Research Article

Improving Packet Delivery Performance in Water Column Variations through LOCAN in Underwater Acoustic Sensor Network

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This paper proposes Lion Optimized Cognitive Acoustic Network (LOCAN) to reduce packet delay and packet loss during packet transmission in Underwater Acoustic Sensor Network (UWASN). Packet delay and packet loss in UWASN are because of water column variations such as Doppler effect and geometric spreading (GS). Doppler effect forms due to sensor node's motion and sea surface variations such as salinity and temperature. Geometric spreading (GS) occurs due to sediment drift wave fronts and frequent changes in node's location and depth. Water column variations change the amplitude of sound propagation, causing channel coherence and multipath interference, which affect packet transmission. The existing UWASN algorithms focus only on temperature and salinity variations. In LOCAN, channel selection through Lion Optimization Algorithm solves the problems of water column variation and improves the battery life, network lifetime, and throughput. The proposed algorithms show a better result in terms of efficiency, when compared to existing UWASN algorithms.

1. Introduction

In UWASN, acoustic signal propagates through water column variations, direct, surface, and bottom reflected path. The propagating acoustic signal interacts with different water column variations. The water column variations are spatial and temporal. The spatial variations are Doppler effect and temperature. The temporal variations (TV) are GS, salinity, and other multipath path interaction on the surface or bottom of the sea surface. The Doppler effect forms due to the water surface variations and movement of sensor nodes. The Doppler effects affect the acoustic signal sound intensity by defocusing and bending the signal and create a noncoherent communication between the acoustic nodes. The water column variations cause the time spreading of acoustic signal which leads to multipath interference. The multipath interference affects the packet transmission in UWASN. The GS leads to acoustical signal attenuation due to change in the location of the node and sedimentation drift. The change in

the distance of the nodes can be due to water column variations such as solitons, eddies, internal waves, and internal tides. The sedimentation drift waves which carry sand particles reduce the magnitude of acoustic signal, affect the direction of signals, and change the nodes' location.

In UWASN, high energy consumption and packet delivery are challenging tasks for nodes in the network. The source node in the acoustic network determines the forwarding relay set based on the forwarder's local information. Fuzzy logic-based relay selection scheme is used for the determination of the relay node. The forwarding relay node set is determined after checking the channel link of the neighboring nodes. In the channel link, the data rate, and node's depth based on the source node, neighbor node is added in the relay set or else discarded. From the relay set, fuzzy logic-based relay selection is used for selection of the optimum relay. Fuzzy logic algorithm performs based on two inputs, namely, Packet Delivery Probability (PDP) and Energy Consumption Ratio (ECR).

In Energy-Efficient Cooperative Opportunistic Routing Protocol, the actual packet transmission happens when the source node broadcasts the packet to the neighboring relay set and the nodes set a holding timer to avoid collision in packet transmission. The process continues until the packet reaches the surface sink. In the above process, if the first best relay node fails to broadcast the packet, then the packet is forwarded by the second best relay node set. If the packet is successfully transmitted to the next hop destination, the other nodes drop the holding timer and packet. The relay set performance is evaluated through average packet delivery ratio, average end-to-end delay, average energy consumption, and average network delay [1].

The energy management in UWASN plays a vital role because of the nonavailability of alternate energy sources such as solar and fuel cells. The energy management is achieved through BEAR protocol, which calculates the relative location distance from the sink and facilitating node. Furthermore, energy-efficient routing in underwater WSN is obtained through ECARP (Existing Channel Aware Routing Protocol) algorithm [2], with sonobuoy sink node on the surface. The ECARP algorithm performs in three-dimensional Euclidean spaces to forward the packet based on the computation of the node's distance and data rate, via the sink node and relay nodes. In addition, the latency in end-to-end delay is solved through a cluster-based heuristic method. End-to-end delay plays a vital role in delay sensitivity of underwater communication. The optimistic routing through a metric called $EEL_{Success}(Fi)$ is implemented [3], where Fi represents the success in receiving the packet for i node. The algorithm consists of packet forwarding prioritization method which reduces the end-to-end delay with increased energy cost.

The problems in underwater acoustic network are the spatial and temporal variation, propagation delay, and water column variation. The propagation delay and spatial and TV are due to ocean current, salinity, and temperature and affect reliable data transmission. Propagation delay in underwater communication occurs because of salinity in seawater which is about 3.5 percent and consists of $NaCl$, Cl , SO_4^{2-} , Mg , Ca , Br -, and K . The salt in the seawater causes the problem of spectrum scarcity and latency. The spectrum and latent problem needs an efficient algorithm to overcome the transmission delay, packet delivery, and energy loss in the UWASN. However, the water column variations such as geometric and Doppler effects lead to amplitude variation in the propagating signals. The amplitude variation increases the packet loss during data transmission. Furthermore, the propagation delay due to Doppler effect creates channel coherence and multipath propagation. The above problems consume more battery power and lead to high bit rate error. A path loss occurs due to scattering, refraction, and dispersion in the acoustic signal because of sedimentation drift and Doppler spread. In addition, GS occurs due to the expansion of wave fronts and increases the distance of propagation. Furthermore, the multipath fading occurs due to the fact that sensor node location varies based on wave front and sedimentation drift.

