	99.36
150	96.49	96.45	96.84	98.02	99.62
200	96.85	97.10	97.24	98.19	99.73
250	96.93	97.10	97.46	98.45	99.80

Table 5 against different values of the packet number. The PDR values of all algorithms are increasing with increasing packets between 50 and 250. The best level of reliability is the ORQET with DAERO with a PDR of 99.80 at 250 packets. Hybrid PSO and CCOA are also doing very well, and HMAC and PSO showed less delivery ratio.

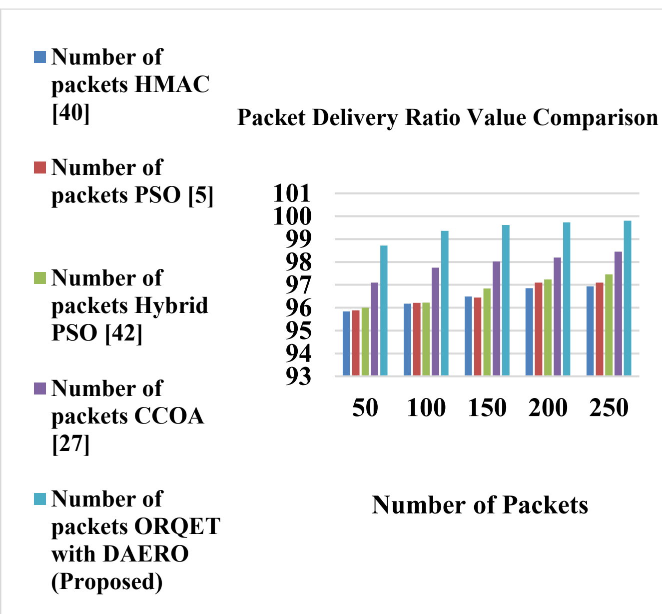

Figure 8 Packet Delivery Ratio Value Comparison Chart

Figure 8 illustrates the PDR pattern for various numbers of packets. The algorithm efficiency of ORQET with DAERO was more stable compared to the other algorithms, which justifies the efficiency of the algorithm in minimising effective packet loss and reliable data delivery during transmission.

4.2.5. Packet Loss Rate (PLR)

PLR measures the percentage of packets lost during transmission. Lower values indicate better reliability and network performance.

Table 6 Packet Loss Rate Value Comparison Table

Packet Size (bits)	HMAC [40]	PSO [5]	Hybrid PSO [42]	CCOA [27]	ORQET with DAERO (Proposed)
1000	0.0020	0.0018	0.0016	0.0013	0.0003
2000	0.0023	0.0020	0.0019	0.0014	0.0005
3000	0.0029	0.0028	0.0026	0.0017	0.0006
4000	0.0035	0.0029	0.0029	0.0018	0.0007
5000	0.0042	0.0038	0.0030	0.0027	0.0009

Table 6: The ORQET plus DAERO as proposed is least affected by the number of packets dropped, which implies that the proposed ORQET is reliable in transmitting the data of packets. The remaining algorithms indicate that HMAC has the largest percentage of lost packets whereas CCOA and Hybrid PSO have lower percentages of lost packets but are still in the shadow of ORQET.

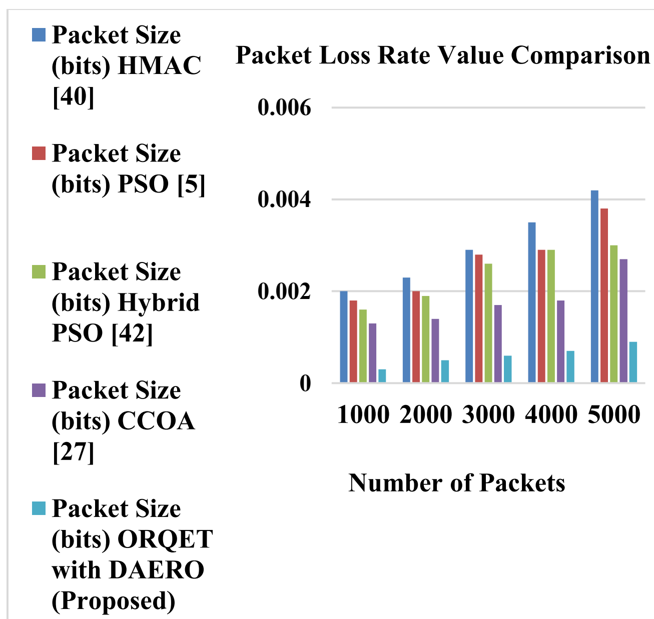

Figure 9 Packet Loss Rate Value Comparison Chart

Figure 9 indicates the PLR versus the quantity of packets of each of the five algorithms. ORQET and DAERO possess a better packet loss rate throughout the research to illustrate the effectiveness of the algorithm in minimizing the packet loss.

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The ORQET methodology (and a DAERO architecture) addresses the problems that are incurred with traditional WSN/IoT routing algorithms, including high power consumption, deterministic routing, and unreliability. ORQET methodology has energy-efficient clustering, intelligent data aggregation, and optimal selection of relay nodes. Another technique of optimising that is provided by the DAERO model is an adaptive mode of optimising to reduce the amount of redundancy and regulate the use of energy and reliability. The integrated architecture attains improved throughput, less energy consumption, less transmission delay, more packet delivery, and minimum packet loss which makes it efficient in energy-constrained WSN/IoT systems.

5. CONCLUSION

Optimized Data Aggregation with Relay Quantization and Selection Algorithm (ORQET)- is an advanced and smart routing algorithm of energy-saving and reliable communications in WSN and IoT. The ORQRET module relies on dynamic node selection schemes; adaptive node clustering and optimization mechanisms of data aggregation to limit redundancy, as well as to balance the energy consumption of the entire network. The principal center of the ORQET module is the Data Aggregation based Entity Relay Optimization (DAERO) module. DAERO An optimization layer to have head selection of clusters in real time, relay optimization, and route path in a moment as residual energy, link quality, data correlation, and load. Multi-objective fitness function drives DAERO to reduce energy consumed, redundancy of data, and delay in transmitting data, and maximize reliability to transmit packets, and is self-adaptive to adjust and re-calculate routes and roles within the network to route the ORQET members in any change that may be necessary in the real-world, and to position the ORQET to maximize the rate of packet delivery (PDR), network lifetime, and low latency where wireless packet delivery is of interest. DAERO uses light security modules to ensure the confidentiality of transmitted data and integrity of transmitted data. This has been facilitated by the optimisation abilities of DAERO embedded in the ORQET solution architecture that provides a very secure, scalable, and energy-sensitive solution to mission-critical, real-time deployments as it applies to environmental sensing, smart agriculture, industrial automation, and health monitoring.

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RESEARCH ARTICLE

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