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Statistical Channel Model and Systematic Random Linear Network Coding Based QoS Oriented and Energy Efficient UWSN Routing Protocol

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Abstract: Considering the significance of an energy efficient, delay tolerant and reliable communication protocol for underwater acoustic wireless sensor network (UWSN), this paper proposes a novel systematic random linear network coding (SRLNC) based transmission system examined over a robust statistical UWSN channel model. The derived statistical channel model deals with both the small-scale fading primarily caused by scattering and small wavelength changes and large-scale fading introduced due to node dislocation in the underwater acoustic medium. The proposed SRLNC transmission-based routing approach has been applied over the proposed underwater acoustic (statistical) channel model, and respective performance assessment has been conducted in terms of throughput, energy efficiency, delay and computational complexity by varying network condition parameters. The contributions such as low coefficient vector and Galois filed, low redundant message requirements, computationally efficient pre-coding scheme, iterative buffer flush and enhanced FEC based decoding make the SRLNC based routing protocol sufficiently robust to enable reliable, energy-efficient and delay resilient communication over UWSN. The proposed SRLNC based UWSN routing protocol and its efficacy over dynamic channel conditions affirm that it can be a potential solution for QoS-oriented mission critical underwater communication purposes.

Keywords: delay tolerant; energy efficient; quality of service; random linear network coding; statistical channel model; underwater acoustic wireless sensor network

1. Introduction

The high-paced emergence of communication technologies and associated applications has gained significant attention across academia and industry to enable efficient low cost, energy efficient and quality of service (QoS) communication support. In the last few decades, providing underwater communication has emerged as a vital research domain for both academicians as well as industries. Recently, underwater wireless sensor networks (UWSNs) [1,2] have been used exponentially in varied applications including environmental monitoring, gas deposit exploration, tsunami warning, assisted navigation, distributed tactical surveillance, mine reconnaissance, oceanographic data collection, oil spill monitoring, real-time warship monitoring, disaster prevention, etc. Although UWSN is stated to be closely related to the WSN, many research reports [3–6] have revealed that generic techniques developed for WSNs cannot be applied for UWSNs, due to the practical operating characteristics of the underwater channel [7]. The main issues allied with the



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Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). underwater channel comprise high propagation latency caused by low propagation speed of acoustic signals (usually, 1500 m/s), strictly confined accessible resources [8], wave caused disturbance, noise presence, dynamic delays [9] and high error rate probability. The dynamic topological variations also make protocols vulnerable to suffering link loss and data drop across multipath and fading channel conditions [10]. This might cause significantly higher data retransmissions, increased latency, high energy exhaustion and cumulative QoS degradation. To alleviate such issues, enabling an efficient routing protocol while ensuring optimal data delivery, throughput and minimal energy exhaustion can be of paramount significance.

Exploring this issue in-depth, it can be found that most existing physical layer approaches are ineffective [11]. In fact, radio waves propagating across conductive salty water at a low-frequency range (i.e., 30–300 Hz) require significantly large antennae and, as a result, more transmission power. Undoubtedly, optical waves avoid major attenuation issues, however, they are influenced by scattering under water surface. This problem demands an efficient UWSN routing protocol to deal with different acoustic environment conditions. Considering the functional characteristics and associated intricacies, it is necessary to assign sufficient resources before system deployment to enable optimal QoS transmission on both the PHY link layer as well as the higher network layers. Providing an efficient channel model to consider realistic network conditions can enable development of an optimal routing approach. In major existing approaches, numerous beam tracing tools, such as Bellhop [11], have been suggested for the deterministic presentation of a UWA channel for certain predefined signal features, such as frequency and network geometry. However, this does not consider the arbitrary nature of channel conditions. To deal with these conditions, statistical channel models have gained appreciation, for example, the Virtual Times series EXperiment (VirTEX) code [12] based channel model, which outperforms the Bellhop model due to its beam tracing efficiency under dynamic channel conditions. However, its computational efficiency remains questionable. For illustration, to simulate a channel with a Doppler distortion of 15 Hz, a minimum of 30 channel simulations per second are needed, which eventually piles up iterations to a significantly higher 5400 Bellhop runs, even with two transmitters and six receivers over a period of 15 s. Similarly, the wave front model [13] provides a deterministic approach to enable approximations to the ray theory. The authors of [14] assessed the impact of warping of the oceanic surface waves on the fluctuations introduced, particularly in terms of transmission latency and throughput. Considering existing acoustic channel models and respective features, it can be found that most of the approaches either suffer from computational complexity or are unable to deal with dynamic acoustic channel conditions. With the intent to alleviate such these limitations, in this paper, a novel statistical acoustic channel model has been derived by considering the key dynamic channel conditions under varied operating conditions [15]. The derived statistical channel model has been applied to examine the effectiveness of an enhanced systematic random linear network coding (SRLNC) based delay tolerant, energy efficient and QoS routing protocol for UWSN.

Generally, UWSN comprises sensors and Autonomous Underwater Vehicles (AUVs), deployed under water to perform collaborative monitoring and communication [16]. Practically, the main intricacy for the implementation of AUVs in UWSNs is to design a robust Medium Access Control (MAC) protocol well-suited for the acoustic channel environment. The UWSN MAC routing protocol must enable maximum network throughput, minimal bandwidth consumption and access delay, and minimal energy consumption, and no doubt transmission security under acoustic channel conditions [17]. To ensure energy efficiency, QoS enriched, reliable communication enhancing UWSN MAC is a must. Similarly, reducing signalling overheads, primarily in forward error check (FEC), can be significant. With this motivation, in this paper, a novel systematic random linear network coding (SRLNC) based transmission model is proposed for UWSNs. The proposed SRLNC based transmission mechanism has been applied over a derived statistical channel model [18]. The results obtained exhibited higher throughput, minimal data loss and minimal retransmission.

mission probability, even under varying link loss probability caused due to scattering and acoustic dynamism.

2. Related Works

This section discusses a brief overview of the existing literature pertaining to UWSN channel modelling and data transmission.

2.1. Channel Mode

A number of studies have been conducted to design a stochastic UWA channel model [17–28] based on the assessment of the experimental acoustic data retrieved at certain specific locations. Authors have suggested Ricean fading [17,18] or Rayleigh fading [19–21], however, in some works, log-normal distribution [22,23] and the Ricean shadowed distribution [26] to enable better fit for measurement. The majority of these approaches apply experiment-specific characteristics, including location of the network deployment and the kind of signals to be applied to perform the test. The available research primarily considers small-scale topological phenomena and suggests that a statistical model is suitable for both small as well as large-scale UWA channel conditions [17,24–26]. In [27], authors applied log-normal fading to derive a channel model from dealing with large-scale phenomena. The authors of [27,28] used the Bellhop model to generate an ensemble of channel responses, which was applied to measure the statistical characteristics of the acoustic channel. For their dynamic channel model design, they considered parameters such as water temperature and salinity level. They applied the Bellhop channel simulator and found that it exhibits statistical characteristics equivalent to those retrieved through the experiment. However, it could not gain consensus due to insufficient information about the acoustic channel conditions and exclusion of the surface dynamism. In [29], the authors applied acoustic environment data with the help of a dynamic surface shape model. These data were then exported to the Bellhop beam tracer to form an associated acoustic field. However, varying wind speeds caused significant deviation from the experimental results, that might be caused due to ineptness towards surface generation such as disrupting waves occurring at relatively higher wind speeds, bubble generation and wave curvature formation [30]. The authors of [31] examined the impact of bubbles on the UWA channels at varying wind speeds.

2.2. Network Coding Schemes for Underwater Networks

Availability of an efficient channel model is essential to ensure efficient network performance; however, enhancing transmission mechanisms at both the physical and higher network layers is also inevitable. The network coding (NC) algorithm has emerged as one of the more robust algorithms to support seamless, reliable and computationally efficient transmission. Particularly, NC has justified its robustness for wireless transmission [31]. To reduce the probability of collision among transmitter-receiver, receiver-transmitter and end-to-end delay, in [31], authors developed a protocol named the Practical Codingbased Multi-hop Reliable Date Transfer (PCMRDT) scheme that exhibited reduced delay and retransmission. The authors of [32] studied data transmitting issues over UWSN and investigated the performance based on Automatic Repeat Request (ARQ), NC and erasure coding (EC) schemes. In [32], authors found that NC results in higher throughput than other schemes. In [33], Time Slot based Routing (TSR) was proposed where the NC algorithm was applied to reduce node conflict issues and energy consumption. In [34], VBF-NC was developed, where authors found that amalgamating NC and multi-path routing can enable better UWSN performance. Authors exploited the error-correction nature of NC to strengthen UWSN performance and to significantly enhance error recovery and energy exhaustion. However, nodes in the UWSNs are forced to wait until all the data from all other nodes reaches the destination before initiating the decoding process. Further, the author found NC to be effective in reducing latency and network delay [34]. The authors of [35] combined partial NC and geographic routing protocol with similar

intent to enhance network performance. They recommended their approach as capable of ensuring minimised data size, minimal energy consumption and network delays, and later authors [36] backed up the same hypothesis. Exploring different approaches to enhance UWSN reliability and energy optimization, the authors of [37] proposed a multiple-path FEC approach (M-FEC) using Hamming Coding. In [38], authors applied ARQ and FEC to form a segmented data reliable transport (SDRT) model to ensure higher data reliability in UWSN. They used an erasure coding scheme and block-by-block coded data transmission on a multi-hop network.

In [39], an NC and CDMA-based combined model was developed for UWSN. A butterfly NC model was applied in [40] for UWSN transmission. They used surface nodes, nodes' underwater column and access points to model the network and focused on achieving maximum data delivery from the surface node to the underwater nodes and vice versa. They stated that the ith higher inter-node distance to the access point demand packet relaying mechanism and sequential transmission over loaded networks could make access points vulnerable to the network overloads. To deal with this, they suggested an NC algorithm that can enable multiple packet transmission simultaneously. Considering broadcast nature and flexible computations, the authors of [41] suggested NC for the UWSN routing protocol so as to increase PDR [42]. Various UWSN related issues have been discussed in [43,44]. A few significant suggestions to enhance UWSN performance can be found in [45–48]. In [49], authors investigated the usefulness of the multilayered energy harvesting approach to increase the performance of UWSN.

3. Our Contribution

The overall research work is performed in three consecutive phases. These are:

- 1. UWSN Channel Model for Dynamic Acoustic Environment;
- 2. Systematic Random Linear Network Coding (S-RLNC) Based transmission system;
- S-RLNC based UWSN Routing Protocol.

