Predictive Analytics Integrated Multi-level Optimization of Offshore Connectivity in Ocean Network

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***Abstract*—One of the primary difficulties of fishermen engaged in deep-sea fishing is the lack of effective communication systems to the shore. The Offshore Communication Network(OCN) resolves this problem by providing Internet over the ocean through a fishing vessel network. OCN is a multi-layered architecture with heterogeneous connectivity ranges, directionality, resources, and mobility patterns. Connectivity maintenance is challenging due to the lack of infrastructure, expanded mobility, network sparsity, and sea-wave-induced movements. This paper discusses a framework to improve OCN connectivity with a multi-level optimization strategy. We propose a predictive model to generate real-time forecasts of link status. At the physical level, node position re-orientations to higher connectivity locations are suggested. The transmission queue management and prioritized scheduling in the link-layer minimize the queuing delay. A reinforcement routing strategy in the network layer determines the best next-hop for message dissemination. The proposed three-level optimization approach facilitates communication capability enhancement in OCN.**

I. Introduction

Lack of low-cost and reliable communication facilities to the shore remain a critical problem confronting fishermen in deep-sea fishing. Existing conventional communication technologies like cellular networks and VHF radio provide offshore connectivity up to 20 km. However, fishing trips typically stretch more than 100 km from the shore. Although satellite telephone systems offer ubiquitous communication facilities, these are not common because of the unaffordable cost. Due to the lack of real-time communication facilities, fishers cannot connect with the world even in life-threatening emergencies.

A promising solution to this problem is a wireless network of intelligent fishing vessels to support reliable communication in the ocean. The network requires more than 100 km of extended connectivity, affordability, and the ability to operate with scalability in extreme environments. (OCN) [1], [2] solve this offshore connectivity issue by providing wireless internet across the ocean with a fishing vessel network. OCN enables fishers to access applications like Skype and WhatsApp to make voice calls, video calls, and send text messages directly using their smartphones on-board internet connection.

A unique communication challenge that distinguishes OCN from terrestrial networks is sea-wave-induced mobility. The connectivity of a link depends on additional factors like antenna alignment and sea propagation effects. Mobility patterns in terrestrial vehicular networks are constrained by the road infrastructure, whereas all OCN nodes have expanded movement freedom at sea. Furthermore, network sparseness and movement of nodes due to the influence of ocean waves create frequent topology changes. Existing connectivity maintenance techniques such as additional infrastructure or transmission power management cannot be applied in OCN because of environmental constraints. The marine environment, the mobility of fishing vessels, and the heterogeneous communication lead to abrupt fluctuations in signal quality. Hence providing seamless internet connectivity at sea is one of the critical challenges in OCN. The wireless link characteristics of different ocean regions are unknown, and to our knowledge, there are currently no studies on communication capability analysis in maritime networks. This paper discusses the questions of what are the characteristics of OCN links, how to estimate and enhance the communication capabilities of nodes to provide continuous connectivity to the shore and to peer nodes.

To address the challenge of estimating the communication capability of nodes, we propose a hybrid machine learning framework leveraging data from extensive marine experiments on multiple fishing vessels. In addition, a node-level metric to quantify the node's connectivity to the shore and the peer nodes is proposed. A three-level optimization scheme is applied across the physical, link, and network layers to improve the communication capability. At the physical level, the positions of the nodes are re-oriented to higher connectivity zones depending on the user requirement at distinct stages of fishing. For link-level optimization, the transmission queue size is estimated for multiple priority messages, and the traffic is scheduled adaptively to minimize queuing delay. An intelligent routing scheme with an OCN-specific reward function in a reinforcement learning model is employed for network-level packet delivery optimization. The major contributions of this paper are as follows:

- the design of a machine learning framework combining offline and online learning for link prediction;
- a node-level metric to quantify the communication capability of OCN nodes;
- the design of algorithms to generate suggestions for node position and re-orientation in different fishing states to optimize communication capability in the physical level.
- an analytical model for queue length estimation of multi-priority messages and an adaptive packet scheduling scheme to minimize queuing delay in link layer;
- the design of a reinforcement learning routing strategy for message dissemination to optimize the communication capability at the network layer.

The rest of this paper is organized as follows. Section II reviews previous works related to link analysis, connectivity management and network routing. In Section III, we present the architecture of the proposed OCN and solution approach. In Section IV we describe the factors impacting connectivity in ocean and a measure to quantify the communication capability. Section V presents the multi-level optimization framework, followed by the concluding remarks of Section VII.