1.1. Contributions

- (i) The problems of spatial and temporal water column variations such as Doppler, GS, and sedimentation drift which occur in UWASN are solved through the proposed Lion Optimized Cognitive Acoustic Networks (LOCAN). LOCAN change the channel and bandwidth based on the water column variations
- (ii) Doppler and GS are avoided through distance matrix topology framework in lion optimization and reduce the delay due to channel coherence
- (iii) The data transmission in different temperature and salinity is optimized based on channel selection, bandwidth, and simulation results validated in UWASN test bed

The rest of this paper is organized as follows. Section 2 introduces the optimization algorithm and explains the existing system and the acoustic network. Section 3 proposes the methodology of the Cat Optimized and Lion Optimized Cognitive Acoustic Network algorithm. These algorithms are simulated in the AquaSim simulation tool, and the results are shown in Section 4. The hardware implementation on the test bed in Doppler and the GS environment is shown in Section 5. Finally, conclusion is in Section 6.

2. Related Work

2.1. Optimization Algorithm in UWASN. In WSN, efficient routing from source to destination node performs through different algorithms such as AODV, DSR, joint energy-aware routing, and opportunistic routing. However, the optimization algorithms in WSN routing increase the battery life and improve the efficiency of routing with high throughput. The ant colony optimization algorithm [4] is applied in WSN for the improvement of routing in the network through position information and searching direction. The path selection in the ant algorithm is according to the probabilistic rule, which consists of pheromone impact factor and heuristic information. The ant optimization algorithm increases the battery life of a node and reduces energy consumption due to the searching direction of destination node and transfer the data. Furthermore, Biogeography-Based Optimization (BBO) algorithm [5] increases the coverage area of the network in static and mobile sensor nodes. The algorithm increases the coverage area on the basis of the immigration and emigration rate calculation and dynamic deployment problem of sensor nodes which solves through fitness values and sorts the best coverage area. Furthermore, the glowworm swarm optimization algorithm [6] increases the coverage and energy efficiency of the node by changing the intensity based on the distance of the nodes. Furthermore, the harmony search algorithm [7] in cluster nodes increases the energy efficiency of sensor nodes and network lifetime through optimizing the distance between the cluster head and intracluster heads of the node. The optimization algorithm finds application in UWASN for the improvement of the range and

TABLE 1: Literature survey.

S. No.	Author (year)	UWASN routing algorithm	Advantages/disadvantages	Remarks
1	Wang et al. [9]	Energy-aware and void-avoidable routing protocol [9]	Opportunistic directional forwarding strategy (ODFS), avoids cyclic transmission, flooding and voids; optimal trajectory of sink node to be optimized	Water temperature-based routing
2	Toso et al. [10]	Revisiting source routing [10]	Scenario-independent and source-initiated routing can work in any connected topology without any prior information. Overhead due to route discovery and maintenance	The water column variation for routing is left.
3	Ghafoor and Koo [11]	Cognitive software-defined networking- (SDN-) based routing [11]	Stable route between the source node and destination node; large amount of energy required for spectrum sensing	The salinity-based routing is left.
4	Bouabdallah et al. [12]	Joint routing and energy management [12]	Overcomes the energy sinkhole problem; uniform distribution of load (energy traffic)—even energy depletion and improves network lifespan; not suitable for UWASNs unless upgraded	The temperature of water-based routing is implemented.
5	Coutinho et al. [13]	Opportunistic routing algorithm [13]	Candidate set selection and candidate coordination procedure redundant transmissions; sleep and awake time interval selection	The wave front movement for routing is left.
6	Coutinho et al. [14]	Geographic and opportunistic routing with depth adjustment-based topology control for communication recovery over void regions (GEDAR) [14]	Each node knows the location of all other nodes; reduces retransmission probability; minimizes collision; depth adjustment	Wave front movement and salinity-based routing is implemented.
7	Proposed	Lion optimized cognitive acoustic network (LOCAN)	Solves spatial and TV; avoids Doppler and GS; reduces delay and packet loss	The water temperature, salinity, sedimentation drift, and water column variations are taken for optimized routing.