3.1. UWSN Channel Model

To derive a robust channel model for UWSN, two different types of channel conditions and corresponding acoustic dynamism have been considered in this paper. The first refers to the one introduced due to the displacements ranging multiple wavelengths (say, large scale deviation (LSD)), and the second refers the dynamism caused due to the displacements in the magnitude of a single or a few of the wavelengths (small scale dynamism (SSD)). LSD is caused due to system dislocations, whose prediction is infeasible using traditional system geometry. Traditional transceiver localization within a predefined constant geometry and definite sound-speed characteristics can generate a constant acoustic field; the practical area might vary over the time because of the uncertainty in the system dimensions. Typically, such uncertainty is arbitrary, which gives rise to LSD that can be easily observed in the form of channel gains and the delay in transmission paths. Meanwhile, with predefined LSD, the supplementary SSD may emerge in both the path gains and end-to-end delays. Such deviations are usually considered as the result of object dislocations and scattering [50].

3.1.1. Nominal Conditions and Large-Scale Deviation (LSD) Nominal Conditions

The channel dimensions in conjunction with certain specific sound-speed characteristics present the nominal response of an acoustic channel symbolising a time-invariant model, which can be examined through specific beam tracing models. The path loss suffered by a transmitted signal with frequency f traversing over the distance influences the received signal (1) [50,51].

$$\operatorname{an}(\mathbf{l},\mathbf{f}) = \mathbf{A}_0 \mathbf{l}^{\mathbf{k}} \mathbf{a}(\mathbf{f})^{\mathsf{I}} \tag{1}$$

where A_0 refers to scaling factor, k presents the spreading factor and an open paren f close paren signifies the absorption coefficient, simulated using Throp's empirical model (2).

$$a(f) = 0.11 * \frac{f^2}{1 + f^2} + 44 \frac{f^2}{4100 + f^2} + 2.75 \times 10^{-4} f^2 + 0.003$$
 (2)

In (2), f is in kHz unit.

Considering multi-path communication with different paths of length \bar{l}_{p} , p = 0, ..., P-1 the individual path functions as a low pass filter (LPF). The transfer function of LPF affecting received signal strength (RSSI) can be derived as (3):

$$\overline{H}_{p}(f) = \frac{\Gamma_{p}}{\sqrt{A(\overline{l}_{p}, f)}}$$
(3)

where Γ_p refers to the cumulative reflection coefficient (CRF) observed over the surface, which signifies the bottom-reflections generated in the direction of the pth path. For illustration, a realizable surface can be formed with reflection coefficient $\gamma_s = -1$, and the individual-bottom reflection can be derived as (4):

$$\gamma_{b}(\theta_{p}) = \begin{cases} \frac{\rho_{b}\sin\theta_{p} - \rho\sqrt{\left(\frac{c}{c_{b}}\right)^{2} - \cos^{2}\theta_{p}}}{\rho_{b}\sin\theta_{p} + \rho\sqrt{\left(\frac{c}{c_{b}}\right)^{2} - \cos^{2}\theta_{p}}}, & \cos\theta_{p} \\ 1, & \text{otherwise} \end{cases}$$
(4)

where θ_p presents "the Grazing angle" associated with the pth path, ρ is the fluid density ($\rho = 1000 \text{ kg/m}^3$) and c signifies the speed of sound in water (c = 1500 m/s). ρ_b and c_b represent the density and the sound speed at the bottom of the water column, respectively. To avoid any destructive reflection, c_b is often kept less than c. With the transfer function for the individual propagation path, the cumulative transfer function (CTF) of the multipath channel is derived as (5):

$$\overline{H}(f) = \sum_{p} \overline{H}_{p}(f) e^{-j2\pi f \overline{T}_{p}}$$
(5)

To achieve a simple channel model, we approximated the function $\overline{H}_{p}(f)$ and, with reference to the reference path p = 0, the function is approximated as (6):

$$\overline{H}_{p}(f) = \frac{\Gamma_{p}}{\sqrt{\left(\frac{\overline{l}_{p}}{\overline{l}_{o}}\right)^{k} a(f)^{\overline{l}_{p} - \overline{l}_{o}}}} \overline{H}_{o}(f)$$
(6)

The frequency-reliance distinguishing pth path from the reference path is combined to form $a(f)^{\bar{l}_p - \bar{l}_o}$. Approximating $a(f)^{\bar{l}_p - \bar{l}_o}$, assuming it as a constant, designing all the paths using equi-shaped impulse response with distinct gain parameter is feasible. For acoustic communication, the absorption factor a(f) possesses near 1 value, and for a wide range of acoustic frequencies, might validate approximation in the form of (7):

$$a(f)^{-(\bar{l}_p - \bar{l}_o)/2} \approx a_0^{-(\bar{l}_p - \bar{l}_o)/2}$$
(7)

where a_0 refers to the absorption parameter for the frequency range $[f_0, f_0 + B]$. Using (7), the CTF is derived as (8):

$$\overline{H}_{p}(f) \approx \overline{h}_{p} \overline{H}_{o}(f) \tag{8}$$

where the corresponding path gain is given in (9):

$$\bar{h}_{\rm p} = \frac{\Gamma_{\rm p}}{\sqrt{\left(\frac{\bar{l}_{\rm p}}{\bar{l}_{\rm o}}\right)^{\rm k} a_0^{\bar{l}_{\rm p} - \bar{l}_{\rm o}}}} \tag{9}$$

In the above expression, the parameter a_0 can be considered as the absorption parameter at a certain frequency within the operating bandwidth range. The frequency can be located anywhere, for example, at the centre frequency or the edge frequency (lower or upper edge). In case frequency exists at the lower edge of the frequency range, it leads to maximum path gain, while frequency at the upper edge may result in minimum path gain. As already stated, a(f) remains constant across the acoustic communication bandwidth, and the frequency can be selected in any way. It signifies that the design of a channel model is feasible by decoupling the effect of path filtering and multipath in such a manner that the individual path provides a gain \bar{h}_p and delay \bar{T}_p , while maintaining the static filtering effect across all propagation paths and being characterized in terms of the function $\bar{H}_o(f)$. Thus, the cumulative CTF can be derived as (10):

$$\overline{H}(f) = \overline{H}_{o}(f) \sum_{p} \overline{h}_{p} e^{-j2\pi f \,\overline{T}_{p}}$$
(10)

Large-Scale Deviations (LSD) Caused Due to Location Dynamism

In an acoustic environment, there are many parameters that significantly influence the geometry and make it uncertain. Some of these parameters are the transceiver movement, variation in the surface height, bottom shape, etc., which make exact system geometry uncertain. Such dislocation introduces variation in the path length (i.e., $l_p = \overline{l}_p + \Delta l_p$). It should be noted that the variation in the path length is often random. Usually, delay T_p is estimated for the lengths l_p . The parameter h_p representing path gain is estimated using l_p (9). Thus, we get:

$$h_{p} = \overline{h}_{p} \frac{1}{\sqrt{\left(1 + \frac{\Delta l_{p}}{\overline{l}_{p}}\right)^{k} a_{0}^{\Delta l_{p}}}}$$
(11)

Considering generic network geometry $\Delta l_p \ll \bar{l}_p$ and $k \ll \bar{l}_p$, we approximate our model as:

$$\left(1 + \frac{\Delta l_p}{\bar{l}_p}\right)^k \approx 1 + k \frac{\Delta l_p}{\bar{l}_p} \approx \left(1 + \frac{k}{\bar{l}_p}\right)^{\Delta l_p}$$
(12)

Now, using (12), the path gain is calculated as (13):

$$h_{\rm p} \approx \bar{h}_{\rm p} e^{-\xi_{\rm p} \Delta l_{\rm p}/2} \tag{13}$$

where

$$\xi_{\rm p} = a_0 - 1 + \frac{k}{\bar{l}_{\rm p}}, \text{ with } a_0 \approx 1 \tag{14}$$

To ensure positive gain, we performed the exponential approximation of (12) and, considering the location of the uncertainty path, gain is considered as log-normally distributed. Thus, the CTF is obtained as (15):

$$H(f) = \overline{H}_{o}(f) \sum_{p} h_{p} e^{-j2\pi f T_{p}}$$
(15)

In (15), the location uncertainty is estimated using the large-scale parameters h_p and T_p .

3.1.2. Characterization of the Small Scale Acoustic Channel

As discussed above, the CTF (14) can achieve only the large-scale effect and is unable to retrieve any small-scale phenomena such as scattering in acoustic medium. On the contrary, scattering plays a decisive role in signal strength over propagation. An acoustic signal with the frequency f suffers scattering on wavy surfaces and the objects having dimension

of the order of a few signal wavelengths equal to c/f. For illustration, the wavelength associated with an acoustic frequency element of 15 kHz is 0.1 m, and hence the distance can be stated as "small." To develop a scattering model in a UWSN channel, it is necessary to place emphasis on a single path, say, p. In the previous section, this path was designed by considering respective path gain h_p and the propagation delay T_p . However, in practice, if scattering exists within the acoustic medium, particularly towards path p, it usually gets split into multiple micro-sized paths. Mathematically,

$$H(f) = \overline{H}_{o}(f) \sum_{p} \sum_{i} h_{p,i} e^{-j2\pi f T_{p,i}}$$
(16)

where $h_{p,i}$ refers to the gain parameter of the intra-paths and $T_{p,i} = T_p + \delta T_{p,i}$ states the delay introduced across the intra-paths formed. Considering dynamicity in the acoustic network, $h_{p,i}$ and $\delta T_{p,i}$ are considered as random variables and, therefore, in our model, the small-scale fading coefficient is defined as (17):

$$\gamma_{p}(f) = \frac{1}{h_{p}} \sum_{i \ge 0} h_{p,i} e^{-j2\pi f \delta T_{p,i}}$$

$$\tag{17}$$

Thus, the eventual CTF can be derived as:

$$H(f) = \overline{H}_{o}(f) \sum_{p} h_{p} \gamma_{p}(f) e^{-j2\pi f T_{p}}$$
(18)