II. Related Work

This section summarizes the state-of-the-art about link estimation techniques, connectivity modelling, and reinforcement learning based routing strategy applied in terrestrial wireless networks.

Several studies on link quality estimation in wireless networks started in the late 90s. A review of link estimation techniques in ad-hoc and mesh networks is presented in [3]. Numerous empirical link estimation models are proposed for terrestrial networks, classified into three fundamental approaches: analytical modeling, probabilistic estimation, and statistical prediction [4]. Nowadays, machine learning approaches are widely used to capture the wireless environment's dynamism and predict link quality. Some of the most commonly used link classification models are neural networks, deep learning networks, support vector machines, logistic regression, and Naïve Bayes classifiers. In addition, regression algorithms and reinforcement learning strategies were also suggested to predict packet reception rates. As the wireless link characteristics changes over time, online machine learning algorithms have also been applied to predict link quality [5], [6]. However, most of the existing prediction methods assumed limited node mobility in the network. In OCN, the mobility and link characteristics are distinctive from the terrestrial network, and variations of real-time data from offline collected data will be high in rough sea states. Hence, it is hard to use existing deterministic models to predict signal behavior in OCN. Instead, the OCN situation requires a context-dependent forecasting model built on available offline data and updated with real-time data.

Connectivity problems in terrestrial networks were analyzed from single-node, two-node and full-network perspectives. Node degree [7] is used as connectivity metric *single-node* point of view analysis. In *two-node* perspective, the number of multi-hop paths between nodes was the evaluated metric. The number of paths between any two random nodes is applied to derive connectivity in *full-network* point of view. Most of the initial studies assumed that nodes in the network were stationary. Static network connectivity results include the analytical models for transmission radius and node density needed to completely connect the network [8], [9]. For mobile ad-hoc networks, bounds on number of nodes required to ensure connectivity [10], [11], [12] was studied. VANET connectivity with varying mobility models and node velocity were also explored [13]. However, most of these investigations were theoretical models assuming a large number of nodes for analysis. These models cannot be applied to OCN with a realistic number of nodes, a sparse network structure and high dynamism.

Reinforcement learning-based routing techniques have been successfully employed to improve performance across a variety of wireless network applications. Mammari et. al presented a survey of reinforcement learning based routing in networks [14]. The first routing algorithm based on Q-learning in telephone networks was developed by Boyan et.al. [15]. Many RL routing schemes have also been applied to MANET [16], wireless sensor networks [17], wireless mesh networks [18] and delay tolerant networks [19] for performance optimization. Some other contexts have been explored, such as underwater sensor networks [20], software-defined networks, and information-centric sensor networks to learn data delivery paths. The major reinforcement learning approaches applied in wireless network routing were model-free learning [15], [17], model-based learning [20], and learning automata. Although many reinforcement routing techniques have been proposed, these protocols were developed to enhance performance following the characteristics of particular networks. Since the adhocness of OCN is very high, the learning model needs to be developed to integrate the parameters that affect connectivity in the marine environment.

III. OCN Architecture and Multi-layer Optimization Framework

OCN is the first vehicular network that provides Internet to fishing vessels over the ocean [1], [2], [21], [22]. The network framework is built on a distributed architecture and integrated with edge computing. The architecture considers fishing vessels as edge nodes that process the data collected locally, directly on board, averting dependency on the base station for analysis. This approach is necessary due to the dynamic and extreme variability experienced in the ocean environment. Figure 1 shows the architecture. A detailed description of the low-cost communication architecture and the routing schemes of OCN can be found in companion paper [1].

OCN edge nodes are categorized into three groups: access nodes, adaptive nodes, and super nodes, based on the communication mechanisms available in the fishing vessels. *Access nodes* are vessels that only bring a wireless *access router* (AR); *adaptive nodes* hold one piece of *adaptive back-haul*