range-free localization for node location. The sequential greedy optimization algorithm performs node location in UWASN through the use of iteration and decision variables in underwater sensor network. Further, the first-order Karush-Kuhn-Tucker (KKT) algorithms does the analysis of diverging properties of the greedy algorithm during the localization of nodes [8]. The challenges in UWASN are Doppler scale which affect the signal path and need an estimating parameter for channels. The channel estimation helps to increase the amplitude for each individual path and reduction in time delay. The proposed algorithm should identify the best path to the destination node in underwater sensor network and avoid the multipath and reduce delay and improve packet transmission. Furthermore, the optimization algorithms address the various challenges such as optimal deployment, node localization, and clustering and data aggregation. Table 1 shows various algorithms in UWASN with advantages and disadvantages.

2.2. Inferences from Literature Survey. The existing WSN and UWASN perform the optimization algorithm for the improvement of the battery life, network lifetime, and

throughput and minimizes the delay and packet loss. However, the challenging problems in UWASN are the spatial and temporal variation, Doppler and GS, and salinity. The proposed optimization algorithms should consider the above problems. The Cat (COCAN) and Lion Optimization Algorithm (LOCAN) which is a multidimensional approach method and velocities of each dimension change with fitness value identified solves the above problem with iteration.

3. Methodology

3.1. Cat Optimization Algorithm in Underwater Cognitive Acoustic Network (COCAN). The cats spend most of the cat's time in resting, still cautious about the surroundings and moving objects nearby. The cautious nature and high alertness lead to the minimum time for chasing the prey and conserve body energy. The cat nature is applied in UWASN for channel selection according to the destination and surrounding environment, i.e., water column and conserves energy as Cat Optimization Algorithm. The Cat Optimization Algorithm is grouped into two modes such as seeking and tracing.

```

Begin
Input parameters to the algorithm
Initialize the nodes  $X_i$  ( $i = 1, 2, \dots, n$ ),  $v$ , and SPC based on water column variation parameter
While (termination criteria not satisfied or  $I < I_{\max}$ )
    Calculate the fitness function value for all the nodes and sort them
     $X_s$  = Node with best solution
    For  $i = 1 : N$ 
        If SPC = 1
            Start seeking mode
             $X_{np}$  = new position of nodes in underwater network
             $X_{cp}$  = current position of nodes in underwater with parameters
             $R$  = random number varies between 0 and 1 based on co-channel interference
             $P_i$  = probability of current node  $i$  based on water column variations
             $FS_i$  = fitness value of node  $i$  based on current Doppler effect and GS
             $FS_{\max}$  = maximum value of fitness function,  $FS_{\min}$  = minimum value of fitness
            function for different water column variations and channel selection
            
$$X_{np} = (1 \pm \text{SRD} \times R) \times X_{cp}$$

            
$$P_i = \frac{|FS_i - FS_b|}{|FS_{\max} - FS_{\min}|}, 0 < i < j$$

        Else
            Start tracing mode
             $X_{best,d}$  = position of the cat with the best solution in water column variation
             $X_{i,d}$  = position of the cat  $i$  in dimension  $d$  of water variation parameters
             $c_1$  = a constant
             $r_1$  = a random value in range  $[0,1]$ 
             $X_{i,d,new}$  = the new position of cat  $i$  in dimension  $d$  varying water column and selects the channel
             $X_{i,d,old}$  = current position of cat  $i$  in dimension  $d$  varying water column with current channel
            
$$v_{i,d} = v_{i,d} + r_1 \times c_1 (X_{best,d} - X_{i,d})$$

            
$$X_{i,d,new} = X_{i,d,old} + v_{i,d}$$

        End if
    End for  $i$ 
End while
    Post-processing the results and visualization
End

```

ALGORITHM 1: Cat Optimized Cognitive Acoustic Networks (COCAN) for UWASN.

In the seeking mode, the cat decides to move slowly and cautiously. It knows the environment for the movement. The seeking mode is represented through parameters such as Seeking Memory Pool (SMP), Seeking Range of selected Dimension (SRD), Counts of Dimension to Change (CDC), and Self-Position Consideration (SPC). SMP is the number of copies of each cat in the seeking process. SRD is the maximum difference between the new and old values in the dimensions selected for mutation. CDC shows the dimensions of mutation. SPC is the Boolean variable representing the current position of the cat as a candidate position for movement.

Algorithm 1 is the Cat Optimization Algorithm pseudo-code which performs for channel selection. In the algorithm, the nodes are initially distributed at random with a velocity and a self-position consideration value based on water column variations. In addition, the fitness value represents the distance between the source and destination node along with current channel selection for packet transmission. The fitness value is calculated until the termination condition is satisfied according to water column variations. A similar fitness value is calculated for all the nodes in the network for the best channel selection based on water column variations. More-

over, the cat selects the seeking mode only when SPC channel is one or else a tracing mode.

