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Quantum Node Clustered Cuttlefish Optimization Based Deep Belief Network for Secured Data Aggregation in UWSN

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Abstract: Underwater Wireless Sensor Network (UWSN) technology is used in different underwater monitoring and exploraten applications. The data aggregation is the process of gathering the data in UWSN to attain better outcomes. A Quantum Node Clustered Cuttlefish Optimization based Deep Belief Network (QNCCO-DBN) Technique is introduced for secured data aggregation in UWSN with lesser packet drop rate and lesser end-to-end delay. QNCCO-DBN Technique comprises two processes, namely clustering and secured data aggregation in UWSN. Deep Belief Network in QNCCO-DBN Technique perform four layers, namely one input layer, two hidden layer and one output layer in UWSN. Initially in QNCCO-DBN Technique, underwater sensor nodes are considered as the input at input layer for performing secured data aggregation. Input layer transmits the number of underwater sensor nodes to the hidden layer 1. In that layer, Quantum k-means Node Clustering is carried out to group the underwater sensor nodes into different clusters depending on the energy level. After that, the underwater sensor node with higher energy level is considered as the cluster head for every cluster. Then, the cluster head aggregates the data from remaining underwater sensor nodes and optimal cluster head is selected using Improved Multi-Criterion Cuttlefish Optimization in QNCCO-DBN Technique for transmitting the data packets to the base station. The proposed technique initializes the populations of the cluster head (i.e Cuttlefish). The fitness of each cluster head is calculated based on distance and trust. Then, aggregated data sent to the optimal cluster head in UWSN. By this way, secured data aggregation is performed in underwater sensor network. We administer considerable simulations to measure the performance of our proposed method and compare it with other two routing algorithms on NS2 platform. Experimental evaluation is carried out in QNCCO-DBN Technique on factors such as energy consumption, packet drop rate, end-to-end delay and data confidentiality rate with respect to number of underwater sensor nodes and number of data packets.

Keywords: Underwater Wireless Sensor Network, Multi-Criterion Cuttlefish Optimization, Quantum Node Clustering, Secured Data Aggregation.

1. Introduction

Under Water Sensor Network (UWSN) is used in marine environments like mineral exploraten, underwater surveillance and habitat monitoring. But, good quality of underwater communication is not easy to achieve because of different limitations like limited bandwidth, delays, battery replacement. Cluster-based sensor network is used to increase load congruency and scalability with minimal energy consumption. A new Energy Efficient Circular Spinning (EECS) dynamic clustering algorithm was introduced in [1] to present cluster setup system and to reduce the energy consumption in cluster setup. EECS mechanism enhanced the system performance through reducing the time complexity. But, the packet drop rate was not minimizedby EECS algorithm. Energy Balanced Reliable and Effective Clustering (EBREC) method was designed in [2] to guarantee that data packets reach at destination. But, the data confidentiality rate was not improved by EBREC method.

An energy-efficient and secure encryption data transmission scheme was designed in [3] depending on chaotic compressive sensing (CCS) to increase underwater wireless sensor network lifetime and data security. But, the throughput level was not improved by designed scheme. An anchor nodes-based range-free cooperative multi-trust management system was designed in [4] to perform reliable underwater localization. The multi-trust-based

scheme preserved the sensor nodes from malicious nodes. The lightweight Mamdani fuzzy model minimized the circuit complexity and memory consumption. However, the delay was not reduced by designed system.
A compressive sensing (CS)-based UWSNs data collection model was designed in [5] to develop underwater data with minimum number of sensor nodes. A packet transmission strategy was employed to guarantee successful reception of number of packets through instantaneous power. But, the aggregation cost was not reduced by CCA technique. A hybrid compressive sensing (CS) method was introduced in [6] to avoid problem linked with the large data at cluster heads (CHs) and delay in data transmission. However, the packet drop rate was not minimized by CS method.

An energy efficient and reliable protocol was introduced in [7] for routing the data packets in UWSN with sector based forwarding system. Though delivery rate was improved, data confidentiality was not improved by designed protocol. An energy-efficient and secure layered routing method (DESLR) was designed in [8] for UASNs to increase energy efficiency and transmission reliability. But, the computational cost was not reduced by designed method.

An anchor node range-free cooperative multi-trust management system was introduced in [9] using fuzzy logic for secured underwater localization. Though designed system minimized the memory consumption, delay was not reduced by designed system. A hybrid Chimp Optimization and Hunger Games Search (ChOA-HGS) algorithm was introduced in [10] for multi-hop routing optimization in UWSNs. ChOA selected the cluster heads and structure clusters. However, the packet drop rate was not reduced by ChOA-HGS algorithm.
The problems identified from the above literature are lesser data confidentiality rate, higher energy consumption, lesser throughput, higher packet drop rate, higher computational complexity, lesser network lifetime, higher computational cost, higher transmission overhead and so on. In order to address these problems, Quantum Node Clustered Cuttlefish Optimization based Deep Belief Network (QNCCO-DBN) Technique is introduced in UWSN.
The main contribution of the work is given as,