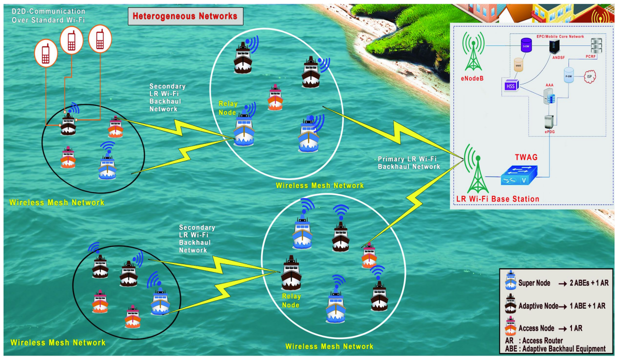


Fig. 1: Architecture of Offshore Communication Network

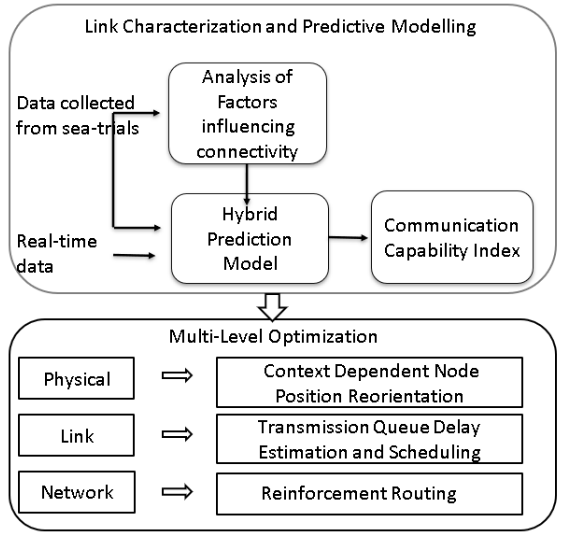


Fig. 2: Multi-level optimization framework

equipment (ABE), while *super nodes* hold two ABEs and one AR. The latter two types of nodes are also called *long-range* (LR) nodes. In fishing vessels, each AR is equipped with an omni-directional antenna that provides a Wi-Fi signal in the range of 500m and is used to connect devices such as smartphones and tablets, as well as other nearby ARs. The ABEs are equipped with 120° sector antennas that provide connectivity up to 20km, using long-range Wi-Fi links.

The architecture of OCN is divided into three layers:

- *Layer 0* is a mesh network of access nodes that communicate through Wi-Fi links;
- *Layer 1* is the backbone ad-hoc network of LR nodes;
- *Layer 2* is the network of base stations.

Layer 0 and Layer 1 nodes are considered as edge nodes. These edge nodes executes intelligent distributed algorithms to enhance communication capability. The proof-of-concept test of the OCN architecture was performed over the Arabian Sea from a coastal village in Kerala, India. LR Wi-Fi equipment from Ubiquiti Networks and Cisco Linksys access routers were utilized in the field trials. The onshore base station is located at an altitude of 56 m, while the boat's ABE at 9m above sea level. In these marine experiments, the network offered a range of at least 40km in the first hop and 20km in every succeeding hop.

Figure 2 demonstrates the overall solution architecture of connectivity optimization. Data collected from marine experiments are used to analyze the factors impacting connectivity and these features are used in a machine learning framework to predict the real-time link status. A node-level measure is formulated to quantify the communication capability employing the link prediction strategy. Connectivity optimization is applied at three levels: opting for the best node positions, scheduling packets with minimal delay, and selecting the optimal neighbor as the next-hop. First, position re-orientations established on the connectivity metric enable the nodes to determine suitable locations for communication at the physical level. Second, queue management and reinforcement learning-based packet scheduling help to reduce the transmission queuing delay in the link layer. Finally, an adaptive routing scheme that applies reinforcement learning allows the node to choose the best next-hop for improving routing performance.

IV. Link Characterization and Predictive Modelling

A. Characteristics of radio links over the ocean

Real-time connectivity quality estimation of links is crucial for resilient communication in OCN due to unexpected extreme variability in the marine environment. The rocking movement of vessels is a unique characteristic that causes abrupt signal variations. We utilized the Douglas Sea Scale [23] to define the intensity of ocean waves in different periods. This scale classifies ocean conditions into ten states from 0 to 9 based on wave surface turbulence. The wave-induced mobility is proportional to the sea state. Data for OCN link analysis were collected through marine experiments comprising multiple fishing vessels. From the analysis, we observe that the primary components influencing radio links between vessels in maritime communication are wave-induced vessel rocking movement, physical distance, antenna misalignment, and propagation effects.