In the tracing mode, the cat chases the destination node with the velocity $v_{i,d}$, i represents the source node and d the dimensions for water column variation. When the channel is selected across the dimension d for water column variation, every new channel of the source node is to be calculated as shown in Algorithm 1.

The workflow of the COCAN algorithm is shown in Figure 1. The next algorithm is the Lion Optimization Algorithm, which removes the problem in Cat Optimization Algorithm such as the dimension for water column variation estimation and mode to wait and analyze the channel selection, which consumes time to a greater extent.

3.2. Lion Optimized Cognitive Acoustic Networks (LOCAN). The Lion Optimization Algorithm inspires the characteristics of a lion such as strong sexual dimorphism in social behavior, appearance, and lifestyle, i.e., hunting in group and lifestyle switching. The Lion Optimization Algorithm includes certain cat characteristics such as the high level of cooperation and antagonism. The lion residing is of two types such as residents and nomads. Residents live

FIGURE 1: COCAN algorithm flowchart.

in groups, called pride. Nomads are the ones who move about sporadically, either in pairs or singular. Another important feature in the lifestyle of a lion is to switch lifestyle—the residents may become nomads or the nomads may become residents.

The lion has a positive feature of hunting in groups for the prey. The lions hunt in groups with other members of their pride whereas cats move in single for prey. Coordinated lion group hunting is done for prey with a high probability of success. The above characteristics of the lion inspire the optimization algorithm.

In Lion Optimization Algorithm, an initial population forms with a set of randomly generated solutions called lions.

From the initial population, $N\%$ represents the nomad lion and the rest of the lion population is considered as residents. The resident lions are randomly partitioned into subgroups called prides. In each pride, $S\%$ represents the members and is considered as females and the rest as males. In nomads, the sex rate is vice versa.

The Lion Optimization Algorithm is implemented in wireless cognitive radio network wherein the “secondary or

cognitive users” are classified as residents and nomads. The resident SUs are assigned according to channel requirement and bandwidth, and the nomad SUs consist of age number of channels for selection. The number of nodes in the network is assigned as $N = x_1, x_2, \dots, x_n$ for $n > 0$ where N is the total number of nodes in the networks as similar to the lions in the optimization. The primary user nodes assign the channels, whereas the secondary nodes are the hunting channels. In the cognitive network, the node channel is represented as

$$\text{Channel} = \frac{\sum \text{SUs}(x_1, x_2, \dots, x_n)}{\text{No. of SUs}}, \quad (1)$$

wherein SUs are the secondary users (nodes). The secondary nodes select the channels according to the fitness of the Lion Optimization Algorithm for data transmission according to water column variations. The primary user channel availability keeps changing as per the usage of the

primary user according to wave fronts and water column variations. The primary user channel change is as follows:

$$\text{Channel}' = \text{Channel} + \text{rand}(0, 1) \times \text{PI} \times (\text{Channel} - \text{SU}), \quad (2)$$

wherein $\text{Channel}'$ represents the availability of next free reliable primary channel and the Channel in the above equation shows the current availability of the channel in the network. Moreover, PI represents the percentage of improvement in SU's fitness according to cochannel analysis, divergence of signal, and water column variation parameters. The secondary users deploy at the left wing or right wing or at the center of the channels available in the primary user network. The SUs are in search of channels continuously according to the variations in the water column and new channels of the SUs are in the left and the right wing as in

$$\text{SU}_{\text{npos}} = \begin{cases} \text{rand}((2 \times \text{Channel} - \text{SU}_{\text{cpos}}), \text{Channel}), \\ (2 \times \text{Channel} - \text{SU}_{\text{cpos}}) < \text{Channel}, \\ \text{rand}(\text{Channel}(2 \times \text{Channel} - \text{SU}_{\text{cpos}})), \\ (2 \times \text{Channel} - \text{SU}_{\text{cpos}}) > \text{Channel}, \end{cases} \quad (3)$$

whereas SU_{npos} represents the new positions of channel selection for the secondary user based on water column parameters, SU_{cpos} for the current channel position of the secondary user, and Channel represents the current position of the available primary channel. The new channel position of the secondary user in the center calculates as in

$$\text{SU}_{\text{npos}} = \begin{cases} \text{rand}(\text{SU}_{\text{cpos}}, \text{Channel}), \text{SU}_{\text{cpos}} < \text{Channel}, \\ \text{rand}(\text{Channel}, \text{SU}_{\text{cpos}}), \text{SU}_{\text{cpos}} > \text{Channel}. \end{cases} \quad (4)$$

The $\text{rand}(\text{SU}_{\text{cpos}}, \text{Channel})$ function in equation (4) generates a random number between the current channel position of the secondary user (SU_{cpos}) and the current position of the available primary channel (Channel) according to the fitness of data transmission based on current parameter of water column.