Probability Density Function (PDF) for $\gamma_{p}(f)$

As the scattering locations can be far apart with the distance of λ , $h_{p,i}$ is supposed to be equivalent for different intra-paths. On the contrary, the phases of $2\pi f \delta T_{p,i}$ may differ between the different intra-paths, thus leading to variation in $\gamma_p(f)$. Assuming that the comprising terms of $\gamma_p(f)$ in (17) are dietetically distributed, the central limit theorem (CLT) applies Gaussian distribution for $\gamma_p(f)$ with a higher number of micro-paths. The component with stable delay can be considered, and hence the distortion can be derived as

$$\gamma_{p}(f) = \gamma_{p,0} + \sum_{i \ge 1} \gamma_{p,i} e^{-2j\pi f \delta T_{p,i}}$$
(19)

where $\gamma_{p,0}$ signifies the coefficient of the stable path with $\delta T_{p,o}=0$. Typically, $\gamma_p(f)$ is a complex Gaussian with the mean and standard deviation of $\overline{\gamma}_p(f)$ and $2\sigma_p^2(f)$, respectively. Such distributions can be applied for both the large-scale parameters h_p and T_p , as well as small-scale parameters $\overline{\gamma}_p(f)$ and $\sigma_p^2(f)$. With the known variables of (17), the parameters $\overline{\gamma}_p(f)$ and $\sigma_p^2(f)$ can be estimated using an analytical or experimental process. To estimate the parameter using analytical measures, consider that the magnitude of the micro-path has the mean and variance of μ_p and $v_p^2 \ll \mu_p^2$, respectively. Let the relative intra-path delays be $\delta T_{p,i}$ with variance $\sigma_{\delta_p}^2$. Typically, Gaussian-distributed delays come into existence due to the height of the Gaussian-distributed surface or bottom and, hence, in that case, represent the variance on both the surface as well as bottom by σ_s^2 and σ_b^2 , correspondingly. Therefore the following could be derived:

$$\sigma_{\delta_{\rm p}}^2 = \frac{1}{c^2} \left(2\sin\theta_{\rm p} \right)^2 \left[n_{\rm sp} \sigma_{\rm s}^2 + n_{\rm bp} \sigma_{\rm b}^2 \right] \tag{20}$$

Thus, the mean and variance parameters of the scattering coefficients can be retrieved as (20) (21) and (22), respectively:

$$\overline{\gamma}_{p}(f) = \mu_{p0} + \mu_{p}S_{p}\rho_{p}(f)$$
(21)

$$2\sigma_{p}^{2}(f) = \mu_{p}^{2}S_{p}\left[1 - \rho_{p}^{2}(f)\right] + S_{p}v_{p}^{2} \approx \mu_{p}^{2}S_{p}\left[1 - \rho_{p}^{2}(f)\right]$$
(22)

where Sp represents the number of intra-paths formed. Hence,

$$\rho_{p}(f) = E \left\{ e^{-j2\pi f \delta T_{p,i}} \right\} = e^{-(2\pi f)^{2} \sigma_{\delta_{p}}^{2}/2}$$
(23)

Intra-Paths Correlation

Scattering remains independent between paths stating that the reflection points of the paths remain noticeable. Therefore,

$$E\left\{\gamma_{p}(f)\gamma_{q}^{*}(f)\right\} = \overline{\gamma}_{p}(f)\overline{\gamma}_{q}(f) + \delta_{p,q}2\sigma_{p}^{2}(f)$$
(24)

Noticeably, though the propagation paths signify uncorrelated scattering,

$$E\left\{\left[\gamma_{p}(f_{1},t+\Delta t)-\overline{\gamma}_{p}(f_{1})\right]\left[\gamma_{p}(f_{2},t)-\overline{\gamma}_{p}(f_{2})\right]^{*}\right\}$$

= $\mu_{p}^{2}S_{p}e^{-(2\pi(f_{1}-f_{2}))^{2}\sigma_{\delta_{p}}^{2}/2} \times e^{-(1-\alpha_{\delta_{p}})(2\pi f_{1})(2\pi f_{2})\sigma_{\delta_{p}}^{2}[1-\rho_{p}(\sqrt{2\alpha_{\delta_{p}f_{1}f_{2}}})]}$
 $\approx \rho_{p}(f_{1}-f_{2})e^{-\pi B_{p}(f_{1,2})\Delta t}2\sigma_{p}(f_{1})\sigma_{p}(f_{2})$ (25)

 $E\left\{\gamma_p(f)\gamma_q^*(f)\right\}$ remains non-zero due to nonzero mean values.

Path Correlation in Frequency Domain

The frequency correlation of the small-scale path coefficients can be defined in terms of the function $E\left\{\gamma_p(f + \Delta f, t)\gamma_q^*(f, t)\right\}$ [24]. To estimate the frequency correlation, the PDF of the intra-path delays $\delta T_{p,i}$ needs to be estimated and, for Gaussian-distributed delays along with zero mean and variance $\sigma_{\delta_n}^2$, the frequency correlation is (25).

$$\begin{split} & E\Big\{\Big[\gamma_{p}(f + \Delta f) - \overline{\gamma}_{p}(f + \Delta f)\Big]\Big[\gamma_{p}(f) - \overline{\gamma}_{p}(f)\Big]^{*}\Big\} \\ &= \mu_{p}^{2}S_{p}\rho_{p}(\Delta f)\Big[1 - \rho_{p}\Big(\sqrt{2f(f + \Delta f)}\Big)\Big] \\ &\approx \rho_{p}(\Delta f)2\sigma_{p}(f)\sigma_{p}(f + \Delta f) \end{split}$$
(26)

Here, it can be found that based on the standard deviation (i.e., $\delta T_{p,i}$), there can be a definite correlation between γ_p coefficients within the signal bandwidth. However, the correlation might vary over the signal bandwidth. Since, in this paper, we intend to develop a multipath channel based data transmission, we assume the full correlation hypothesis across the signal bandwidth. However, it cannot be accepted universally with all conditions, especially when σ_{δ_p} remains in the order of $1/f_0$ even with low Ricean factor and, therefore, low correlation between $\gamma_p(f_0)$ and $\gamma_p(f_0 + B)$ in a wideband communication.

Path Correlation in the Time Domain

Similar to the frequency correlation, the time correlation of the scattering coefficients is defined in terms of $\{\gamma_p(f, t + \Delta t)\gamma_p^*(t)\}$, that obtains the motion-affect in the communication field, which further influences the coefficients $\gamma_p(f, t)$ due to the time-varying micro-path delays. To assess $E\{\gamma_p(f, t + \Delta t)\gamma_p^*(t)\}$, at first, we have estimated the PSD of $\delta T_{p,i}(t)$. Here, without losing the generality, we consider that $\delta T_{p,i}(t)$ follows the first-order autoregressive process, given by:

$$\delta T_{p,i}(t + \Delta t) = \alpha_{\delta p} \delta T_{p,i}(t) + w_{\delta p,i}(t)$$
(27)

where

$$w_{\delta p,i}(t) \sim \mathcal{N}\left(0, \sigma_{\delta_p}^2 \left(1 - \alpha_{\delta_p}^2\right)\right)$$
 (28)

$$\alpha_{\delta p} = e^{-\pi B \delta_p \Delta t} \tag{29}$$

We selected $B\delta_p$ as the 3-dB width of the PSD of $\delta T_{p,i}(t)$. The derived relationship states that the two delay parameters can be similar if they are narrowly spaced in the time domain. The time correlation function is (29):

$$\begin{split} & E\left\{\left[\gamma_{p}(f,t+\Delta t)-\overline{\gamma}_{p}(f)\right]\left[\gamma_{p}(f,t)-\overline{\gamma}_{p}(f)\right]^{*}\right\}\\ &=\mu_{p}^{2}S_{p}e^{-(1-\alpha_{\delta p})(2\pi f)^{2}\sigma_{\delta p}^{2}}\left[1-e^{-\alpha_{\delta p}(2\pi f)^{2}\sigma_{\delta p}^{2}}\right]\\ &\approx 2\sigma_{p}^{2}(f)e^{-\pi B_{p}(f)\Delta t} \end{split}$$
(30)

With the approximation for $\Delta t \ll 1/B_{\delta p}$, the parameter signifying the effective Doppler bandwidth of $\gamma_p(f,t)$ is defined as:

$$B_{p}(f) = (2\pi f \sigma_{\delta p})^{2} B_{\delta p}$$
(31)

Considering (25) and (29), the generalized expression can be obtained as (31), where the variable $f_{1,2}$ refers to either of the two distinct frequencies f_1 or f_2 in the considered signal bandwidth.

Statistical Model for $\gamma_p(f, t)$

Consider a supplementary auto-regressive process

$$\Delta \gamma_{p}(f, t + \Delta t) = \alpha_{p}(f) \Delta \gamma_{p}(f, t) + w_{p}(f, t)$$

$$\gamma_{p}(f, t + \Delta t) = \overline{\gamma}_{p}(f) + \Delta \gamma_{p}(f, t + \Delta t)$$
(32)

where $w_{p}(t)$ represents the complex Gaussian random process

$$\boldsymbol{w}_{p}(t) \sim C\mathcal{N}(0, 2\sigma_{p}^{2}(f)(1-\alpha_{p}^{2}(f))) \tag{33}$$

where

$$\alpha_{\rm p}(f) = e^{-\pi B_{\rm p}(f)\Delta t} \tag{34}$$

The autoregressive process (29) can be presented in terms of a Gaussian probabilistic distribution function, given as:

$$\gamma_{p}^{\prime}(\mathbf{f},\mathbf{t}) \sim C\mathcal{N}\Big(\overline{\gamma}_{p}(\mathbf{f}), 2\sigma_{p}^{2}(\mathbf{f})\Big)$$
 (35)

Similarly, the auto-covariance function is

$$E\left\{\Delta\gamma_{p}(f,t+\Delta t)\Delta\gamma_{p}^{*}(f,t)\right\} = 2\sigma_{p}^{2}(f))e^{-\pi B_{p}(f)\Delta t}$$
(36)

The statistical equivalent model states that the two processes are statistically equivalent. To derive a complete acoustic channel model, embedding the frequency correlation to the auto-regressive process $\Delta \gamma_p(f, t)$ is a must. In this paper, the frequency axis is split into multiple steps of Δf_s . Similarly, the time axis is split into multiple steps of Δt_s . Thus, the eventual vector derived would be:

$$\Delta \gamma_{p}[n] = \left[\Delta \gamma_{p}(f_{0}, t_{0} + n\Delta t_{s}), \Delta \gamma_{p}(f_{1}, t_{0} + n\Delta t_{s}), \ldots \right]^{1}$$
(37)

Defining matrix A_p, given as:

$$A_{p} = diag[\alpha_{p}(f_{k})]$$
(38)

where

$$\alpha_{\rm p}(f_k) = e^{-\pi B_{\rm p}(f_k)\Delta t_{\rm s}} \tag{39}$$

Thus, applying the above derivations, an autoregressive process is obtained as:

$$\Delta \gamma_{p}[n+1] = A_{p} \Delta \gamma_{p}[n] + W_{p}[n], \quad n = 0, \tag{40}$$

where

$$W_{p}[n] \sim C\mathcal{N}(0, W_{p}) \tag{41}$$

and

$$W_p]_{k,l} = \left[1 - \alpha_p(f_k)\alpha_p(f_l)\right]\rho_p(f_k - f_l)2\sigma_p(f_k)\sigma_p(f_l)$$
(42)