Fishing vessels at sea experience six degrees of movement freedom: *translational* movements include linear vertical up/down (*heave*), side-to-side motion (*sway*) and, front/back motion (*surge*), while *rotational* ones include left/right (*yaw*), up/down (*pitch*) and front/rear (*roll*) motion. Signal variations are proportional to the roughness of the ocean surface. Hence we define rocking degrees from 0 to 9 as Douglas State 0 (calm) to 9 (phenomenal) [23]. Figure 3 shows real-time data collected from marine experiments in three rocking states - State 3, State 4, and State 5. Here, we can observe that the signal loss is distinctive for a certain distance in each sea state. There is a significant difference in signal strength at

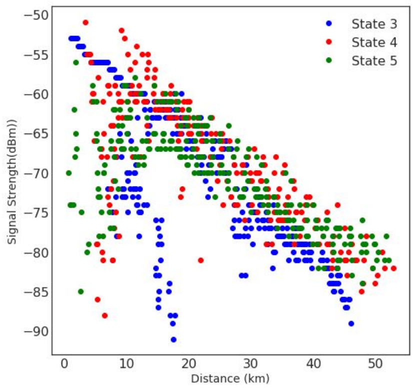


Fig. 3: Signal strength variation in different sea states with distance: In higher sea states, more signal degradation is observed. A relationship between distance and signal strength has been noticed in all sea states after a distance ≈ 15km.

three different sea states for the equal distance between the transmitter and the receiver antenna.

Similar to terrestrial networks, the signal strength in OCN also decreases with the distance between transmitter and receiver that is evident in Figure 3. The angle between the transmitting and the receiving antennas also plays a significant role in the quality of signals as the LR nodes utilize a 120° sectored antenna. In addition, the characteristics of radio wave propagation over the sea surface are distinctive from those of terrestrial wireless channels.

B. Machine Learning Framework for Link Prediction

Wave-induced mobility and propagation effects directly influence the quality of signals in OCN. These parameters produce frequent topology changes and constitute a significant challenge for routing packets. Intelligent data-driven models employing machine learning approaches can approximate the data distribution and predict the future characteristics of wireless links to provide reliable communication. Link status forecasting facilitates the nodes to predict forthcoming changes in topology and reduce packet drops.

Data gathered from marine experiments demonstrate a general idea of the signal strength variation in different sea states. This historical data are helpful to develop offline data-driven predictive models for link status forecasting. Because the ocean environment is highly dynamic and the link properties are time-dependent, the actual prediction may deviate from the offline generated model. Spatio-temporal variation in path loss parameters further complicates the prediction of link features. Thus, we require a model to learn the link features using real-time data continuously.

Since the signal strength data is collected incessantly and the network connectivity is intermittent, it is not preferable to forward it to an onshore server for analysis. The concept of edge computing can be utilized for online data processing by considering fishing vessels as the network edge. Online machine learning facilitates edge intelligence to capture link

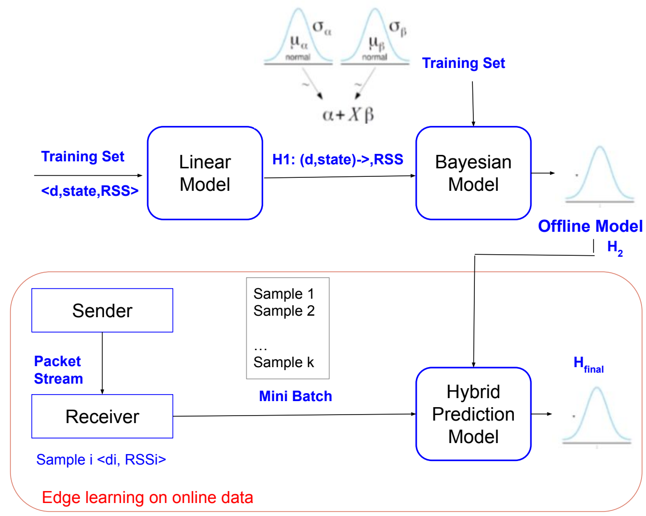


Fig. 4: Hybrid Learning Framework: A Bayesian offline learning scheme with a prior from linear model integrated with online learning.

features continuously in the vessels themselves. This online processing will accelerate the learning process and incorporate node-specific local knowledge into the prediction system. Integrating the real-time learning scheme with the offline model provides a hybrid predictive system that combines the benefits of offline and real-time measurements as shown in Figure 4.