- The main aim of QNCCO-DBN Technique is to perform secured data aggregation in UWSN with lesser packet drop rate and lesser end-to-end delay. QNCCO-DBN Technique performed clustering and secured data aggregation in UWSN.
- Deep Belief Network in QNCCO-DBN Technique includes one input layer, two hidden layer and one output layer in UWSN. The underwater sensor nodes are considered as the input for performing secured data aggregation.
- Quantum k-means Node Clustering group the underwater sensor nodes into different clusters depending on energy and bandwidth. Then, the underwater sensor node with higher energy level is taken as cluster head for every cluster.
- Improved Multi-Criterion Cuttlefish Optimization selects the optimal cluster head for aggregating and transmitting the data packets to the base station. The proposed technique initializes the populations of the cluster head (i.e Cuttlefish) and fitness of each cluster head is calculated based on distance and trust. After finding the optimal cluster head, aggregated data is transmitted in secured manner.
- Experimental evaluation is carried out in QNCCO-DBN Technique on factors such as energy consumption, packet drop rate, end-to-end delay and data confidentiality rate with respect to number of underwater sensor nodes and number of data packets.

The roadmap of the paper is. Section 2 discusses the existing secured data transmission method in UWSN. Section 3 discusses the proposed Quantum Node Clustered Cuttlefish Optimization based Deep Belief Network (QNCCO-DBN) Technique. Section 4 discusses the simulation environment with performance parameters. Section 5 discusses the graphical results of secured data transmission. Section 6 concludes the research work.

Related Works

A clustering method was introduced in [11] to manage the spatial similarity between node observations. The readings were sent from sensor nodes to their suitable cluster heads (CHs). Every node removed their readings to avoid the redundancies before transmitting to CH. But, the transmission cost was not reduced by designed clustering method. A NA-TORA was designed in [12] depending on Normalized Advancement (NA). NA was determined from Transmission Count and node energy consumption for identifying the forwarding node. However, the transmission cost was not reduced by NA-TORA. An UWSN with data aggregation was carried out in [13] to emphasize their advantages and drawbacks. The fraternity towards future challenges identified with existing techniques to aggregate the data into cluster based and non-cluster based one. But, the clustering time was not reduced. CLUster-based Secure Synchronization (CLUSS) protocol was designed in [14] to enhance the synchronization security in underwater environments. CLUSS minimized the propagation delay caused by node movement to increase time synchronization accuracy. Though accuracy level was improved by designed protocol, delay was not minimized. An Improved Data Aggregation technique was designed in [15] for

Cluster Based UWSN. An efficient sleep-wake up algorithm was employed for sensed data aggregation. TDMA based transmission schedule eliminated intra and inter cluster collisions. But, the data aggregation accuracy was not improved by designed technique. An energy-efficient compressed data aggregation framework was designed in [16] for underwater sensor networks. The framework reduced the energy consumption during data transmission with less number of sampling nodes. But, the computational complexity was not reduced by designed framework. A new Energy Efficient Circular Spinning (EECS) dynamic clustering algorithm was designed in [17] to reduce the energy usage in cluster setup. EECS mechanism increased system performance with lesser energy consumption. Though energy consumption was reduced, the computational cost was not reduced by EECS algorithm. An improved energy-balanced routing (IEBR) was introduced in [18] for UWSN with routing establishment and data transmission. A mathematical model was built for computing transmission distance to identify the neighbors at optimal distances. But, the energy consumption was not minimized by IEBR. An improved Energy-efficient Slice-Mix-Aggregate (ESMART) algorithm was introduced in [19] to vary the data slices consistent with data sensed by sensor nodes. The data transmission minimized the overhead on sensor with limited energy with higher data security. Though overhead was reduced, the computational complexity was not minimized by ESMART algorithm. A Multi-Slot Scheduling was carried out in [20] with integrated aggregation to increase lifetime with less energy consumption and collision avoidance. The data aggregation was carried out with aggregator node selection. Though energy consumption was reduced, the complexity level was minimized.

2. Methodology

UWSN comprise the large number of sensors deployed in a particular area for collaborative monitoring and routing. Oceanographic sensors are used for recording the data at particular location and for recovering the sensors after task completion. The key issue of conventional method is absence of interactive communication between diverse sensors. Sensor node mobility is another problem focused in UWSNs. However, different classification methods attained lesser accuracy due to the deficiency for sentiment analysis. Consequently, novel QNCCO-DBN Technique is introduced to perform efficient secured data aggregation with higher accuracy. QNCCO-DBN Technique employed quantum clustering and cuttlefish optimization for secured data aggregation analysis. The architecture diagram of QNCCO-DBN Technique is listed in figure 1.

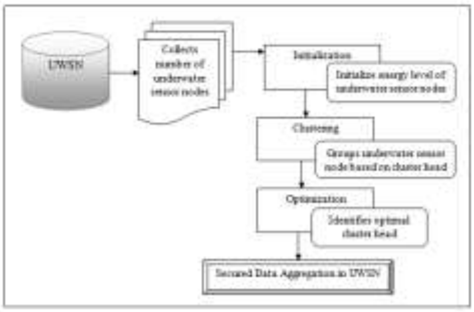

Figure 1 Architecture diagram of QNCCO-DBN Technique

Figure 1 describes the architecture diagram of the QNCCO-DBN Technique. The proposed QNCCO-DBN Technique comprised four layers, namely input layer, two hidden layer and one output layer for secured data aggregation. Initially, the number of underwater sensor nodes is considered as an input. After that, clustering and optimization process is carried out in two hidden layers for secured data aggregation in UWSN. Finally, the data aggregation is carried out in output layer. The different layers of QNCCO-DBN Technique are discussed in figure 2.