The LOCAN in the cognitive network process has five steps, i.e., random channel selection of the SUs according to the current acoustic signal time spreading and physical forcing, check channel availability, calculate the fitness of the identified channel according to water column variation, select the channel with the optimal fitness value, and reiterate the channel selection process with improved fitness. In equation (5), n represents the number of SUs searching towards for the channel in d dimensions of water column variations and the position matrix M_N as

below with current position to avoid the cochannel interference.

$$M_N = \begin{bmatrix} M_{N_{1,1}} & M_{N_{1,2}} & M_{N_{1,d}} \\ M_{N_{2,1}} & M_{N_{2,2}} & M_{N_{2,d}} \\ \vdots & \vdots & \vdots \\ M_{N_{n,1}} & M_{N_{n,2}} & M_{N_{n,d}} \end{bmatrix}. \quad (5)$$

The optimal channel position in the wireless sensor node matrix in equation (5) does the analysis for the corresponding values through the fitness function and attains the optimal solution with minimum or maximum value depending upon the channel selection of the SUs according to water column variation. The fitness function is as in

$$F_{v-f} = \begin{bmatrix} F_{v-f1} \\ \vdots \\ F_{v-fn} \end{bmatrix}. \quad (6)$$

The distance of current node from the destination varies according to Doppler effect and sedimentation drift generates the corresponding fitness value as shown in Algorithm 2. Corresponding fitness value matrix is as in

$$O_{M_N} = \begin{bmatrix} O_{M_{N_1}} \\ \vdots \\ O_{M_{N_n}} \end{bmatrix}. \quad (7)$$

The SUs search the primary user channel in spiral motion according to current node distance and divergence of signal as specified in

$$P_{m_{i,fj}} = F_{v-fj} + d \times \cos(2\pi r) \times e^{br}. \quad (8)$$

$P_{m_{i,fj}}$ represents the updated channel positions of the primary node using the spiral motion for identifying the channel for SUs, b is a constant to define the shape of the motion. r is used for the definition of the SU, and when the value of r is 1, then the SU follows, resulting in the selection of the reliable channel or else the SU selects a reliable position far from the neighbor. This updated channel position is used for movement towards optimization. The distance d is given by

$$d = |F_{v-fj} - F_{v-mi}|. \quad (9)$$

Figure 2 shows the flowchart of the Lion Optimization Algorithm (LOCAN). The fitness value matrix O_{M_N} gives the channel position matrix of the reliable neighbor node according to current node location and water column. The complete process is explained in Algorithm 2.

Initialize the network:
 For $i = 1 : N$
 For $j = 1 : N$
 $M_{N_{i,j}} = \text{random position between given network area based on the parameter of water column}$
 End for
 Calculate fitness value based on node distance which varies according to Doppler effect and wave front

$$M_{N_i} = \sqrt{M_{N_{d,1}} - M_{N_{i,1}}^2 + M_{N_{d,2}} - M_{N_{i,2}}^2 + M_{N_{d,3}} - M_{N_{i,3}}^2}$$

 End for
 $F_N = \text{Best}(M_{N_i})$
 $OFN = \text{Best}(M_{F_N})$
 Current Node = Source
 While Current node $\neq$ Destination
 $d = |F_j - M_i|$
 $M_{M_i, F_j} = d * e^{bt} * \cos(2\pi t) + F_j$
 Generate the Distance matrix
 Select next node in the route for optimum channel selection.
 $F_N = \text{Best}(M_{\text{current_node}}, F_{\text{current_node}})$
 $OFN = \text{Best}(M_{\text{current_node}}, F_{\text{current_node}})$
 Update b and t
 Update Current_{node}
 End While
 Exit

ALGORITHM 2: LOCAN pseudocode for UWASN variation.

FIGURE 2: LOCAN algorithm flowchart.

TABLE 2: LOCAN simulation parameters.

Parameter	Value
Sensor nodes	50
Network dimension	2000 m × 2000 m
Transmission range of nodes	120 m
Packet size	50 bytes
Depth threshold	10 m
Transmission power	2.0 W
Reception power	0.75 W
Queue length	500
Initial energy	10000 J

Algorithm 2 is used for the generation of an optimized channel selection. The implementation and results of the algorithm are discussed in Section 4.