In the proposed framework, a linear prediction model is fitted on the historical offline data. In many fishing contexts, data available from fishing vessels are not sufficient to generate a good prediction model. Also, the distribution of data varies dynamically with the environmental conditions. Hence, a deterministic prediction model may not work well in all scenarios of OCN. A Bayesian probabilistic learning approach is suitable here because it can generate prediction models with less volume of data. Besides, it is possible to incorporate prior knowledge about the parameters into the model. This probabilistic learning makes use of the linear model to generate the distribution of parameters for each state. During network operation, each node will receive real-time data on the signal strength in its local context. Based on the availability of real-time data, the offline model is updated online per mini-batch basis. This model update will help the nodes to incorporate their local context into the learning model and to provide edge intelligence.

C. Communication Capability Analysis

Analysis of the communication capability plays a critical role in connectivity maintenance since the ad-hocness of OCN is very high compared to other terrestrial networks. Forecasting the connectivity levels of nodes in different layers of network hierarchy helps in communication planning. Also, this awareness helps the nodes to choose locations of high connectivity and to avoid isolation. A node-level measure called *dynamic connectivity index (DCI)* is proposed to quantify the quality of connectivity of nodes in OCN. *DCI* of a node is recursively defined in terms of probability of neighbor links and the *DCI* of its neighbors as in equation 1.

$$DCI(x) = \sum_{i \in AN(x)} w_i \cdot \alpha_i \cdot DCI(i) \tag{1}$$

where w_i is the weight assigned to neighbor i, α_i is the probability of link from node x to neighbor i, $AN(x)$ is the active neighbors of node x and $DCI(i)$ is the dynamic connectivity index of neighbor i. The real-time forecast of neighbor signal quality from the machine learning framework is utilized to compute the link probability. All neighboring nodes will not contribute equally to the connectivity of a given node. Hence an adaptive algorithm [24] is employed to prioritize and assign weights to neighbors in the dynamically changing link conditions.

V. Multi-level Optimization of Communication Capability

For enhancing OCN node communication capability, we propose optimizations in three levels shown in Figure 2. First, the possible location options including distance and direction to improve connectivity are suggested to each vessel at the physical level. Second, transmission queue management with multiple priority messages is employed at the link level to obtain shorter queuing delays. Finally, adaptive message dissemination using reinforcement learning strategy is employed at the network level for packet delivery maximization.

A. Physical Level Optimization

The node's position plays an essential role in ensuring connectivity since the link quality in dynamic environments changes over time. Adjusting the positions of the nodes to highly connected zones improve the user experience. Suggestions for direction and distance to relocate for better connectivity will be immensely beneficial for fishers at sea. Therefore, we present context-aware methods of node position re-orientation to maintain connectivity. According to the fishing activity, the states of nodes can be categorized into four groups: sailing, searching, fishing, and resting. The *sailing state* represents the journey towards the deep sea and the return to the shore. When the vessels reach a required depth, it starts searching potential fishing zones, and the state is called *searching state*. After discovering the fishing zones, the state changes to *fishing state*. During the night, the vessels stop fishing and move to *resting state*. The communication requirements and mobility patterns of each state were identified from a survey conducted with fishermen. Based on this analysis and computed *DCI* levels, context-dependent node position reorientation suggestions are provided to each node for connectivity restoration. Table I shows position reorientation algorithms for different fishing states.

To effectively optimize connectivity at the physical level, it is mandatory to determine the direction of movement and the distance to be shifted. In a static resting state, nodes

Node Type	Connectivity Stage	Position Re-orientation Strategy	Fishing State
LR node	low BS connectivity	Single Node Static Global Re-orientation	Resting
		Group Static Re-orientation Intra-cluster	Resting
		Full cluster Static Re-orientation	Resting
		Single node Dynamic Re-orientation	Sailing Searching
		Full cluster Dynamic Re-orientation	Sailing Searching
		Single Node Intra-cluster Re-orientation	Searching
		No Re-orienttaion	Fishing
	low cluster connectivity	Single Node Intra-cluster Re-orientation	All states except Sailing
Access node	low BS connectivity	Single node Re-orientation	All states except Fishing
	low cluster connectivity	Single Node Intra-cluster Re-orientation	All states

TABLE I: Summary of position re-orientation algorithms in different fishing contexts

are expected to have limited mobility; hence, the neighbor with maximum *DCI* is preferred, and the direction towards that node will be the new direction. For dynamic fishing states, neighbors' availability time within the effective communication radius represents an essential factor to consider before re-orientation. The availability time can be calculated from the vessel rocking degree, mobility model, speed, and neighbor type. The re-orientation will only take place when the availability time is longer than the required minimum availability period. The new direction is the direction towards a neighbor with a maximum *DCI* and availability time. Table I list the type of re-orientations in different fishing contexts. Dynamic re-orientation refers to location change in mobile states.