The optimal W_p can ensure the expected frequency correlation as:

$$\mathsf{E}\left\{\Delta\gamma_{p}(f_{k},t)\Delta\gamma_{p}^{*}(f_{l},t)\right\} = \rho_{p}(f_{k}-f_{l})2\sigma_{p}(f_{k})\sigma_{p}(f_{l}) \tag{43}$$

Once executing equation (40) iteratively over an expected time interval and for frequencies associated to the expected signal bandwidth, it becomes inevitable to add the mean values $\overline{\gamma}_p(f_k)$ to $\Delta \gamma_p(f_k, n\Delta t_s)$. This results in a discrete time/frequency random process $\gamma'_p(f, t)$, with statistical characteristics similar to the sampled process $\gamma_p(f, t)$. We ensure that the channel exhibits a precise replica of the actual channel, and it is further strengthened because of the statistical equivalence to the autoregressive process $\gamma_p(f, t)$. Moreover, our model considers dynamic and rough surface scattering, and hence, it does not consider any specific surface shape and applies the associated Doppler factor as $a_{dp} = v_{dp}/C$. In case drifting occurs in different directions and with a different value for each transmitter and receiver, then $E\left\{e^{j2\pi fa_{dp}\Delta t}\right\}$ considers averaging over the parameters θ_{td} and θ_{rd} . With similar drifting in all directions, we obtain

$$E\left\{e^{j2\pi fa_{dp}\Delta t}\right\} = E\left\{e^{j2\pi(v_{td}/c)f\cos\left(\theta_{p}-\theta_{td}\right)\Delta t}\right\} \times E\left\{e^{j2\pi(v_{rd}/c)f\cos\left(\pi+\theta_{p}+\theta_{rd}\right)\Delta t}\right\}$$
$$= \frac{1}{2\pi} \int_{0}^{2\pi} e^{j2\pi(v_{td}/c)f\cos\left(\theta_{td}'\right)\Delta t} d\theta_{td}' \times \frac{1}{2\pi} \int_{0}^{2\pi} e^{j2\pi(v_{rd}/c)f\cos\left(\theta_{rd}'\right)\Delta t} d\theta_{rd}' \qquad (44)$$
$$= J_{0}\left(2\pi \frac{V_{td}}{c}f\Delta t\right) J_{0}\left(2\pi \frac{V_{rd}}{c}f\Delta t\right)$$

where $\theta'_{td} = \theta_p - \theta_{td}$ and $\theta'_{rd} = \pi + \theta_p + \theta_{rd}$ are homogeneously distributed in the range of $[-\pi, \pi]$, and $J_0(.)$ refers the Bessel function of the zero order. With $v_{td} = v_{rd} = v_d$ and $a_d = v_d/c$, (44) minimized to $J_0^2(2\pi a_d f\Delta t)$. The moving component of the Doppler-effect can be obtained in the same way as discussed above, except for the motion components that can be compensated for by means of synchronization. Once performing initial synchronization, $a_{vp} = v_{vp}/c$ can be stated as the residual Doppler factor. If synchronization balances the Doppler factor (DF) in conjunction with the projection of the transceiver velocity onto the reference path p = 0, the resulting DF will be (45):

$$\begin{aligned} \mathbf{a}_{\mathrm{vp}} &= \frac{1}{\mathrm{c}} \left[\left[\mathbf{v}_{\mathrm{tv}} \cos(\theta_{\mathrm{p}} - \theta_{\mathrm{tv}}) - \mathbf{v}_{\mathrm{rv}} \cos(\theta_{\mathrm{p}} + \theta_{\mathrm{rv}}) \right] - \left[\mathbf{v}_{\mathrm{tv}} \cos(\theta_{\mathrm{0}} - \theta_{\mathrm{tv}}) - \mathbf{v}_{\mathrm{rv}} \cos(\theta_{\mathrm{0}} + \theta_{\mathrm{rv}}) \right] \right] \\ &= \frac{1}{\mathrm{c}} \left[\mathbf{v}_{\mathrm{tv}} \left[-2\sin\left(\frac{\theta_{\mathrm{p}} + \theta_{\mathrm{0}} - 2\theta_{\mathrm{tv}}}{2}\right) \sin\left(\frac{\theta_{\mathrm{p}} - \theta_{\mathrm{0}}}{2}\right) \right] + \mathbf{v}_{\mathrm{rv}} \left[2\sin\left(\frac{\theta_{\mathrm{p}} + \theta_{\mathrm{0}} + 2\theta_{\mathrm{rv}}}{2}\right) \sin\left(\frac{\theta_{\mathrm{p}} - \theta_{\mathrm{0}}}{2}\right) \right] \right] \end{aligned} \tag{45}$$

Considering the similar transmitter and receiver movement across the network region in any direction $\theta_{tv/rv}$, the autocorrelation function with respect to the transceiver motion can be obtained as:

$$E\left\{e^{j2\pi f a_{vp}\Delta t}\right\} = J_0\left(2\pi \frac{2v_{tv}\sin\left(\frac{\theta_p - \theta_0}{2}\right)}{c} f\Delta t\right) \times J_0\left(2\pi \frac{2v_{tv}\sin\left(\frac{\theta_p - \theta_0}{2}\right)}{c} f\Delta t\right)$$
(46)

Our applied channel model considers only vertical surface motion. A signal interrupting jth reflection point along pth path achieves it randomly, at the longitudinal velocity of $v_w \sin(\psi_{p,j} + 2\pi f_w t)$, where $\psi_{p,j} \sim u[-\pi, \pi]$ and $v_w = 2\pi f_w A_w$. Thus, the protrusion of the vertical or the longitudinal velocity onto pth path, across entire surface points, generates (47)

$$v_{sp} = 2v_w \sin \theta_p \sum_{j=1}^{n_{sp}} \sin \left(\psi_{p,j} + 2\pi f_w t \right)$$
(47)

In case the surface reflection points are located far apart in the way that $\psi_{p,j}$ are independent and hence the time correlation can be estimated by taking the expectation over $a_{sp} = v_{sp}/c$ with $\psi_{p,j}$ distributed uniformly over 2π . Mathematically,

$$\mathrm{E}\left\{\mathrm{e}^{\mathrm{j}2\pi\mathrm{f}a_{\mathrm{sp}}\Delta\mathrm{t}}\right\} = \left[\mathrm{J}_{0}\left(2\pi\mathrm{a}_{\mathrm{wp}}\mathrm{f}\Delta\mathrm{t}\right)\right]^{\mathrm{n}_{\mathrm{sp}}} \tag{48}$$

where $a_{wp} = 2v_w \sin \frac{\theta_p}{c}$ and n_{sp} signify the surface encounters found in the path p. Now, combining (27) and (44)–(48), the cumulative autocorrelation $\tilde{\gamma}_p(f, t)$ is derived as:

$$\begin{split} R_{\widetilde{\gamma}_{p}}(\Delta t) &= \left[\overline{\gamma}_{p}^{2}(f) + 2\sigma_{p}^{2}(f)e^{-\pi B_{p}(f)\Delta t} \right] J_{0}^{2}(2\pi a_{d}f\Delta t) \\ &\times J_{0} \left(2\pi \frac{2v_{tv}\sin\left(\frac{\theta_{p}-\theta_{0}}{2}\right)}{c} f\Delta t \right) \\ &\times J_{0} \left(2\pi \frac{2v_{rv}\sin\left(\frac{\theta_{p}-\theta_{0}}{2}\right)}{c} f\Delta t \right) \\ &\times \left[J_{0} \left(2\pi \frac{2v_{w}\sin\theta_{p}}{c} f\Delta t \right) \right]^{n_{sp}} \end{split}$$

$$\end{split}$$

$$(49)$$

The autocorrelation function derived in (49) depicts Bessel-type characteristics, dampened by the exponentially depleting correlation of γ_p [in (49)].

3.1.3. Channel Gain Characterization

The time varying CTF is derived as in (50),

$$H(f,t) = \overline{H}_0 \sum_{p} h_p \widetilde{\gamma}_p(f,t) e^{-j2\pi f T_p}$$
(50)

where $\tilde{\gamma}_p(f,t) = \gamma_p(f,t)e^{j2\pi a_pft}$. The CTF characterizes the channel for the specific set of large-scale parameters (h_p and T_p), path statistics $\tilde{\gamma}_p(f)$, $\sigma_p^2(f)$ and the Doppler scaling factors a_p . In practice, these channel parameters might change over time, with a personalized rate. The time range at which these channel parameters change results in the derivation of the "figures of merit" of the considered acoustic communication system design. Channel gain is considered as one of the key figures of merit characterizing the efficacy of a communication system. In our mode, the instantaneous channel gain of a communication system working in the frequency range [f_0 , $f_0 + B$] is derived as:

$$\widetilde{G}(t) = \frac{1}{B} \int_{f_0}^{f_0 + B} |H(f, t)|^2 df$$
(51)

Thus, the regionally averaged gain can be defined as (52):

$$\mathbf{G} = \mathbf{E}_{\widetilde{\gamma}} \Big\{ \widetilde{G}(\mathbf{t}) \Big\}. \tag{52}$$

In case the radio bandwidth is sufficient so that all multipaths are precisely retrieved, the gain by each multipath component is:

$$G = \sum_{p} G_{p} h_{p}^{2}$$
(53)

where

$$G_{p} = \frac{1}{B} \int_{f_{0}}^{f_{0}+B} \overline{H}_{0}^{2}(f) \Big[\overline{\gamma}_{p}^{2}(f) + 2\sigma_{p}^{2}(f) \Big] df$$
(54)

In our model, the gain parameter G is stated as the large-scale gain that primarily relies on both path coefficients h_p and related statistics $\overline{\gamma}_p(f)$, $\sigma_p^2(f)$. With the known path gain, the gain distribution is estimated analytically. Considering (13), gain parameter can be derived as:

$$G(t) = \sum_{p} G_{p} \overline{h}_{p}^{2} e^{-\xi_{p} \Delta l_{p}(t)}$$
(55)

With the path lengths of Gaussian distributed with mean l_p and variance $\sigma_{l_p}^2$, the gain parameters can be estimated as the sum of log-normally distributed random processes [51]. We used the Fenton–Wilkinson method described in [51] to estimate the parameters, l_p and $\sigma_{l_p}^2$. Thus,

$$\overline{G} = \sum_{p} G_{p} \overline{h}_{p}^{2} e^{\xi_{p}^{2} \sigma_{l_{p}}^{2}/2}$$
(56)

$$=\sum_{p}G_{p}^{2}\overline{h}_{p}^{4}e^{\xi_{p}^{2}\sigma_{l_{p}}^{2}}\left(e^{\xi_{p}^{2}\sigma_{l_{p}}^{2}}-1\right)$$
(57)