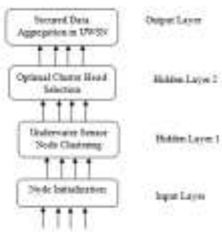

Figure 2 Different Layers of QNCCO-DBN Technique

Figure 2 explains the different layers of QNCCO-DBN Technique. In designed technique, the input layer gathers the number of underwater sensor nodes at time period 't' denoted as '$Inp(t)$'. The underwater sensor nodes are connected from one layer of DBN to another layer with help of dynamic weights. It is formulated as,

$$Inp(t) = \sum_{i=1}^{N} UWSN_i * w_{inp} + bias \quad (1)$$

From (1), '$Inp(t)$' symbolizes the neuron activity at an input layer. '$UWSN_i$' symbolizes the number of underwater sensor nodes. 'w_{inp}' denotes the initial weight. Then, the input is sent to the hidden layer 1 to perform node clustering process with lesser time consumption

Quantum k-means Node Clustering

In hidden layer 1, underwater sensor node clustering is carried out in efficient manner. Quantum k-means Node Clustering (QNC) is a type of node clustering algorithm with mathematical concepts from quantum mechanics. QNC belongs to the density based clustering. The clusters are defined through higher density of underwater sensor nodes. In QNC, number of underwater sensor nodes is distributed in n-dimensional space. QNC symbolizes the every underwater sensor node with multi-dimensional Gaussian distribution with width sigma positioned at every location in dimensional space. Gaussians are joined together to generate the single distribution. Let us consider 'N' number of underwater sensor nodes and assigned the vectors to one of k labels. At initial stage, number of underwater sensor node used elbow method to identify the best cluster. Manhattan distance is employed to group the similar underwater sensor nodes for cluster formation. Quantum k-means Node Clustering identified the preliminary value of centroid (i.e., cluster center). Let us consider that cluster centroid as '$cc_1, cc_2 \ldots.. cc_{n-1}, cc_n$'. The manhattan distance is used to determine the distance between cluster centroid and individual underwater sensor nodes. The underwater sensor node energy consumption is calculated with transmitting power and attenuation function. Let us consider that '$power_0$' as minimal power. An underwater sensor node requires data packet reception and power transmission. '$Atten$' symbolizes the attenuation function. Then, energy consumption for data transmission and reception in UWSNs is computed as,

$$ET(Dis) = T_{time} * T_{power} * Atten(Dis) \quad (2)$$

$$ER(Dis) = R_{time} * T_{power} \quad (3)$$

$$EE = \frac{ER(Dis)}{ET(Dis)} * 100 \quad (4)$$

From (2), (3), and (4), 'ET' represents the energy consumption for transmission, 'ER' symbolizes the energy consumption for reception. 'Dis' denotes the distance between transmission and reception of underwater sensor node. 'T_{time}' denotes the transmission time for underwater sensor node. 'R_{time}' symbolizes the reception time for underwater sensor node with power transmission 'T_{power}'. 'EE' denotes the energy efficiency of underwater sensor nodes. Bandwidth utilization is the process transmitting the data packets from source node to the receiving node in UWSN for time period. It is given as,

$$BC = \sum_{m=1}^{n} DP_m [SUWSN \rightarrow DUWSN] \quad (5)$$

From (5), bandwidth 'BC' is computed based on the number of data packets 'DP_m' that is transmitted between the source underwater sensor node '$SUWSN$' and destination underwater sensor node '$DUWSN$' correspondingly. The flow process of quantum k-means cluster is shown in figure 3.

Figure 3 Flow process of Quantum K-means Node Clustering

Figure 3 explains the flow process of quantum k-means node clustering to group the underwater sensor nodes based on energy efficiency and bandwidth consumption. A quantum algorithm encoded the data into quantum data through quantum computing approach. The quantum system is denoted by N-dimensional Hilbert space.

The quantum system comprised 'V' points and located them through initializing the quantum register '$|\psi\rangle$' with 'n' qubits.

Let us consider 'N' number of underwater sensor nodes and it is partitioned into 'k' number of clusters '$c_1, c_2, c_3, \ldots . c_k$'. The objective is to design a cluster for each underwater sensor nodes. Quantum k-means is a statistical technique to determine the soft clusters where particular point fit into number of cluster with accurate probability. Quantum k-means clustering comprised the underwater sensor nodes represented in two-dimensional vector space and distance is calculated.