B. Link Level Optimization

A crucial function of OCN medium access control is the intelligent scheduling of packets with service differentiation for quality of experience(QoE) enhancement. Using a Markov decision process, each priority configuration evaluates the performance level and selects a new configuration based on the estimation. This reinforcement learning strategy helps to adapt the packet scheduling in presence of dynamic flows. Each node keeps track of its state which consists of its present queue status and performance factor. The scheduler acts as an agent, which assigns priority to packets in every epoch to maximize its expected discounted reward. The goal of the scheduler is to maximize the QoE of the user. Figure 5 shows

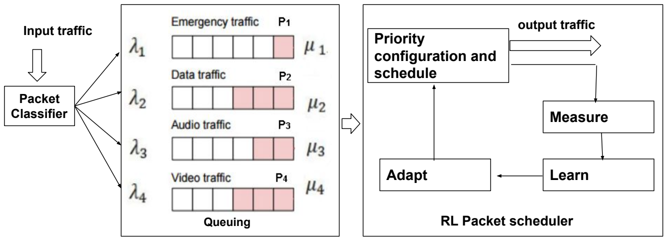


Fig. 5: Reinforcement learning based packet scheduler with Quasi-Birth-Death queuing model

the reinforcement learning based scheduler and the queuing model.

To estimate the queuing delay for each type of packet, we used a quasi-birth-death model. An OCN node can transmit or receive four classes of messages: emergency E, data D, voice A and video message V. Emergency messages have a higher priority than all other types of traffic. Each node maintains four queues $Q_{emergency}$, Q_{data}, Q_{audio}, and Q_{video} to handle traffic types E, D, A, and V. A four dimensional irreducible continuous-time Markov chain in equation 2 is used.

$$\chi = \{(n_t, i_t, j_t, k_t), 0 \leq n_t, i_t, j_t, k_t \leq \theta, t \geq 0\} \tag{2}$$

where n_t, i_t, j_t, k_t are the number of emergency, data, audio and video messages at time t. The states of χ are arranged in lexicographic order as

$$\iota = \{(n_t, i_t, j_t, k_t) | 0 \leq n_t, i_t, j_t, k_t \leq \theta\} \tag{3}$$

These state transitions form a quasi-birth-death process [25]. We used matrix geometric method to compute the stationary probability distribution. Analysis of this distribution provides the queue status of each type of message in every node.Based on the real-time status of queued messages, the scheduler will assign priorities to the queues dynamically following the reinforcement learning strategy. This dynamic prioritization reduces message drops from the queue and improves user experience.

C. Reinforcement Routing for Network Level Optimization

The mobility due to ocean waves results in dynamic topology, and rough sea conditions will not guarantee the desired link quality. As a consequence, discovering reliable paths with multiple hops is a challenging task. These difficulties in maritime communication demand the development of a packet routing strategy that is reliable and effective. Combining intelligence into the routing process enables the network to adapt to the environment and optimize performance parameters. Recently, machine learning-based routing algorithms have been implemented in many wireless network scenarios. Reinforcement models perform well in these scenarios where agents interact with the wireless environment and take actions based on the feedback signal.

We formulate routing in OCN as a reinforcement learning problem. An adaptive routing approach called OCN-AR is designed for inter-vessel and onshore communication to improve the packet delivery ratio. An agent works on each node and decides the appropriate neighbor to forward packets such that the message will reach the destination as effectively as possible. A reward function is designed based on the neighboring node's connectivity quality, link availability duration, path probability, and geographical distance to the destination. Based on this feedback, the node learns the optimal neighbor to forward packets in time-varying environments in a distributed manner.

The MDP model with the state, action, and reward function with Q value update rule is defined as follows:

Agent states: The state of the RL system is the set of all nodes in the network. If a node i generates a packet P or is forwarded to i by another node, then the state of the learning agent is stated to be S_i related to the packet P.

Agent Actions: An action for a packet P in node i at time t is to choose one of the neighbors from Nb to forward the packet P. Thus, the action space is the set of actions carried out by all nodes in OCN.