For very small zero-mean Gaussian path length displacements, the gain is (in dB),

$$\mathbf{g}(\mathbf{t}) = \overline{g} + \Delta \mathbf{g}(\mathbf{t}) \tag{58}$$

where

$$\overline{g} = 10 \left[2 \log_{10} \overline{G} - \frac{1}{2} \log_{10} \left(\overline{G}^2 + \sigma_G^2 \right) \right]$$
(59)

In (58), $\Delta g(t)$ refers the zero-mean Gaussian with variance

$$\sigma_{\rm g}^2 = 10^2 \left(\log_{10} e\right) \left[\log_{10} \left(\overline{G}^2 + \sigma_{\rm G}^2\right) - 2\log_{10} \overline{G}\right]$$
(60)

The gain model, as depicted in (58), refers to a fixed channel geometry characterizing the nominal attenuation at the distance $d = l_0$. However, due to movement over time, scale \overline{g} varies accordingly. It is expected that \overline{g} maintains a log-distance relationship, given as (58):

$$\overline{g}(d) = g_0 - k_0 10 \log \frac{d}{d_{rel}}$$

where d_{ref} states a reference distance taken as 1 m. The other factors, g_0 and the path loss exponent k₀, can be calculated from averages of the gains retrieved at changing distances. The relationship between gain and distance is [52]

$$g(d,t) = \overline{g}(d) + \Delta g(t)$$

Our proposed acoustic channel model addresses the multipath transmission, small and large-scale deviations, rough surfaces and resulting topology changes, Doppler variations,

etc. This paper proposes a novel multipath transmission model for UWSN. The derived channel model has been used in this paper to model a multipath transmission where an enhanced random linear network coding (RLNC) scheme has been developed to perform data transmission.

The discussion of the proposed RLNC algorithm for multipath transmission over UWSN is presented in following sections.

3.2. Systematic-RLNC Based Data Transmission System

To enhance transmission effectiveness, we have proposed a systematic-RLNC algorithm. A brief of the proposed RLNC mechanism is given as follows:

3.2.1. Systematic Random Linear Network Coding (SRLNC)

Our proposed Systematic-RLNC (SRLNC) algorithm applies different optimization measures to strength multipath transmission for UWSNs. The goal of the proposed transmission model is focused on ensuring delay sensitive multipath transmission over UWSNs to enable reliable and mission critical communication.

SRLNC introduces Coefficient Vector Overhead (CVO) optimization, where it performs linear combination of the data packets using a set of vectors called Coefficient Vectors (CV). Generally, connected sinks have the CV information that helps them to decode the data. A matrix named the coefficient matrix (CM) contains all the CVs. Despite transmitting CVs themselves, the information signifying row (i.e., index location) of the coefficient matrix is applied to generate a particular linear combination to be transmitted along with the coded data packets. The combined CV and CM are stated to be the coefficient information (CI). Once receiving CI, the intermediate node in the developed UWSN network model decompresses it and, after appending it, forwards the (appended) data to the next hop node towards sink. Since the initial CM used at the source node remains unshared to the intermediate nodes, thus, the probability of data decoding at any intermediate node is avoided. This makes SRLNC based communication seamless across multipath transmission based UWSN. Retrieving the packets, the sink node decompresses CI and the substitute coefficient index with the original CV in the correct manner. The retrieved CI is decoded to obtain the original transmitted data. Obtaining the original data, the sink node sends acknowledgement (ACK) to the transmitter and, thus, the transmitter stops transmitting the data packets.

With the multipath transmission over UWSN, the SRLNC function can be visualized in three phases:

- (1) Process at the source node,
- (2) Process at the intermediate node, and
- (3) Process at the sink node.

A brief discussion of the RLNC processes at the source, intermediate and the sink node is presented as follows:

Process at the Source Node

In SRLNC transmission, at first, the RLNC coefficients are obtained at the source node and, accordingly, n data packets (s_1, s_2, \ldots, s_n) are generated, where each packet signifies a 1 × s vector from the Galois field (GF)2^F. Implementing m × n CM, a total of n packets are combined to generate m linear combinations. The generated linear combinations are (61):

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{bmatrix}_{m \times 1} = \begin{bmatrix} q_{1,1} & q_{1,2} & \dots & q_{1,n} \\ q_{2,1} & q_{2,2} & \dots & q_{2,n} \\ \vdots & \vdots & & \vdots \\ q_{m,1} & q_{m,2} & \cdots & q_{m,n} \end{bmatrix}_{m \times n} \begin{bmatrix} s_1 \\ s_2 \\ \vdots \\ s_n \end{bmatrix}_{n \times 1}$$
(61)

where $(x_1, x_2, \ldots x_m)$ represents the generated linear combinations. To improve multipath transmission, m - n packet combinations are transmitted in each generation. Further, to enhance the computational efficiency, we used relatively lower size $m \times n$ CM than the original one. Here, CM is known to all connected nodes in UWSN. Being a non-zero element, CM taken from the GF is generated in such a way that the total rank of the $n \times n$ part is always n. It enables SRLNC to perform linear combination of the individual data packets over generations and enhances the likelihood of data packet combinations to reach the sink node without suffering packet loss. In most of the NC schemes, the coefficients applied for generating the linear combinations are also needed to be transmitted along with the data packet, and thus the output data packet x_p from the transmitter becomes $\left[q_{p,1} q_{p,2} \ldots q_{p,n} \mid x_p\right]$, where $1 \leq p \leq m$. SRLNC indicates the particular rows of the CM used to generate a particular packet combination. As stated, the generated CM and combined information represent the CI, in which each element is I_{p_w} , where p and w are presented in terms of b number of bits, with conditions, $1 \leq p \leq m$ and $1 \leq w \leq m$. The output x_p with associated CI $\left[I_{p_1} I_{p_2} \cdots I_{p_m}\right]$ is presented as

$$\begin{bmatrix} I_{p_1} & I_{p_2} \cdots & I_{p_m} & x_p \end{bmatrix}$$
(62)

Let the final generated packet x_p be generated using CI belonging only to the pth row of the CM, then the elements of the CM for x_p are obtained as:

$$I_{p_m} = \begin{cases} 1 \quad ; p = w \\ 0 \quad ; p \neq w \end{cases}$$
(63)

Considering the fact that combining all the generated packets is not significant for UWSNs, therefore, we assume major CM's elements as zero. The CI is then compressed using a simple arithmetic (lossless) compression scheme that minimizes the requirement of the higher CM transmission overhead. SRLNC applies a simple arithmetic compression scheme where the value and the position of the non-zero CI elements are identified before compression. Here, the non-zero elements are localized using [log₂(generation time)] number of bits. Since only non-zero elements of the CM are considered, therefore, I_{pm} can be sufficient to perform the task. Based on CI, different low-lossy compression scheme can be identified using N bits from the packet header, where N depends on the number of compression techniques used. Here onwards, we state N bits as the compression technique Identification Flag (CTIF). If compression needs to transmit more data, then it meets this need by transmitting uncompressed CI, and the smaller of either the compressed CI or the uncompressed CI is transmitted to the next hop. This reduces the computational overhead significantly.

Process at the Intermediate Node

Once receiving a single data packet (combination) from the transmitter, the intermediate node forwards the same unaltered data to the next-hop. On the contrary, in the case of multiple data packets from the same packet generation, it alters data by adding received packets and associated elements over the applied finite field. It retrieves l combinations and generates final data x'' (64):

$$x'' = [1 \ 1 \dots 1]_{1 \times l} \begin{bmatrix} x'_1 \\ x'_2 \\ \vdots \\ x'_l \end{bmatrix}_{1 \times 1}$$
(64)

where $(x'_1, x'_2, \dots, x'_l)$ signifies the l combinations.

Extracting the received packets, CTIF is obtained and, accordingly, the compression scheme used at the transmitter or intermediate node is identified. The pre-coded data and the compressed CI are decompressed. The intermediate node then updates the CI $(I''_1, I''_2, ..., I''_1)$ by adding m number of k bits from each combination. Thus, the updated CI at the intermediate node is obtained as (65):

$$[I''_{1}I''_{2}\dots I''_{m}]_{1\times m} = [1 \ 1\dots 1]_{1\times l} \begin{bmatrix} I'_{11} & I'_{12} & \dots & I'_{1m} \\ I'_{21} & I'_{22} & \dots & I'_{2m} \\ \vdots & \vdots & & \vdots \\ I'_{11} & I'_{12} & \dots & I'_{1m} \end{bmatrix}$$
(65)

Based on the identified compression scheme, the intermediate node updates the DTIF information and compresses CI along with the linear packet combination forwards to the next-hop node.

Process at the Sink Node

Retrieving the data elements, the sink node extracts the compressed CI. Receiving the sufficient packet combinations, the sink node performs decoding of the original transmitted packets and identifies the CM used to generate each packet combination. In case of multipath transmission, the final sink node collects a total of n packet combinations $(\hat{x}_1, \hat{x}_2, \dots, \hat{x}_n)$, having linearly independent CVs, and thus the originally transmitted data packets from the source node are obtained as (66).

$$\begin{bmatrix} \hat{S}_{1} \\ \hat{S}_{2} \\ \vdots \\ \hat{S}_{n} \end{bmatrix}_{n \times 1} = \begin{bmatrix} \hat{q}_{1,1} & \hat{q}_{1,2} & \dots & \hat{q}_{1,n} \\ \hat{q}_{2,1} & \hat{q}_{2,2} & \dots & \hat{q}_{2,n} \\ \vdots & \vdots & & \vdots \\ \hat{q}_{n,1} & \hat{q}_{n,2} & \dots & \hat{q}_{n,n} \end{bmatrix}_{n \times n} \cdot \begin{bmatrix} \hat{x}_{1} \\ \hat{x}_{2} \\ \vdots \\ \hat{x}_{n} \end{bmatrix}_{n \times 1}$$
(66)

Applying the above-mentioned approach, our proposed systematic-RLNC scheme ensures packet error resilience, and thus outputs (66) are usually the same as the original packets transmitted. Undoubtedly, the proposed SRLNC algorithm works optimally so as to ensure higher throughput; however, realizing the need for a robust computationally efficient transmission system for UWSN, we made an effort to reduce CI. Reduction in the CI bits can enable a swift and computationally effective model for UWSNs. A brief of the CI bits' optimization is presented as follows:

(1) Optimization of the Coefficient Information Bits

Considering the process of SRLNC based transmission over the proposed UWSN channel model, it can be observed that the selection of CV can make SRLNC more efficient to deliver bandwidth and time efficient transmission, which is vital for mission critical data transmission. We intend to select the best size of bits b needed to provide CV for efficient data transmission. In our model, the selection of b is performed in such a way that no packets are combined more than 2^b times. To achieve this, we used a probe-packet generation based technique, where the individual packet contains m network coded packets. The number of bits assigned to b is increased continuously throughput generations and is continued in such a manner that the packet combinations belonging to the gth generation apply b = g bits so as to obtain the accurate elements of the uncompressed CIs. In case a source packet is combined more than 2^b times at an intermediate node, the source node is informed for the generation of the specific packet combination that it belongs to. In this way, the source node applies the minimum number of bits b so that no intermediate node might combine a data packet more than 2^{b} times. One of the key novelties of the proposed SRLNC scheme is that it applies the iterative buffer flush (IBF) mechanism that, after receiving ACK from the sink or receiver node, flushes its buffer to preserve bandwidth. It can enhance the resource utilization efficiency of the routing scheme. The following

section discusses the SRLNC based UWSN routing protocol which has been simulated over the developed channel model.