In quantum k-means clustering, the underwater sensor nodes included the coefficients for providing degree in the k^{th} cluster. The cluster centroid is the mean distance of every underwater sensor nodes weighted by their degree. Cluster centroid is a mean distance of entire underwater sensor nodes in a cluster. The distance among underwater sensor nodes and cluster centroid is determined by Manhattan distance. It is measured as,

$$MD_{ij} = \sqrt{\sum_{i=1}^{N} \sum_{j=1}^{k} \left(cc_j - UWSN_i\right)^2} \qquad (6)$$

From (6), 'D_{ij}' denotes distance between cluster centroid and underwater sensor nodes. Node clustering is employed to cluster the underwater sensor nodes. Therefore, the quantum k-means clustering reduces the objective function (i.e., distance between cluster centroid and underwater sensor nodes). The argument of minimum function is employed for minimizing the objective function. It is formulated as,

$$h_t = \arg\min MD_{ij} \qquad (7)$$

From (7), the minimum distance between the centroid and underwater sensor nodes is grouped into particular cluster. The underwater sensor node closer to the cluster centroid belongs to that particular cluster. Each underwater sensor node is allocated to some cluster depending on the distance measure. Then, cluster centroid gets updated through taking the weighted mean of entire underwater sensor node in that cluster. The recalculation of cluster centers leads to improved clustering results. The process gets repeated until there is no variation in the cluster centroid. The pseudo code representation of quantum k-means clustering is given below,

Input: Underwater sensor nodes 'UW' = {$USN_1, USN_2, \ldots, USN_n$}
Output: Perform node clustering
Step 1: **Begin**
Step 2: **For each** underwater sensor nodes 'UW'
Step 3: Measure the energy and bandwidth consumed to transmit the data packet at time 't'
Step 4: Initialize the k number of clusters as centroid in random manner
Step 5: Measure distance between cluster centroid and underwater sensor nodes
Step 6: **If** distance is closer to the centroid
Step 7: Group underwater sensor node to that particular cluster
Step 8: **else**
Step 9: Check another cluster centroid
Step 10: **Return** cluster
Step 11: **End for**
Step 12: **End**

Algorithm 1 Quantum K-means Node Clustering

As described in algorithm 1, quantum k-means node clustering process is carried out for reducing the energy consumption and end-to-end delay in UWSN. Subsequently, energy and bandwidth is computed for every underwater sensor node. Every underwater sensor node is assigned to the particular cluster to increase the sum of weights of the edges. The cluster head is chosen based on the highest residual energy and bandwidth. Subsequently, number of clusters with cluster head is sent to the hidden layer 2 for cluster head optimization in UWSN.

Improved Multi-Criterion CuttleFish Cluster Head Optimization

Cuttlefish is a type of cephalopods with their abilities to vary color for their environment or to generate stunning displays. Improved Multi-Criterion CuttleFish Cluster Head Optimization (IMCFCHO) is a programming process that mimics the Cuttlefish with search strategy to identify the optimal cluster head. Cuttlefish has an ability to vary their color consistent with the environment circumstances. Cuttlefish create the patterns and colors from reflected light passing trough different cell layers with chromatophores, iridophores and leucophores. IMCFCHO comprised the refection task and visibility task. Refection process is used to simulate the light reflection concept. Visibility process is used to simulate the matching pattern concept. Refection (Re) and visibility (Vi) tasks are the search process to identify the global optimal solution. The new solution is generated from the combination of refection and visibility process. The color varying in cuttlefish depend on the cells of chromatophore, iridophore and leucophore layers. Color changing cuttlefish concept at different layers is employed as search strategy for cluster head selection with help of fitness value. In IMCFCHO, the population (i.e., cluster head) is initialized with 'N' number of individuals that are randomly generated. It is formulated as,

$$P[N] = \{ch_1, ch_2, ch_3, ch_4, , \ldots\ldots\ldots\ldots . ch_N\} \qquad (8)$$

For every generated individual, fitness function is computed. Griewank fitness function is employed to compute the fitness of random selected subset from population.

$$FF = Higher\ Trust\ \&\&\ Lesser\ Distance \qquad (9)$$

From (9), the fitness function of the cluster head is calculated. After that, the best fittest solution is partitioned into two average best subset and best subset. The size of best subset is one less than average best subset. The colour changing of six cases cuttlefish mechanism at different layers of cells is used as the simulation of subset generated in cluster head selection in underwater sensor network.

Case 1 and Case 2:

In IMCFCHO, reflection and visibility is used to identify the new subset. The light reflected mechanism is carried out because of interaction between the chromatophore and iridophore cells. Chromatophore cell slow down their muscles to reduce saccule and iridophore cell to reflect the light from the chromatophore cells. The stretch and contract process in chromatophore and reflected light in iridophore. The visibility of cuttlefish matching patterns identified the new solution. It is formulated as,

$$Re_{ch_j} = R * G_1[ch_i].Pts[ch_j] \qquad (10)$$

$$Vi_{ch_j} = V * (B\,Pts[ch_j] - G_1[ch_i].Pts[ch_j]) \qquad (11)$$

From (10) and (11) 'G_1' denotes the collection of chromatophore cells in case 1 and 2. 'i' symbolize the i^{th} cell in the group 'G_1'. '$Pts[ch_j]$' represent j^{th} cluster head at the i^{th} cell and '$B\,Pts[ch_j]$' symbolizes the best solution points. 'R' represents the reflection degree and 'V' denotes the final patterns. The value of 'R' and 'V' are computed as,

$$R = random\,() * (r_1 - r_2) + r_2 \qquad (12)$$

$$V = random\,() * (v_1 - v_2) + v_2 \qquad (13)$$

From (12) and (13), '$random\,()$' is a function used to generate the random numbers between (0, 1). 'r_1' and 'r_2' are constant values used to identify the stretch interval of the chromatophore cells. 'v_1' and 'v_2' are constant values to identify the visibility degree interval to the final view point of the pattern. 'P' is sorted in descending order based on the fitness values for selecting the first 'k' cluster heads from P. 'k' is the random number between $(1, \frac{N}{2})$. 'N' denote the size of 'P'. The new subset is created from every cluster head in 'k' through reflection set and visibility set. When new generated cluster head is higher than average best cluster head, then average best cluster head is restored with new cluster head.