In the simulation, all the nodes are deployed at the same point and then disbursed to their desired positions in the target area of 1200 m × 1200 m × 10 m. The distance between the nodes is set at 120 m. The nodes are assigned with the properties of underwater communication such as water column variation and aligned in the form of a matrix according to the current position of node due to Doppler effect and GS nature due to sedimentation drift. They have a mild movement of 3 inches/sec as they are deployed in the underwater environment. The underwater communication works under 25 kHz frequencies. The parameters used for the configuration of the simulations are shown in Table 2.

Figure 3 shows the Lion Optimized Cognitive Radio Channel Management Mechanism. In Figure 3, the resident SUs, namely, SU3 and SU4 and SU1 and SU2, represent the nomad SU. The status of the resident SU is fixed based on bandwidth and data size. For a larger bandwidth and a data size requirement, the resident SU status is allotted and the nomad SU status is allotted for smaller bandwidth and data size requirement. In the resident status of SU, the channel is fixed with a particular band of PU. The nomad status of SU remains in search of the left out bands of resident SU.

4. Performance Metrics of LOCAN and COCAN

The performance of LOCAN and COCAN is analyzed with PDR and end-to-end delay based on water column variation. The packet delivery ratio is the ratio of a number of packets successfully delivered to the surface buoy to the number of packets generated by the source node. Further, end-to-end delay is defined as the time taken for a packet to be transmitted from the source to the destination across the network. The end-to-end delay, $d_{\text{end-end}}$, can be given as

$$d_{\text{end-end}} = N[d_{\text{trans}} + d_{\text{prop}} + d_{\text{proc}} + d_{\text{queue}}], \quad (10)$$

where d_{trans} is the transmission delay, d_{prop} is the propagation delay, d_{proc} is the processing delay, d_{queue} is the queuing delay, and N is the number of links (number of routers – 1).

Throughput refers to the volume of data successfully transmitted in a period of time, over a specific communication link.

Energy consumption occurs at various locations such as packet transmission, packet reception, and processing each node during network operation. Retransmission in the network happens during the packet loss between the source and destination nodes in underwater acoustic networks. The packet loss ratio is the number of packets lost to the number of packets sent. The normalized overhead is defined as the total number of routing packets transmitted per data packet.

Jitter is defined as the variations in delay in the packet arrival due to the time taken by the packets from source to the sink node. The total jitter (J) is a combination of random jitter (R) and deterministic jitter (D) and computed as $J = D + 2 \times n \times R$, where the value of n is based on the BER required of the link. Bit Error Rate (BER) is the number of bit errors divided by the total number of bits transmitted during a time interval.

The performance of Cat Optimization Algorithm in underwater cognitive acoustic network for channel selection is compared with Ad hoc On-Demand Distance Vector Routing Protocol (AODV) and the Opportunistic Routing Protocol (OR) implemented in the underwater acoustic environment using AquaSim simulator of NS2. The packet delivery ratio of COCAN is similar to the opportunistic routing algorithm, as the number of node increases. The PDR of AODV is lower than COCAN due to the exclusive property of seeking mode, cautious about the nearby nodes, and delivers the packet only after proper acknowledgment. The PDR of LOCAN is greater than OR, AODV, and COCAN as in Figure 4. Moreover, the lifestyle switching character of the lion, i.e., the channel selection based on the current water column variation of LOCAN, allocates a reliable channel thereby increasing the packets delivered to the sink without any cochannel interference.

In COCAN, the time taken by the node in identifying the channel is reduced due to the property of tracing mode. In the tracing mode, the node continuously targets the channel for reliable communication in random over a distance of node which varies according to Doppler effect. Moreover, when the reliable channel is identified, the end-to-end delay of COCAN shows the delay time a smaller number of nodes. As the node increases, the delay time decreases; the decrease is less than the AODV and OR as in Figure 5. Figure 5 shows the end-to-end delay due to Doppler effect. The spherical search of the nomad nodes for the channel selection according to water column reduces the time delay in LOCAN which is lower than COCAN, AODV, and OR. Furthermore, Figure 6 shows the throughput of the nodes in Lion and Cat Optimized Network during sedimentation drift. The throughputs for the AODV, OR, and COCAN are identical, whereas AODV shows the less throughput with increase in packet size due to a change in node topology and their corresponding notifications, whereas the throughput of LOCAN is greater than AODV and OR for larger packet size. Figure 7 shows the energy consumption of each node during sedimentation drift and Doppler effect of different algorithms such as LOCAN, COCAN, AODV, and OR. The OR algorithm

FIGURE 3: LOCAN channel management mechanisms.