3.3. Systematic RLNC Based UWSN

This section discusses the SRLNC based routing for UWSNs.

3.3.1. UWSN Network Model

Figure 1 illustrates a three-dimensional (3D) UWSN model applied to examine the efficiency of the proposed SRLNC based UWSN routing protocol. The proposed network model contains multiple acoustic sensor nodes and multiple sink nodes. The sensor nodes possess similar architecture and are distributed randomly. The individual sink node can be assumed to have a radio frequency modern and an acoustic modern, and is aware of its 3D position and associated node information using location services and can save this for making routing decisions.



Figure 1. Three-dimensional acoustic network structure.

Consider the sensor nodes being deployed across an underwater acoustic network in a Euclidean space $D \in \Re^3$. At time t, the network can be modelled as an undirected graph $G(t) = (V, \epsilon(t))$ [4], where $V\{n_i | 1 \le i \le M\}$ refers to the sensor nodes and $\epsilon(t) = \{e_{ij} | 1 \le i, j \le M, i \ne j\}$ signifies a set of connecting links between the sensor nodes at time t. With $\forall e_{ij}(t) \in \epsilon(t)$, nodes n_i and n_j are the neighbouring nodes at t and can communicate with each other directly through an acoustic link over the applied channel. If $\forall n_i \in V$, the neighbouring nodes at time t can be $N_i(t) = \{n_i \in V | \exists e_{ij}(t) \in \epsilon(t)\}$. Here, all nodes are assumed to have equal transmitting power as well as radio range R.

3.3.2. SRLNC Based Routing Protocol

The proposed routing protocol applies geographic route information on individual nodes to perform routing using SRLNC based transmission. To enable a simple transmission measure, the node nearest to the sink is considered as a data forwarding node that reduces the data loss probability significantly. Nodes apply the SRLNC transmission approach, where receiving N linear independently encoded packets, sink decodes the original transmitted data packets. As a simple solution, we applied a greedy forwarding model to estimate the best forwarding node.

Consider n_i to be the source node willing to transmit the data, $N_i(t)$ to be the n_i 's neighboring nodes at certain time t, and $S_i(t)$ to be n_i 's predefined or known sink nodes at time t. With node $n_i \in N_i(t)$, packet distribution is obtained as [4]:

$$SPD(n_j) = D(n_i, s_i) - D(n_j, s_j)$$
(67)

where $D(n_i, s_i)$ states n_i 's Euclidean distance from its nearest sink $s_i \in S_i(t)$. The variable $D(n_i, s_j)$ refers n_i 's Euclidean distance to its nearest sink $s_i \in S_i(t)$. The higher packet

distribution states higher priority for the neighbouring node selection and, thus, at time t, the next hop forwarding node of n_i is

$$C_{i}(t) = \{n_{j} \in N_{i}(t), SPD(n_{j} > 0)\}$$
(68)

For forwarding node $n_f \in C_i$, $D(n_i, n_f)$ presents the Euclidean distance between the source node n_i and the forwarding node n_f . Let the probability of the data delivery of m bits over $D(n_i, n_f)$ be $p(D(n_i, n_f), m)$. Then, the normalized packet distribution of n_f can be presented as:

$$NSPD(n_f) = SPD(n_f) \times p(D(n_i, n_f), m)$$
(69)

Based on the respective node energy and the normalized packet spread (NSPD), a weighting model is derived that executes the forwarding nodes for further path selection:

$$W = \partial \frac{E_r}{E_o} + (1 - \partial)NSPD$$
(70)

where ∂ refers to the equivalence factor between the energy of a response node and NSPD. Among the other parameters in (70), E_o refers the initial energy, while E_r gives the residual energy of the response node. The weighing model (70) is applied to estimate the weight of the individual forwarding nodes where the candidate nodes with respective weight score are sorted in high to low order and updated to a matrix $F_i(t)$. The first node having the highest weight score is selected as the data forwarding node to the sink. In case the first node fails in delivering the data, the next node in $F_i(t)$ is selected as the forwarding node and it continues until the complete data are delivered to the sink. In such way, the q-th node in $F_i(t)$ initiates transmitting if no preceding node has delivered data successfully within a defined duration T_w^q (71).

$$T_{w}^{q} = T_{d} + \sum_{j=1}^{q} D(n_{j}, n_{j+1}) / v + q \times T_{p}$$
(71)

In (71), v represents the sound speed in water medium, T_p refers the processing time of the packets and parameter $T_d = (R_c - D(n_i, n_f))/v$ signifies the delay during data transmission.

Applying best forwarding node (BFN) selection approach, the source node forwards the packet to the BFN, which is followed by SRLNC based data transmission over UWSN.

Implementing the aforementioned approach, the packet delivery probability (PDP) is estimated as follows.

3.3.3. Packet Delivery Probability (PDP)

Initially, the individual sink transmits its information with transmission power \mathcal{P} to all neighbouring UWSN nodes, and each node estimates its distance to the destination based on the received signal strength (RSSI) or signal to noise ratio (SNR). If the distance in between the transmitter and receiver is x, then, with the signal propagation topology characterized with the spreading factor k (k = 1.5), the attenuation is derived as (72)

$$A(x) = x^k a^x \tag{72}$$

where $a = 10^{a(\mathcal{P})/10}$ and $a(\mathcal{P}) = \frac{0.11\mathcal{P}}{1+\mathcal{P}^2} + \frac{44\mathcal{P}^2}{4100+\mathcal{P}^2} + 2.75 \times 10^{-4}\mathcal{P}^2 + 0.003$. Applying the developed channel model with both the LSD as well as small scale

Applying the developed channel model with both the LSD as well as small scale deviation over signal propagation, data receiving is achieved and, using binary phase shift keying (BPSK), the average Bit Error Rate (BER) is obtained where SNR of a symbol r_s and bit SNR r_b are equal ($r_s = r_b$). Defining $\overline{r_s} = 10^{r_s/10}$, BER is obtained as (73):

$$p_{b}(r_{b}) = \frac{1}{2} \left(1 - \sqrt{\frac{\overline{r_{s}}}{1 + \overline{r_{s}}}} \right)$$
(73)

Each bit SNR of the underwater signal information at the receiver node is obtained as (74)

$$\mathbf{r}_{b} = \mathbf{A} - \mathbf{k} \times 10 \times \log \mathbf{d} - \mathbf{a}(\mathcal{P}) \times \mathbf{d} \times 10^{-3} - 50 + 18 \times \log \mathcal{P}$$
(74)

where A states the sound intensity level (normally 118 dB). Finally, for any pair of nodes with the distance d, the PDP with m bits size is obtained as:

$$p(d,m) = (1 - p_b(r_b))^m$$
 (75)

3.3.4. Statistical Significance

The probability that a relationship between two or more variables is not the result of random chance is referred to as statistical significance. In essence, it serves as a means of demonstrating the accuracy of a particular statistic. Sample size and effect size make up its two main parts. If you have attained a particular level of confidence in the result, you can use statistical hypothesis testing to determine whether a dataset's outcome is statistically significant. This indicates that, given the null hypothesis, the hypothesis is unlikely to have occurred in statistical hypothesis testing. A null hypothesis states that there is no association between the variables.

4. Results and Discussion

This section discusses the results obtained and their respective significances.

4.1. Characterization of UWSN Channel Model

Considering the need for a computationally efficient model for UWSN, at first, a robust channel model was developed with intent to consider the small scale fading and deviation as well as the large-scale deviations caused due to dynamic network conditions. The inter-path correlation was estimated in both the time as well as frequency domain. Before implementing the proposed model for the SRLNC based UWSN routing protocol design, the derived channel model was assessed for its effectiveness for small- as well as large-scale fading conditions. Since we intended to enable the proposed routing model with multipath communication, the inter-path correlation was investigated, where it exhibited satisfactory outputs among different paths. Here, we selected the operating frequency range as 13 kHz, and the distance between transmitter and receiver was maintained at 0.2–1 KM. For simulation, the depth of the water column was fixed at 10 m and the transmitter and receiver heights from the bottom surface were assigned at 4 and (approx.) 2 m, respectively. For data transmission as performed for routing, the carrier frequency was fixed at 13 kHz where the transmission rate was maintained at 6.5 kb/s. For channel assessment, the pseudo-noise sequence was used and repeated iteratively and BPSK modulated onto the centre frequency. Before processing for performance analysis, the signals were re-sampled based on the retrieved data packet length so as to compensate for the motion-caused frequency shifting and time scaling. We used a Doppler factor to compensate for the aforementioned variations and, due to the sensor movement, it formed a Doppler rate in the order of 10^{-3} and, hence, required data re-sampling. We applied a fine Doppler compensation using a recursive least square model and 2nd order phase-locked loop. To estimate the underwater acoustic channel, a generic least square (LS) based algorithm orthogonal matching pursuit (OMP) was applied. It performs better for sparse channel estimation [53]. Based on the channel response, the path gains were estimated. Figure 2 presents the time advancement of the magnitude baseband impulse response for the developed channel model.



Figure 2. Time advancement of the magnitude baseband impulse response.

In this experiment, numerous local minima and maxima were observed over a delay that characterizes the channel taps where the impulse repost is the strongest. As depicted in Figure 3, the path delays allied with the channel geometry are labelled as P_0 , P_b and P_s . It signifies the reflections from the bottom and the surface. Here, the minor deviations in path delays can be observed from the nominal ones due to change in node locations, motion caused Doppler effect and, without a doubt, the delay spreading across intra-paths.



Figure 3. Channel gain.