Case 3 and Case 4:

The iridophore cells are light reflecting cells. The iridophore cells reflect the inward light coming from outside. The reflected colour is a particular colour for light reflection. Iridophore cells are employed to hide the organs. The hidden organs are denoted by the best solution. The 'R' value is fixed to '1' and 'V' value is computed as case 1 and case 2. It is given as,

$$Re_j = R * B\,Pts[j] \qquad (14)$$

From two cases, single feature exchanging operator is employed to create the new solutions from best solutions. A random cluster head is selected and get exchanged with another randomly selected cluster head. When new attained solution is better than best cluster head, then replace best cluster head with the new cluster head.

Case 5:

The light is reflected from leucophore cells are similar to the light coming from chromatophore cells. Through computing similarity between the reflected light and incoming light, best solution considered is incoming light. The reflected color is any colour near best solution considered as average best solution (i.e., optimal cluster head)). The difference between best solution points and average solution points is functioned in a small area created in region of best solution. It is computed as,

$$Re_{ch_j} = R * B\,Pts[ch_j] \qquad (15)$$

$$Vi = V * (B\,Pts[ch_j] - AVbest) \qquad (16)$$

From (15) and (16) '$AVbest$' denotes the average value of best points. 'R' value is pre-defined as 1 and 'V' value is determined. In ICFCHO, 'p' new cluster head are generated from average best subset through eliminating one cluster head each time. When any cluster head is improved results than the best cluster head, then best cluster is restored.

Case 6:

The leucophore cells mechanism is taken as the mirror and returns the inward light from environment. The cuttlefish is able to combine itself into the environment. Any inward light approaching from environment gets reflected the same and denoted by random solution. The remaining solutions of 'P' get generated in random manner. When the new solution is better than average best cluster head, then average best solution is taken as optimal solution. The algorithm process gets terminated when it returns the optimal cluster head in UWSN.

Input: Number of cluster heads '$\{CH_1, CH_2, CH_3, CH_4, \ldots, CH_n\}$'
Output: Identifies optimal cluster head for secured transmission

Step 1: **Begin**
Step 2: Initialize the population, reflection 'Re' and visibility 'V'
Step 3: Calculate the fitness for population
Step 4: Set $i = 0$
Step 5: **While** $(i \leq i_{max})$
Step 6: Update [illegible]
Step 7: Update new solution through global search
Step 8: Evaluate fitness of new solution 'FF_n'
Step 9: *If* $(FF_n < FF)$
Step 10: **Replace** new solution
Step 11: **End if**
Step 12: Update best solution
Step 13: Compute average points of best solution
Step 14: Set $i = i + 1$
Step 15: **End while**
Step 16: **Return** optimal cluster head
Step 17: **End**

Algorithm 2 describes process of identifying the optimal cluster head for secured data aggregation in UWSN. The population initialization is performed initially. After that, fitness is calculated for every cluster head. If the current fitness of the cluster head is higher than the other, then current solution considered as new solution. Best solution gets updated to compute the fitness of best solution. The process is iterated to attain the optimal cluster head for secured data aggregation in UWSN. Then the hidden layer result is obtained as,

$$Hid(t) = \sum_{i=1}^{N} UWSN_i * w_{inp} + [w_{inhi} * Hid(t-1)] \quad (17)$$

From (17), '$Hid(t)$' symbolizes the hidden layer output. 'w_{inhi}' denotes the weight between the input layer and hidden layer. '$Hid(t-1)$' denotes the preceding hidden layer. Finally, the hidden layer result is sent to the output layer. The output layer of QNCCO-DBN Technique is symbolized as,

$$Out(t) = w_{ouhi} * Hd(t) \quad (18)$$

From (18), '$Out(t)$' represent the output layer result. 'w_{ouhi}' symbolizes the weight between hidden layer and output layer. By this way, secured data communication is carried out in UWSN with higher packet drop rate and lesser end-to-end delay.

Performance Analysis and Experimental Results

Experimental evaluation is carried out in Quantum Node Clustered Cuttlefish Optimization based Deep Belief Network (QNCCO-DBN) Technique for secured data aggregation in UWSN. The experiment is conducted on factors like energy consumption, end-to-end delay, data confidentiality rate and packet drop rate with respect to numbers of underwater sensor nodes and number of data packets. The experiment is conducted in NS2 simulator. Performance analysis of proposed method has been compared with existing Energy Efficient Circular Spinning (EECS) [1] and Energy Balanced Reliable and Effective Clustering (EBREC) method [2] for UWSN. The existing methods and proposed techniques are simulated on same platform to attain improved results. For experimental analysis, number of underwater sensor nodes '50, 100, 500'are positioned in dynamic manner in 500×500 m^2. Table 1 discusses the simulation settings for conducting experiments.