FIGURE 4: Packet delivery ratio of LOCAN, COCAN, OR, and AODV.

consumes a larger energy due to unavailability of accurate past topological information. The AODV consumes more energy due to the need for maintenance of precursor nodes. The COCAN consumes less energy because of the mode switching property according to present water column conditions. In mode switching property, energy is saved when the node is not in tracing mode for identifying the channel and takes rest in the seeking mode. In COCAN, the energy consumed by the nodes in the seeking mode is small. The energy consumed per packet in LOCAN is 1 (Joule) lower than 1.5 (J) of COCAN, AODV, and OR.

Figure 8 illustrates the number of nodes retransmitted and packet loss due to multipath interference in sand particles in LOCAN as very much less compared to the retransmissions in COCAN, AODV, and OR. This is due to the characteristic of the lion hunting in groups, i.e., SU's nomad and resident

property. In LOCAN, the node waits for a certain period of time to transmit due to estimation of distance, which varies according to water column variations, and never makes trials once the distance matrix is evaluated. However, the number of retransmissions in COCAN is less than that in AODV and similar to that in OR. Further, the packet loss ratio due to all water column variations such as geometric, Doppler, and sedimentation drift of LOCAN is less than that of COCAN, AODV, and OR as in Figure 9. In COCAN, the cat's cautious nature towards the Doppler effect limits the packet loss and thereby reduces the retransmission. Figure 10 shows the overhead caused in the network due to noncoherent signal; the LOCAN has the minimum overhead compared to OR and AODV. The COCAN shows a better result than OR and AODV due to the cautious nature of the node during water column variation. While being cautious about Doppler effect

FIGURE 5: End-to-end delay during Doppler effect in the nodes.

FIGURE 6: Throughput during the sedimentation drift in seawater.

and sedimentation drift, each node watches the surroundings and channel changes with respect to adaptability.

The variation in delay called jitter is shown in Figure 11 for temperature and salinity. The jitter arises due to the packet queue or delay at any point of the network. The jitter of the LOCAN is less than COCAN as the reliable channel allocation done by the nodes in the underwater network reduces the delay between the successive packets. The jitter of COCAN is less than AODV and OR due to the self-position property of cat algorithm, which fixes with a particular channel and adapts them in the network. In self-position property, each node is aware of the exact characteristics and the position of their neighbor node with respect to channel characteristics and allocation. Figure 12 shows the relationship between the Bit Error Rate and the Signal to Noise Ratio (SNR) of LOCAN, COCAN, AODV, and OR for water channel

variations such as Doppler and GS. The rate at which the error occurs in the transmission system is lower than the LOCAN and higher in AODV. In the COCAN algorithm, BER is low when the SNR is high. The simulation values are tabulated in Table 3, for energy consumed, end-to-end delay, and throughput with different number of nodes, for AODV, COCAN, and LOCAN. Table 4 shows the simulation values of throughput under Doppler effect and GS. The above algorithms, namely, COCAN and LOCAN, have been implemented in the test bed.

5. Test Bed Step for Doppler and Spreading Environment

The performance of algorithm is analyzed in 25 kHz frequency and tested in underwater communication through a tank with the capacity of 50 liters of seawater. The hardware

FIGURE 7: Life of network during both Doppler effect and sedimentation drift.

FIGURE 8: Number of retransmissions during multipath interference of sand particles.

setup for the algorithms such as LOCAN and COCAN implementation is shown in Figure 13. The data transmission between the hardware sensor nodes has been carried out in seawater. The seawater has been collected from Bay of Bengal for the water bath. Moreover, the data transmission in seawater has been carried out for LOCAN algorithm.

The hardware setup consists of controller, acoustic transmitter, and acoustic receiver. MSP430 microcontroller is used for the six channel formation through different frequency inputs for 555 IC, and among six channels, three channels have been allotted for transmission and the other three are receiving channels.

The microcontroller sends the data to ASK modulator circuit for ASK modulation, and then, ASK modulated signal is sent to the other nodes through the hydrophone. Each node in the LOCAN or COCAN has microcontroller with ASK modulation setup with hydrophone to transmit

acoustic signal and mems acoustic sensor ADMP40 for receiving signal.

Analysis of the data transmission has been done at different depths. The depth ranges vary from 6 to 7 inches and from 10 to 12 inches for testing the performance of LOCAN algorithm in GS due to wave fronts. In the test bed, the Doppler effect is created with help of wave maker model NoWM-3000 pump for artificial internal wave front creation in the tank. The maximum flow rate of the pump is 3000 l/hr. The wave maker waves make the node movement and create the Doppler effect. Further, sea sand mixed with the seawater in the tank for the GS due to sedimentation drift is created. Based on the above scenario, the data are transmitted to the nodes and calculated for response time and power consumption.