Reward function: A crucial factor in Q-routing is to formulate the reward function. The parameters to be optimized specifically for the network should be included in the design of the reward function. In OCN, neighborhood connectivity, neighborhood link availability time, and the possibility of a path to the destination, and distance to the destination, comprises the key factors to consider for a positive reward.

Reward for forwarding a packet from node i to node j for action a_j is defined as:

$$\begin{aligned} R(a_j|(s_i, s_j)) = \beta_1.DCI(j) + \beta_2.\tau(i,j) \\ + \beta_3.\mathcal{P}(j, dest) + \beta_4 \frac{\Delta d(i,j)}{d(i,j)} \end{aligned} \tag{4}$$

where $DCI(j)$ is the connectivity quality of node j, $\tau(i,j)$ is the availability time of link $i-j$, $\mathcal{P}(j, dest)$ is the probability of path from node j to destination and $\Delta d(i,j)$ is the difference in distance between i to destination and j to destination. $\mathcal{P}(j, dest)$ is used as an optional parameter for LR nodes. β_1 to β_4 are the weights assigned to these parameters.

VI. Results

A pilot implementation of the OCN architecture has been tested over the Arabian Sea and collected data for analyzing the factors influencing radio communication at sea. For forecasting the link status, a linear model was fitted on the data collected from three sea states and evaluated the prediction error. Ten-fold cross-validation was executed and obtained the best parameter vector θ. For different sea states, θ differs significantly. We noticed an increase in the slope of fit in states with a high wave effect that indicates a small difference in distance causes more signal disruption in rough sea conditions.

The linear model is extended to a Bayesian probabilistic model to predict the distribution of model parameters. This model further tested with real-time data and evaluated whether the online update can improve the accuracy of prediction. We used mini-batches real-time data for online model update. A higher prediction accuracy compared to the offline model in the selected data set is observed. Additionally, we compared

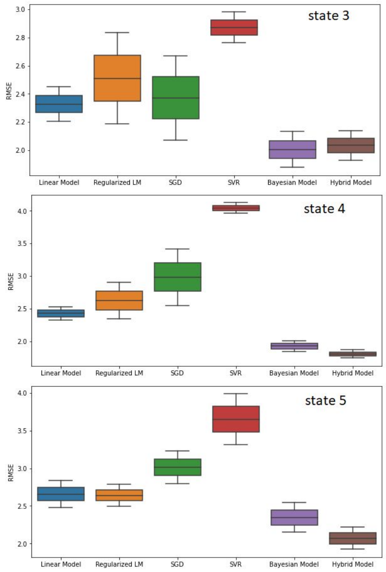


Fig. 6: RMSE comparison of predictive model with existing algorithms: In all three sea states, prediction accuracy of hybrid learning scheme is better than other models.

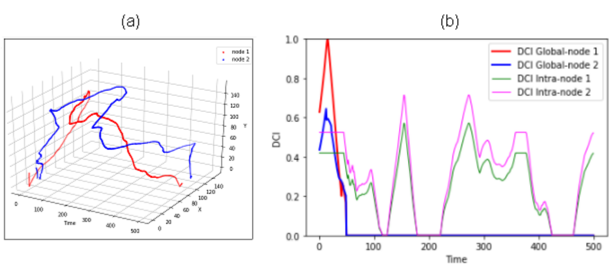
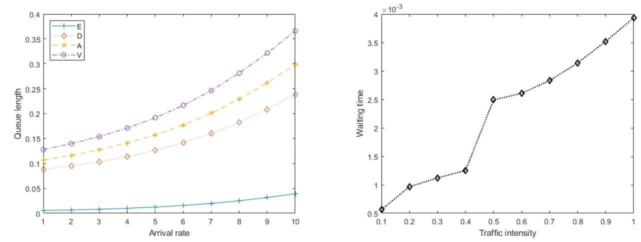


Fig. 7: (a) Trajectory of two nodes (b) Communication capability variation of nodes to the base station and with in the cluster.

the prediction accuracy with existing algorithms, Stochastic Gradient Descent(SGD), linear regression, and Support Vector Regression(SVR). Here also, root mean square error is comparatively low for the hybrid learning scheme. The comparison plot is shown in Figure 6.