Table 1 Simulation parameters

S. No	Parameters	Description
1	Size of the region	500 m * 500 m
2	Number of underwater sensor nodes	[illegible]
3	Number of sink node	1
4	Maximum transmission radius (m)	[illegible]
5	Propagation delay (S)	[illegible]
6	Transmission time (S)	[illegible]
7	Node initial energy (J)	[illegible]
8	Data packet size	[illegible] Bytes
9	Control message size	[illegible] Bytes
10	Communication range	[illegible] m
11	Minimum communication range	[illegible] m
12	Maximum communication range	[illegible] m
13	Initial energy	[illegible]
14	Simulation time	[illegible]
15	Simulation runs	10

The parameters in the table are same for all existing and proposed method.

3. Simulation Results

The performances of four metrics, namely energy consumption, end-to-end delay data confidentiality rate and packet drop rate are discussed. Performance analysis of proposed QNCCO-DBN Technique has been compared with existing Energy Efficient Circular Spinning (EECS) [1] and Energy Balanced Reliable and Effective Clustering (EBREC) method [2] for UWSN.

Performance Analysis of Energy Consumption

Energy consumption (TEC) is the product of amount of energy consumed by one underwater sensor nodes and number of underwater sensor nodes. It is calculated as,

$EC = \sum_{i=1}^{n} USN_i * EC\ (Sensing\ single\ USN\ )$ (19)

From (19), energy consumption 'EC' is measured through network samples 'USN_i' involved in simulation process and the time consumed in sensing single node '$EC\ (Sensing\ single\ USN\ )$'. It is measured in terms of joules (J).

Table 2 Tabulation of Energy Consumption

Underwater sensor nodes	Energy consumption (J)		
	Proposed QNCCO-DBN Technique	EECS	EBREC method
50	500	700	600
100	570	755	650
150	625	820	710
200	695	985	750
250	730	1055	820
300	800	1105	900
350	890	1215	990
400	970	1345	1100
450	1050	1455	1180
500	1180	1585	1250

Table 2 explains the energy consumption performance results for three different methods namely, proposed QNCCO-DBN Technique, existing EECS [1] and EBREC method [2] correspondingly. The energy consumption performance versus number of underwater sensor node is illustrated in above table. For experimental consideration, the number of underwater sensor node ranges from 50 to 500. With different number of underwater sensor nodes, ten different energy consumption performance runs are conducted for proposed and existing algorithms. When considering 200 underwater sensor nodes as input, energy consumption performance attained by proposed QNCCO-DBN Technique is 695J whereas existing EECS [1] and EBREC method [2] attains 985J and 750J respectively. The table value illustrates that energy consumption is considerably reduced by using QNCCO-DBN Technique when compared to EECS [1] and EBREC method [2]. The simulation results of energy consumption are shown in figure 4.

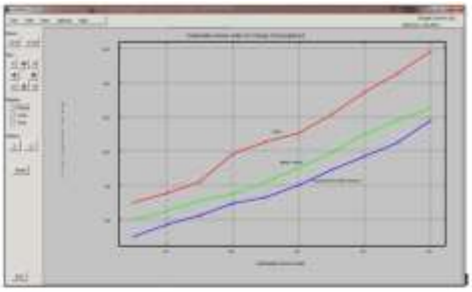

Figure 4 Measurement of Energy Consumption

Figure 4 explains the energy consumption based on different number of underwater sensor nodes using proposed QNCCO-DBN Technique, existing EECS [1] and EBREC method [2]. The green line and red line represents the data confidentiality rate of existing EECS [1] and EBREC method [2] whereas blue line represents the data confidentiality rate of proposed QNCCO-DBN Technique. As shown in figure, proposed QNCCO-DBN Technique attains higher data confidentiality rate when compared to the conventional methods. This is because of using Improved Multi-Criterion Cuttlefish Optimization in QNCCO-DBN Technique for secured data aggregation in UWSN. This in turn helps to reduce the energy consumption during data aggregation. Consequently, proposed QNCCO-DBN Technique reduces the energy consumption by 27% and 11% as compared to existing EECS [1] and EBREC method [2] respectively.

Performance analysis of End-to-End Delay

End-to-end delay ($Delay_{EE}$) is described as the average consumed by data packet transmission from source to any sink nodes. '$Delay_{EE}$' is computed based on number of network samples 'USN_i' involved and the difference between actual time consumed 't_{act}' and expected time of consumption 't_{ex}' correspondingly.

$Delay_{EE} = \sum_{i=1}^{n} USN_i * \{[t_{act}\ ] - [t_{ex}\ ]\}$ (20)

From (20), the end-to-end delay is computed in terms of milliseconds (ms).