The nodes are positioned with different distances and depths in the tank of dimension 60 cm × 45 cm × 30 cm as shown in Table 5. The power consumed and the packet

FIGURE 9: Packet loss ratio during water column variation.

FIGURE 10: Normalized overhead during noncoherent signal.

FIGURE 11: Jitter during salinity and temperature variations.

FIGURE 12: Bit Error Rate during water column variations.

TABLE 3: Simulation values of energy consumed and end-to-end Delay (Doppler effect, GS).

Number of nodes	AODV		COCAN		LOCAN	
	Life of network	End-to-end delay	Life of network	End-to-end delay	Life of network	End-to-end delay
2	0.57	2.7	0.54	2.5	0.32	2
10	1.69	3.37	1.6	3.3	0.95	2.7
20	2.24	3.78	1.97	3.6	1.15	3.1

TABLE 4: Simulation values of throughput (Doppler effect, GS).

Packet size	AODV	COCAN Throughput	LOCAN
50	0.184	0.22	0.25
100	0.21	0.28	0.31
150	0.224	0.31	0.34
200	0.242	0.318	0.348
250	0.269	0.339	0.361

TABLE 5: Network topology configuration and node location.

Topology 1 (right wing, left wing) in cm	
Node 1	(10, 17) to (node 3, node 2)
Node 2	(17, 10) to (node 1, node 4)
Node 3	(17, 10) to (node 4, node 1)
Node 4	(10, 17) to (node 2, node 3)

delivery ratio are measured for different water column variations and tabulated in Table 6.

Table 7 shows the comparative study of readings for Lion Optimized Cognitive Acoustic Networks (LOCAN) and Cat Optimization Algorithm (COCAN).

6. Conclusions

In underwater communication, the end-to-end delay and packet loss arise as a result of spatial and temporal variations (TV) in seawater. The losses improve through various underwater sensor network algorithms. The performance of LOCAN improves the efficiency and battery life of the node in Doppler and geometric spreading (GS) environment through appropriate channel selection based on water column variation.

The performance of the Cat Optimization Algorithm (COCAN) in cognitive underwater acoustic networks is better

FIGURE 13: Hardware implementation model.

TABLE 6: Performance evaluation of LOCAN and COCAN on test bed with 4 nodes.

Water column variations	Temperature		Salinity		Doppler effect		Sedimentation drift	
	20-25°C	25-50°C	30-50 ppt	50+ ppt	1000-2000 l/hr	2000-3000 l/hr	1000-2000 l/hr+sand	2000-3000 l/hr+sand
LOCAN								
Power consumed	0.421	0.601	0.523	0.531	0.410	0.581	0.452	0.593
Packet delivery ratio	1.287	1.159	1.202	0.997	1.332	1.011	1.258	0.978
COCAN								
Power consumed	0.617	0.688	0.599	0.701	0.611	0.698	0.621	0.687
Packet delivery ratio	0.878	0.684	0.759	0.598	0.721	0.501	0.658	0.498

TABLE 7: Comparison of performance of LOCAN and COCAN in different water column variations.

Water column variations	Temperature, salinity, Doppler effect, sedimentation drift									
	20-25°C, 30-50 ppt, 1000-2000 l/hr +sand	25-50°C, 30-50 ppt, 1000-2000 l/hr +sand	20-25°C, 50+ ppt, 1000-2000 l/hr +sand	20-25°C, 50+ ppt, 2000-3000 l/hr +sand	20-25°C, 30-50 ppt, 2000-3000 l/hr +sand	25-50°C, 50+ ppt, 1000-2000 l/hr +sand	25-50°C, 30-50 ppt, 2000-3000 l/hr +sand	25-50°C, 50+ ppt, 2000-3000 l/hr +sand	25-50°C, 30-50 ppt, 2000-3000 l/hr +sand	25-50°C, 50+ ppt, 2000-3000 l/hr +sand
LOCAN										
Power consumed	0.423	0.487	0.512	0.598	0.499	0.574	0.569	0.587		
Packet delivery ratio	1.385	1.314	1.287	1.105	1.214	1.198	1.076	1.119		
COCAN										
Power consumed	0.621	0.634	0.622	0.698	0.667	0.647	0.699	0.711		
Packet delivery ratio	0.812	0.805	0.789	0.699	0.745	0.712	0.667	0.654		

than that of the existing AODV algorithm. Energy saving due to the cautious nature of cat inspired node performance and high alertness of the nodes. The multidimensional approach with fitness values based on the input parameter of water column environment enables the efficient performance of the Lion Optimized Cognitive Acoustic Networks (LOCAN) to perform well than COCAN in the cognitive network.

The LOCAN algorithm can be tested in various environments such as spherical, cylindrical, and macrocellular mobile environment.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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