Now, before implementing proposed network coding based UWSN routing protocol, the effectiveness of the SRLNC scheme is examined in terms of throughput, data drop, etc. The following section presents the result obtained for SRLNC.

4.2. Characterization of SRLNC Transmission Model

The effectiveness of the SRLNC algorithm for efficient data transmission over a multipath channel was assessed in terms of throughput while varying payload (samples per generation), packet loss rate, throughput with link loss variation and need for redundant packets, etc. The proposed SRLNC algorithm applies a Galois field of size 8 that enabled it to time as well as the computation efficient. Typically, higher redundant packets enable more accurate decoding at the receiver, however, at the cost of added computational overheads. Considering it, SRLNC was tested with one and two redundant packets per generation and relative performance was obtained (Figure 4). Initially the number of redundant packets was considered as 1, and the generation size was fixed at 10. Considering practical UWSN, where there can be continuous variations in the link quality to assess SRLNC, throughput was examined by varying link loss probability. We applied the Gilbert Elliot Model to generate the link loss pattern. The throughput of SRLNC was obtained for different link loss probability (0.0025, 0.005, 0.0075, 0.01, 0.0125, and 0.015). Figure 4 presents the throughput of the SRLNC algorithm. The data packet loss due to continuous payload increase is given in Figure 5. The results signify that throughput varies as per payload; however, SRLNC exhibits satisfactory output. Figure 6 presents the throughput varies, where, with increase in link loss, the throughput decreases, and result affirms the same.



Figure 4. Effect of payload (symbol per generation) on S-RLNC throughput.



Figure 5. Effect of payload on data packet drops.



Figure 6. Effect of link loss on S-RLNC throughput.

To enable an optimal computationally efficient routing scheme over UWSNs, enriching FEC is vital. Maintaining a minimum number of redundant packets to decode the data packets can be advantageous. It can reduce the computational overheads as well as unwanted bandwidth utilization. To estimate the minimum number of redundant packets per generation to have maximum data decoding at the receiver node, we tested SRLNC with one and two redundant packets per generation, where the proposed approach exhibited higher throughput with two redundant packets per generation. It signifies that with two redundant packets per generation. SRLNC can provide higher throughput and, hence, optimal performance towards efficient communication (Figure 7).



Figure 7. Effect of the number of redundant packets on S-RLNC throughput.

Observing the results obtained, it can be found that the proposed S-RLNC scheme achieves throughput up to 99–100% with ideal (or near ideal) network condition.

4.3. Characterization of S-RLNC for UWSNs

Upon assessing the effectiveness of the proposed SRLNC scheme for efficient data transmission and finding it optimal, it was applied for data transmission over UWSN. To examine the effectiveness of the proposed UWSN routing protocol, we considered [53,54] as a reference routing protocol. The overall algorithm including channel model and systematic RLNC based UWSN routing protocol has been developed using the MATLAB 2015a simulation platform. To perform the simulation, a total of 800 nodes were distributed across UWSN in 3D network environment (Figure 1). Here, the acoustic signal's propagation speed was taken as 1500 m/s. Each sensor node has the radio range of 250 m, and the initial energy was 100 J per nodes. Further, the rate of consumption was 60 uJ/bit. A number of packets of 64 kB size were generated by the source node. Now, considering SRLNC implementation for UWSN simulation, the number of packet combinations per generation is fixed at 10, with Galois Field size 8. As presented in Figure 8, our proposed SRLNC based routing protocol outperforms GPNC based UWSN routing. However, the effect of link loss on the packet delivery ratio (PDR) can be easily observed. In Figure 8, the average PDR of the GPNC protocol is 82.8%, while our proposed SRLNC based routing exhibits 94.85% PDR. SRLNC exhibited 12.5% higher PDR than GPNC based UWSN routing. Figure 9 depicts the effect of the number of nodes on PDR. Results reveal that with an increase in the number of nodes, PDR increases gradually. GPNC has exhibited on average 81.9% of the PDR, while SRLNC ensures 90.28% PDR, which is almost 8.4% higher than GPNC. The similar result can be observed from Figure 10, where our proposed SRLNC scheme exhibits approximately 4.8% higher throughput than GPNC. In UWSN's delay is one of the key factors required to be optimal [55].



Figure 8. Effect of link loss rate on packet delivery ratio.



Figure 9. Effect of number of nodes on packet delivery ratio.



Figure 10. Effect of number of nodes on overall throughput.

Figure 11 presents the results obtained for the effect of the number of nodes on the average delay. The proposed SRLNC based UWSN routing exhibits 12.53% lower delay than the GPNC protocol. This is because of increased throughput, reduced data drop and, no doubt, enhanced FEC mechanism. Observing the above discussed results and their significances where the proposed routing scheme provides higher data delivery rate, throughput and minimal delay, it can be understood that with such accomplished performance, the probability of retransmission should be minimal and so should the energy exhaustion. To confirm this, Figure 12 justifies that the proposed routing scheme results in lower energy consumption than the GPNC based routing protocol. Here, SRLNC consumes approximate 24.3% less energy than the GPNC based routing approach [56–58].



Figure 11. Effect of number of nodes on the average delay.



Figure 12. Effect of number of nodes on the energy consumption.

Thus, observing overall results and their inter-relations with the proposed channel model, systematic RLNC and its implementation with the UWSN routing scheme affirm that the proposed approach can be vital to ensure an efficient communication system for UWSNs.

5. Conclusions

Exponentially rising technologies and allied applications have always prompted the exploration of better systems. The underwater acoustic wireless sensor network (UWSN) has emerged as one of the most sought after research domains in communication systems to serve civil as well as defense purposes. However, encompassing exceedingly dynamic environment and channel conditions, it demands a more effective and optimal transmission model so as to enable reliable and QoS oriented communication. This paper presented multiple contributions targeted to enable an optimal channel model, transmission model and routing protocol for energy efficient, delay tolerant and QoS enriched UWSN communication. Realizing the need for a robust channel model with small scale as well as large scale deviations (fading conditions), at first, a novel computationally efficient statistical channel model was developed. Incorporating principle physical concepts of acoustic propagation as well as arbitrary topological variations, the proposed channel model was intended to derive an efficient and realistic channel model for acoustic communication. Unlike traditional channel models, consideration of the proposed statistical model can provide more accurate and real-time responses. In the next research phase, a robust systematic random linear network coding (RLNC) based transmission model will be developed. The simulation of the proposed systematic RLNC or SRLNC based UWSN routing protocol has exhibited better performance in terms of higher PDR and throughput, minimal delay and energy consumption. The performance with a dynamicc and computationally efficient channel model

exhibits that the proposed SRLNC based UWSN routing scheme can be significant for those cases where small scale fading (due to scattering and small wavelength deviation) as well as large scale fading (primarily due to node movement or dislocation) occur frequently. The proposed routing protocol with iterative buffer flush-based SRLNC strengthens it to be used for large scale UWSNs where QoS oriented mission critical data transmission and energy efficient communication is required. In the future, the enhancement scopes could allow the proposed channel model to enhance spatial correlation between acoustic paths. In addition, enriching SRLNC data compression and encoding/decoding can also be explored to make FEC more productive.

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References

- Heidemann, J.; Stojanovic, M.; Zorzi, M. Underwater Sensor Networks: Applications. Advances, and Challenges. *Philos. Trans. R.* Soc. A 2012, 370, 158–175. [CrossRef] [PubMed]
- Guo, Z.; Luo, H.; Hong, F.; Yang, M.; Li, N. Current Progress and Research Issues in Underwater Sensor Networks. J. Comput. Res. Dev. 2010, 47, 377–389.
- 3. Qarabaqi, P.; Stojanovic, M. Statistical Characterization and Computationally Efficient Modeling of a Class of Underwater Acoustic Communication Channels. *IEEE J. Ocean. Eng.* **2013**, *38*, 701–717. [CrossRef]
- Coutinho, R.W.L.; Boukerche, A.; Vieira, L.F.M.; Loureiro, A.A.F. GEDAR: Geographic and opportunistic routing protocol with Depth Adjustment for mobile underwater sensor networks. In Proceedings of the 2014 IEEE International Conference on Communications (ICC), Sydney, NSW, Australia, 10–14 June 2014; pp. 251–256. [CrossRef]
- Hong, F.; Zhang, Y.L.; Yang, B.Z.; Guo, Y.; Guo, Z. Review on Time Synchronization Techniques in Underwater Acoustic Sensor Networks. Acta Electron. Sin. 2013, 41, 960–965.
- 6. Peng, J.; Hong, C.J.; Liu, T. Strategy of routing based on layered for underwater wireless sensor networks. *J. Commun.* **2014**, 35, 25–31.
- 7. Stojanovic, M.; Freitag, L. Recent Trends in Underwater Acoustic Communications. Mar. Technol. Soc. J. 2013, 47, 45–50. [CrossRef]
- 8. Sozer, E.; Stojanovic, M.; Proakis, J. Underwater acoustic networks. IEEE J. Ocean. Eng. 2000, 25, 72–83. [CrossRef]
- 9. Proakis, J.G.; Rice, J.A.; Sozer, E.M.; Stojanovic, M. Shallow-Water Acoustic Networks. *IEEE Commun. Mag.* 2003, 39, 114–119. [CrossRef]
- 10. Stojanovic, M. Acoustic (underwater) communications. In *Encyclopedia of Telecommunications*; Proakis, J.G., Ed.; John Wiley and Sons: Hoboken, NJ, USA, 2003.
- 11. Porter, M.B. Bellhop Code. Available online: http://oalib.hlsresearch.com/Rays/index.html (accessed on 10 February 2016).
- 12. Peterson, J.C.; Porter, M.B. Ray/Beam Tracing for Modeling the Effects of Ocean and Platform Dynamics. *IEEE J. Ocean. Eng.* **2013**, *38*, 4. [CrossRef]
- 13. Tindle, C.T. Wavefronts and waveforms in deep-water sound propagation. J. Acoust. Soc. Am. 2002, 112, 464–475. [CrossRef]
- 14. Deane, G.B.; Preisig, J.C.; Tindle, C.T.; Lavery, A.; Stokes, M.D. Deterministic forward scatter from surface gravity waves. *J. Acoust. Soc. Am.* **2012**, *132*, 3673–3686. [CrossRef]
- 15. Akyildiz, I.F.; Pompili, D.; Melodia, T. Underwater acoustic sensor networks: Research challenges. *Ad Hoc Netw.* **2005**, *3*, 257–279. [CrossRef]
- 16. Pompili, D.; Akyildiz, I.F. Overview of networking protocols for underwater wireless communications. *IEEE Commun. Mag.* 2009, 47, 97–102. [CrossRef]
- 17. Qarabaqi, P.; Stojanovic, M. Statistical modeling of a shallow water acoustic communication channel. In Proceedings of the Underwater Acoustic, Measurements Conference, Nafplion, Greece, 21–26 June 2009; pp. 1341–1350.
- Radosevic, A.; Proakis, J.G.; Stojanovic, M. Statistical characterization and capacity of shallow water acoustic channels. In Proceedings of the OCEANS 2009-EUROPE, Bremen, Germany, 11–14 May 2009; pp. 1–8. [CrossRef]
- 19. Socheleau, F.; Passerieux, J.; Laot, C. Characterisation of timevarying underwater acoustic communication channel with application to channel capacity. In Proceedings of the Underwater Acoustic, Measurements Conference, Nafplion, Greece, 21–26 June 2009.
- 20. Galvin, R.; Coats, R. A stochastic underwater acoustic channel model. Proc. MTS/IEEE Oceans Conf. 1996, 1, 203–210. [CrossRef]