Table 3 Tabulation of End-to-End Delay

Underwater sensor nodes	End-to-end delay (ms)		
	Proposed QNCCO-DBN Technique	EECS	EBREC method
50	39.2	52.5	45.2
100	41.32	75.35	52.81
150	52.69	95.25	68.34
200	65.28	105.15	79.57
250	72.69	120.35	89.27
300	82.64	125.35	99.97
350	95.23	140.25	108.34
400	105.97	155.35	120.68
450	115.68	175.35	139.41
500	128.98	190.35	150.48

Table 3 describes the end-to-end delay performance results for three different methods namely, proposed QNCCO-DBN Technique, existing EECS [1] and EBREC method [2] correspondingly. The end-to-end delay performance versus number of underwater sensor node is shown in above table. For conducting experiments, the number of underwater sensor node ranges from 50 to 500. With different number of underwater sensor nodes, ten different end-to-end delay performance runs are conducted for proposed and existing algorithms. When considering 450 underwater sensor nodes as input, end-to-end delay performance attained by proposed QNCCO-DBN Technique is 115.68ms whereas existing EECS [1] and EBREC method [2] attains 175.35ms and 139.41ms correspondingly. The above table value shows that end-to-end delay is considerably reduced by using QNCCO-DBN Technique when compared to EECS [1] and EBREC method [2]. The simulation results of end-to-end delay are illustrated in figure 5.

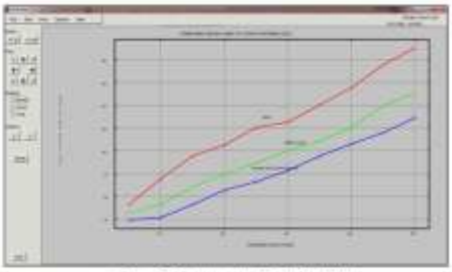

Figure 5 Measurement of End-to-End Delay

Figure 5 illustrates the end-to-end delay performance for different number of underwater sensor nodes using proposed QNCCO-DBN Technique, existing EECS [1] and EBREC method [2]. The green line and red line represents the end-to-end delay results of existing EECS [1] and EBREC method [2] whereas blue line represents the end-to-end delay of proposed QNCCO-DBN Technique. As shown in figure, proposed QNCCO-DBN Technique attains lesser end-to-end delay when compared to the conventional methods. This is due to application of Quantum k-means Node Clustering and Improved Multi-Criterion Cuttlefish Optimization for secured data aggregation in UWSN. Quantum k-means Node Clustering group the underwater sensor nodes into many clusters based on energy and bandwidth Then, Improved Multi-Criterion Cuttlefish Optimization chooses the optimal cluster head with higher trust value for data aggregation in UWSN. This in turn helps to minimize the end-to-end delay during data aggregation. Consequently, proposed QNCCO-DBN Technique reduces the end-to-end delay by 36% and 17% as compared to existing EECS [1] and EBREC method [2] respectively.

Performance Analysis of Data Confidentiality Rate

The data confidentilaity rate is defined as the rate of number of data packets received by authorized receiver. The data confidentiality rate is measured as,

$$C_{Rate} = \sum_{i=1}^{m} \frac{S_{ID}}{S_i} * 100 \quad (21)$$

From (21), data confidentiality rate 'C_{Rate}' is measured based on the devices data received by the intended recipient device 'S_{ID}' with respect to the total number of devices sample sent by the source device as input 'S_i' for simulation. The data confidentiality rate is measured in terms of percentage (%).

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Table 4 Tabulation of Data Confidentiality Rate

Underwater sensor nodes	Data confidentiality rate (%)		
	Proposed QNCCO-DBN Technique	EECS	EBREC method
50	95	88	90
100	93.45	84.35	89.54
150	91.25	84	88.13
200	90.24	83.33	87.65
250	89	82	85
300	88.75	81.25	83.32
350	87	79	81.65
400	84.38	78	79.33
450	83	77.35	78.65
500	82.2	76	76.58

Table 4 explains the data confidentiality rate performance results for three methods, proposed QNCCO-DBN Technique, existing EECS [1] and EBREC method [2] correspondingly. The data confidentiality rate versus number of underwater sensor node is illustrated in above table. For conducting the experiments, the number of underwater sensor node is ranging from 50 to 500. With different number of underwater sensor nodes, ten different runs are conducted for proposed and existing algorithms. When considering 350 underwater sensor nodes as input, data confidentiality rate attained by proposed QNCCO-DBN Technique is 87% whereas existing EECS [1] and EBREC method [2] attains 79% and 81.65% correspondingly. The above table value shows that data confidentiality rate is considerably increased by using QNCCO-DBN Technique when compared to EECS [1] and EBREC method [2]. The simulation results of data confidentiality rate are shown in figure 6.