Each node in OCN is aware of its communication capability through two metrics: $DCIGlobal$ and $DCIIntra$ that represents the connectivity to the base station and the cluster, respectively. To demonstrate the communication capability variations of node in different fishing stages, we plotted the trajectory and *DCI* of two nodes in a fish searching stage as shown in Figure 7. After 50 units of time, base station connectivity drops, but we can observe that the nodes are connected to the cluster. Utilizing this *DCI* measure nodes can apply re-orientations to high connected zones depending on the communication requirements.

At the link level, we experimented with different types of flows and arrival rate to compute the queue length distribution. Figure 8a shows the difference in transmission queue length



(a) (b)

Fig. 8: (a) Variation of queue length of emergency, data, audio and video type of messages with increase in arrival rate; (b) Variation of waiting time of emergency message with increase in traffic intensity.

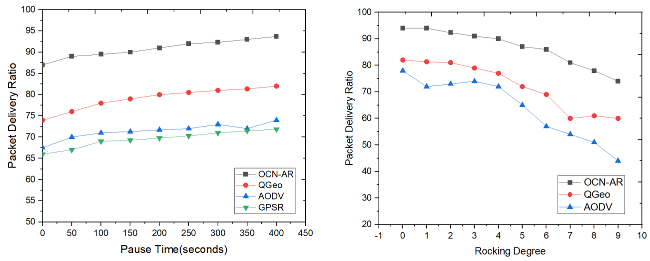
of each type of message with change in packet arrival rate. Increase in waiting time of emergency message with traffic intensity is shown in Figure 8b.

The reinforcement routing algorithm OCN-AR is simulated in ns2 and compared with existing a reactive protocol AODV, location based protocol GPSR, and a reinforcement learning protocol Q-Geo. For the simulation, 50 nodes were used, including a base station, 12 LR nodes, and 38 access nodes arranged in a 1000 x 1000 area. The packet generation rate in the source nodes ranges from 2 to 64, and the size of each default packet is 512 bytes. The traffic used for the scenarios is mainly constant bit rate traffic over UDP. To evaluate the protocol, we employed the metric packet delivery ratio. Although fishing vessels move only at a speed of 3-5 m/s, the rocking movement creates a significant impact on routing performance.

To simulate the moving effect, we adjusted the pause time of the nodes. The mobility degree of the node reduces with increasing pause time. High pause time indicates low mobility degree.Figure 9a shows the packet delivery ratio for various pause times. The rocking movement of the nodes often causes link breakages. Packet delivery ratio of OCN-AR was compared with that of AODV and Q-Geo as shown in Figure 9b. As the rocking degree increases, the performance of AODV decreases significantly due to link failures. Compared to other protocols, OCN-AR performs better in higher rocking states because it uses signal strength data and the estimate of link availability duration.

VII. Conclusion

Connectivity of fishing vessels to the onshore base station and peer nodes is essential to disseminate emergency and personal messages. In this paper, we proposed a multi-level optimization strategy to enhance the communication capability of nodes in a network of fishing vessels to provide Internet at sea. Data collected from multiple marine experiments were employed to explain the wireless link characteristics and identify factors influencing connectivity in the ocean. We developed a hybrid machine learning model by applying the collected and real-time data to predict the signal strength. With the aid of this forecast link status, a node-level metric is designed to



(a) (b)

Fig. 9: Packet delivery ratio:(a) Comparison of OCN-AR performance with existing routing schemes. (b) Impact of rocking movement degree on OCN-AR performance

estimate the communication capability of nodes to the shore and peer groups. In addition, the connectivity metric integrated context-dependent node position re-orientations are suggested to improve the user experience from a physical point of view. The transmission queue size is estimated for multiple priority messages, and the traffic is scheduled to minimize the delay in the link layer. A reinforcement learning routing scheme is developed using a reward function specific to maritime conditions for message dissemination. The proposed three-level optimization helped to achieve improved communication capability in OCN.

Acknowledgment

The authors would like to express their immense gratitude to Sri. Mata Amritanandamayi Devi (AMMA), Chancellor, Amrita Vishwa Vidyapeetham, who gave us the motivation and inspiration to pursue this research work. This research work was partially funded by a grant (Project title: Mobile Infrastructure for Coastal Region Offshore Communications & Networks, ITRA / 15(65) / Mobile / MicroNet / 01) from Information Technology Research Agency (ITRA), Department of Electronics and Information Technology (DeitY), Govt. of India and Amrita Vishwa Vidyapeetham.

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