- 21. Chitre, M. A high-frequency warm shallow water acoustic communications channel model and measurements. *J. Acoust. Soc. Am.* **2007**, *122*, 2580–2586. [CrossRef]
- Qarabaqi, P.; Stojanovic, M. Modeling the large scale transmission loss in underwater acoustic channels. In Proceedings of the 2011 49th Annual Allerton Conference on Communication, Control, and Computing, Monticello, IL, USA, 28–30 September 2011; pp. 445–452. [CrossRef]
- Tomasi, B.; Casari, P.; Badia, L.; Zorzi, M. A study of incremental redundancy hybrid ARQ over Markov channel models derived from experimental data. In Proceedings of the Fifth ACM International Workshop on UnderWater Networks—WUWNet'10, Woods Hole, MA, USA, 30 September–1 October 2010. [CrossRef]
- 24. Yang, W.-B.; Yang, T.C. High-frequency channel characterization for M-ary frequency-shift-keying underwater acoustic communications. J. Acoust. Soc. Am. 2006, 120, 2615–2626. [CrossRef]
- Zhang, J.; Cross, J.; Zheng, Y.R. Statistical channel modeling of wireless shallow water acoustic communications from experiment data. In Proceedings of the 2010—Milcom 2010 Military Communications Conference, San Jose, CA, USA, 31 October–3 November 2010; pp. 2412–2416. [CrossRef]
- Ruiz-Vega, F.; Clemente, M.C.; Otero, P.; Paris, J.F. Rician shadowed statistical characterization of shallow water acoustic channels. In Proceedings of the Conference on Underwater Communications: Channel Modelling and Validation, UCOMMS, Sestri-Levante, Italy, 12–14 September 2012.
- Tomasi, B.; Zappa, G.; McCoy, K.; Casari, P.; Zorzi, M. Experimental study of the space-time properties of acoustic channels for underwater communications. In Proceedings of the Oceans'10 IEEE Sydney, Sydney, Australia, 24–27 May 2010. [CrossRef]
- Socheleau, F.-X.; Laot, C.; Passerieux, J.-M. Stochastic Replay of Non-WSSUS Underwater Acoustic Communication Channels Recorded at Sea. *IEEE Trans. Signal Process.* 2011, 59, 4838–4849. [CrossRef]
- 29. Heitsenrether, R.M.; Badiey, M. Modeling acoustic signal fluctuations induced by sea surface roughness. *Proc. AIP Conf.* 2004, 728, 214–221.
- 30. Preisig, J.C.; Deane, G.B. Surface wave focusing and acoustic communications in the surf zone. J. Acoust. Soc. Am. 2004, 116, 2067–2080. [CrossRef]
- Mo, H.; Zhou, Z.; Zuba, M.; Peng, Z.; Cui, J.H.; Shu, Y. Practical Coding-based Multi-hop Reliable Data Transfer for Underwater Acoustic Networks. In Proceedings of the IEEE Globecom, Anaheim, CA, USA, 3–7 December 2012; pp. 5751–5756.
- 32. Chitre, M.; Soh, W.-S. Network coding to combat packet loss in underwater networks. In Proceedings of the Fifth ACM International WUWNet, Woods Hole, MA, USA, 30 September–1 October 2010; p. 106. [CrossRef]
- Wu, H.; Chen, M.; Guan, X. A Network Coding Based Routing Protocol for Underwater Sensor Networks. Sensors 2012, 12, 4559–4577. [CrossRef]
- Guo, Z.; Wang, B.; Xie, P.; Zeng, W.; Cui, J.H. Efficient error recovery with network coding in underwater sensor networks. *Ad Hoc Netw.* 2009, 7, 791–802. [CrossRef]
- Kun, H.; Zhigang, J.; Ping, H.A. New Opportunistic Routing Mechanism Based on Partial Network Coding. In Proceedings of the 5th International Conference on Intelligent Networks and Intelligent Systems, Bucharest, Romania, 19–21 September 2012; pp. 154–157.
- Kebkal, V.; Kebkal, O.; Kebkal, K. Network coding for underwater acoustic sensor networks. In Proceedings of the 2013 MTS/IEEE Oceans, Bergen, Norway, 10–14 June 2013; pp. 1–5.
- Xu, J.; Li, K.; Min, G. Reliable and Energy-Efficient Multipath Communications in Underwater Sensor Networks. *IEEE Trans.* Parallel Distrib. Syst. 2011, 23, 1326–1335. [CrossRef]
- Xie, P.; Cui, J.-H. An FEC-based Reliable Data Transport Protocol for Underwater Sensor Networks. In Proceedings of the 16th International Conference on Computer Communications and Networks ICCCN, Honolulu, HI, USA, 13–16 August 2007; pp. 747–753. [CrossRef]
- Kulhandjian, H.; Melodia, T.; Koutsonikolas, D. CDMA-Based Analog Network Coding for Underwater Acoustic Sensor Networks. *IEEE Trans. Wirel. Commun.* 2015, 14, 6495–6507. [CrossRef]
- Kebkal, V.; Kebkal, O.; Kebkal, K. Network coding for underwater acoustic networks of butterfly topology. In Proceedings of the Oceans 2014—Taipei, Taipei, Taiwan, 7–10 April 2014; pp. 1–5. [CrossRef]
- Kulhandjian, H.; Melodia, T.; Koutsonikolas, D. CDMA-based analog network coding through interference cancellation for underwater acoustic sensor networks. In Proceedings of the Seventh ACM International Conference on Underwater Networks and Systems WUWNet '12, Los Angeles, CA, USA, 5–6 November 2012.
- 42. Isufi, E.; Leus, G.; Dol, H. Network Coding for Flooding-Based Routing in Underwater Sensor Networks. In Proceedings of the Seventh ACM International Conference on Underwater Networks and Systems WUWNet '14, Rome, Italy, 12–14 November 2014.
- Pramod, H.B. Performance and Methodologies of Underwater Sensor Acoustic Network: Research Challenges. In Proceedings of the International Conference on Recent Advances in Science and Engineering, Bangalore, India, 1 February 2014.
- 44. Pramod, H.B.; Kumar, R. Time Critical Appliction and Design Issues in Underwater Sensor Network. *Int. J. Comput. Corp. Res.* **2016**, *6*, 2.
- 45. Evaluation of Parallel Application's Performance Dependency on RAM using Parallel Virtual Machine. *Int. J. Comput. Sci. Commun. Netw.* **2014**, *2*, 641–646.
- 46. Pramod, H.B.; Kumar, R. An Effective Algorithmic for Integrity and Performance Enhancement in Underwater Sensor Networks. *IEAE Int. J. Eng.* **2016**, *1*, 1.

- Pramod, H.B.; Kumar, R. Effective Security and Energy Aware Approach for Performance Augmentation of Underwater Sensor Networks. Int. J. Sci. Eng. Res. 2016, 7, 7.
- Pramod, H.B.; Kumar, R. On-Cloud Deep Learning Based Approach for Performance Enhancement in Underwater Acoustic Communications. In Proceedings of the IEEE International Conference on SCOPES-2016 Centurian University of Technology and Management, Paralakhemundi, India, 3–4 October 2016.
- Pramod, H.B.; Kumar, R. Multilayered Energy Harvesting and Aggregation in Underwater Sensor Acoustic network for Performance Enhancement. In Proceedings of the IEEE International Conference on Emerging Technological Trends, Baselios Mathew II College of Engineering, Sasthancotta, Kerala, India, 21–22 October 2016.
- 50. Brekhovskikh, L.M.; Lysanov, Y.P. Fundamentals of Ocean Acoustics, 3rd ed.; Springer: New York, NY, USA, 2003.
- 51. Cardieri, P.; Rappaport, T. Statistics of the sum of lognormal variables in wireless communications. In Proceedings of the IEEE Vehicular Technology Conference, Tokyo, Japan, 15–18 May 2000; pp. 1823–1827.
- Radosevic, A.; Ahmed, R.; Duman, T.M.; Proakis, J.G.; Stojanovic, M. Adaptive OFDM Modulation for Underwater Acoustic Communications: Design Considerations and Experimental Results. *IEEE J. Ocean. Eng.* 2013, 39, 357–370. [CrossRef]
- 53. Li, W.; Preisig, J.C. Estimation of Rapidly Time-Varying Sparse Channels. IEEE J. Ocean. Eng. 2007, 32, 927–939. [CrossRef]
- Hao, K.; Jin, Z.; Shen, H.; Wang, Y. An Efficient and Reliable Geographic Routing Protocol Based on Partial Network Coding for Underwater Sensor Networks. Sensors 2015, 15, 12720–12735. [CrossRef]
- 55. Nguyen, N.T.; Le, T.T.; Nguyen, H.H.; Voznak, M. Energy-efficient clustering multi-hop routing pro tocol in a UWSN. *Sensors* 2013, 21, 627. [CrossRef]
- Subramani, N.; Mohan, P.; Alotaibi, Y.; Alghamdi, S.; Khalaf, O.I. An Efficient Metaheuristic-Based Clustering with Routing Protocol for Underwater Wireless Sensor Networks. *Sensors* 2022, 22, 415. [CrossRef]
- 57. Mohan, P.; Subramani, N.; Alotaibi, Y.; Alghamdi, S.; Khalaf, O.I.; Ulaganathan, S. Improved metaheuristics-based clustering with multihop routing protocol for underwater wireless sensor networks. *Sensors* **2022**, *22*, 1618. [CrossRef]
- Haque, K.F.; Kabir, K.H.; Abdelgawad, A. Advancement of routing protocols and applications of underwater wireless sensor network (UWSN)—A survey. J. Sens. Actuator Netw. 2020, 9, 19. [CrossRef]