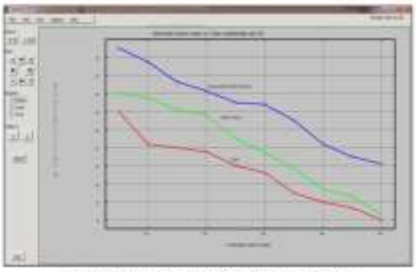

Figure 6 Measurement of Data Confidentiality Rate

Figure 6 describes the data confidentiality rate based on different number of underwater sensor nodes using proposed QNCCO-DBN Technique, existing EECS [1] and EBREC method [2]. The green line and red line represents the data confidentiality rate of existing EECS [1] and EBREC method [2] whereas blue line represents the data confidentiality rate of proposed QNCCO-DBN Technique. As shown in figure, proposed QNCCO-DBN Technique attains higher data confidentiality rate when compared to the conventional methods. This is because of using Improved Multi-Criterion Cuttlefish Optimization in QNCCO-DBN Technique for secured data aggregation in UWSN. Improved Multi-Criterion Cuttlefish Optimization selects the optimal cluster head with higher trust value for data aggregation from other sensor nodes. This in turn helps to increase the data confidentiality rate during data aggregation. Consequently, proposed QNCCO-DBN Technique increases the data confidentiality rate by 9% and 5% as compared to existing EECS [1] and EBREC method [2] respectively.

Performance Analysis of Packet Drop Rate

Packet drop rate (PDR) is the rate of number of data packets successfully received by the sink node to total number of data packets sent by source nodes. The packet drop rate is mathematically expressed as,

$$PDR = \sum_{i=1}^{m} \frac{DP_{nds}}{DP_i} * 100 \qquad (22)$$

From equation (22), 'DP_{nds}' symbolizes the number of data packets not delivered successfully and the number of data packets 'DP_i' sent at particular time period correspondingly. The packet drop rate is computed in percentage (%).

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Table 5 Tabulation for Packet Drop Rate

Underwater sensor nodes	Packet Drop Rate (%)		
	Proposed QNCCO-DBN Technique	EECS	EBREC method
50	9	16	12
100	10.65	16.85	13.55
150	11.80	17.55	13.60
200	12.85	18	14.85
250	13.95	19.45	15.35
300	14.55	21.65	16.90
350	15.85	24.75	17.45
400	16.35	25.85	18.50
450	17.95	26.65	19.85
500	18.75	29	20.85

Table 5 illustrates the packet drop rate performance results for three methods, proposed QNCCO-DBN Technique, existing EECS [1] and EBREC method [2] correspondingly. The packet drop rate versus number of underwater sensor node is described in above table. For experimental consideration, the number of underwater sensor node is varied from 50 to 500. With number of underwater sensor nodes, ten different runs are carried out for proposed and existing algorithms. When considering 250 underwater sensor nodes as input, packet drop rate attained by proposed QNCCO-DBN Technique is 13.95% whereas existing EECS [1] and EBREC method [2] attains 19.45% and 15.35% correspondingly. The above table valus shows that packet drop rate is considerably reduced by using QNCCO-DBN Technique when compared to EECS [1] and EBREC method [2]. The simulation results of packet drop rate are shown in figure 7.

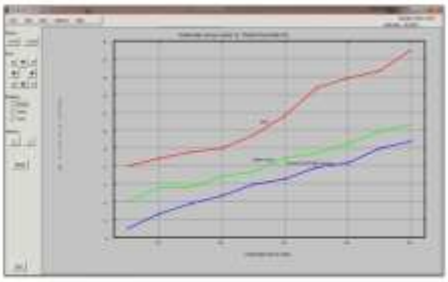

Figure 7 Measurement of Packet Drop Rate

Figure 7 describes the packet drop rate based on different number of underwater sensor nodes using proposed QNCCO-DBN Technique, existing EECS [1] and EBREC method [2]. The green line and red line represents the packet drop rate of existing EECS [1] and EBREC method [2] whereas blue line represents the packet drop rate of proposed QNCCO-DBN Technique. As illustrated in graph, proposed QNCCO-DBN Technique attains lesser packet drop rate when compared to the existing methods. This is due to the application of Quantum k-means Node Clustering and Improved Multi-Criterion Cuttlefish Optimization for secured data aggregation in UWSN. Quantum k-means Node Clustering group the underwater sensor nodes into many clusters depending on energy level and bandwidth. Then, Improved Multi-Criterion Cuttlefish Optimization is carried out to choose the optimal cluster head with higher trust value for data aggregation in UWSN. This in turn helps to minimize the packet drop rate during data aggregation. Therefore, proposed QNCCO-DBN Technique reduces the packet drop rate by 34% and 14% as compared to existing EECS [1] and EBREC method [2] respectively.

4. Conclusion

A new technique termed QNCCO-DBN Technique is introduced for secured data aggregation in UWSN with lesser end-to-end delay. The number of underwater sensor nodes is collected as input. Then, Quantum k-means Node Clustering groups the underwater sensor nodes into clusters depending on the energy and bandwidth. The cluster head aggregates the data and optimal cluster head is selected for transmitting the data packets to the base station using Improved Multi-Criterion Cuttlefish Optimization in QNCCO-DBN Technique. The fitness of each cluster head is calculated based on distance and trust. After that, aggregated data sent to the optimal cluster head in UWSN. By this way, secured data aggregation is performed in underwater sensor network. From that, QNCCO-DBN Technique attains secured data aggregation performance with minimal delay when compared to conventional techniques. The performance of QNCCO-DBN Technique is estimated in terms of energy consumption, packet drop rate, end-to-end delay and data confidentiality rate when compared with two existing works. The experimental result shows that secured data aggregation performance provides better performance with an improvement of data confidentiality rate and minimization of delay, energy consumption and packet drop rate when compared to state-of-the-art works.

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