SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V13I9P114

Volume 13 Issue 9, 174-187, September 2026

Original Article

Disaster Severity Weighted GCN-LSTM Routing Framework in Underwater Sensor Networks

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Received: 21 August 2026 Revised: 11 September 2026 Accepted: 17 September 2026 Published: 26 September 2026

Abstract - *The events such as earthquakes, tsunamis and underwater landslides occur; communication reliability becomes a big challenge in Underwater Wireless Sensor Networks (UWSNs). These events lead to a fast change of channels, failure of links, loss of packets and higher power usage, which diminishes the efficiency of the conventional routing protocols. Most of the protocols that are available today are based on the existing network information and do not anticipate link failure in advance. In this context, a novel Graph Convolutional Network-Long Short-Term Memory-Disaster Severity Weighting (GCN-LSTM-DSW) framework is proposed in this work to support reliable and energy-efficient routing in the presence of disasters. The GCN represents spatial relationships between the neighboring sensor nodes, and the LSTM is used to model temporal variations of the RSSI, SNR, traffic load and residual energy. The Disaster Severity Weighting (DSW) mechanism dynamically adjusts routing costs based on the prediction of network conditions and the severity of the disaster so as to identify unstable links early and select suitable paths. The proposed framework was compared with the individual GCN and LSTM models. GCN achieved an MAE of 0.071, RMSE of 0.099, and R^2 of 0.917, while LSTM achieved an MAE of 0.086, RMSE of 0.121, and R^2 of 0.891. The performance of GCN-LSTM-DSW was the best with MAE of 0.048, RMSE of 0.067, and R^2 of 0.958. In the synthetic disaster scenarios, the proposed framework achieved PDR values ranging from 94.0% to 97.5% across different severity levels, an average end-to-end delay of 185 ms, average energy consumption of 0.82 J, a 12.6% improvement in network lifetime, and a 34.8% reduction in route recovery time. The results show the reliability, energy efficiency and resilience enhancement in dynamic underwater disaster environments.*

Keywords - *Underwater sensor networks, Disaster-resilient communication, Energy-efficient routing, LSTM, Acoustic wireless networks.*

1. Introduction

The use of Underwater Wireless Sensor Networks (UWSNs) has expanded across numerous marine applications. These networks support tasks such as observing underwater environments, gathering oceanographic information, inspecting offshore oil and gas facilities, monitoring submerged infrastructure and providing early indications of potential disasters. These networks use sensor nodes that communicate through acoustic signals to collect and transmit information from underwater environments where normal terrestrial communication technologies cannot be used effectively. A key advantage of reliable communication is the ability to rapidly transmit sensing data in disaster management, which enables early detection and monitoring of disaster events, such as tsunamis, underwater, earthquakes, submarine landslides, and offshore structural failures [1]. Although they are useful, reliable communication in UWSN systems is still difficult to be realized because of the unreliable underwater acoustic channels. Communication performance can be severely impaired by factors like limited bandwidth, propagation delays, signal attenuation, multipath interference, Doppler shifts, and background noise. In addition, the difficulty of accessing, replacing, and recharging batteries in underwater sensor nodes adds to the challenge, as they are often difficult to access or modify once deployed. This can cause the links to become unstable and repeat transmissions of data, which can lead to poor routing decisions, creating additional energy use and reducing the overall network lifespan.

Figure 1 shows the architecture of the UWSNs. The network is structured into three underwater zones, like shallow zone (0-200 m), medium zone (200-1000 m) and deep zone (above 1000 m). Devices used in each zone will be different depending on the devices to be monitored. The Maritime Command Station is connected to the underwater network by satellite communication at the surface. The function of the command station is to process data, visualize events and monitor underwater activities. In the shallow zone, which supplies continuous data input, surface buoys with environmental sensors are utilized for obtaining data such as temperature and salinity. These buoys also play a role in the transfer of the information collected from the waterborne devices to the surface network [2, 3].

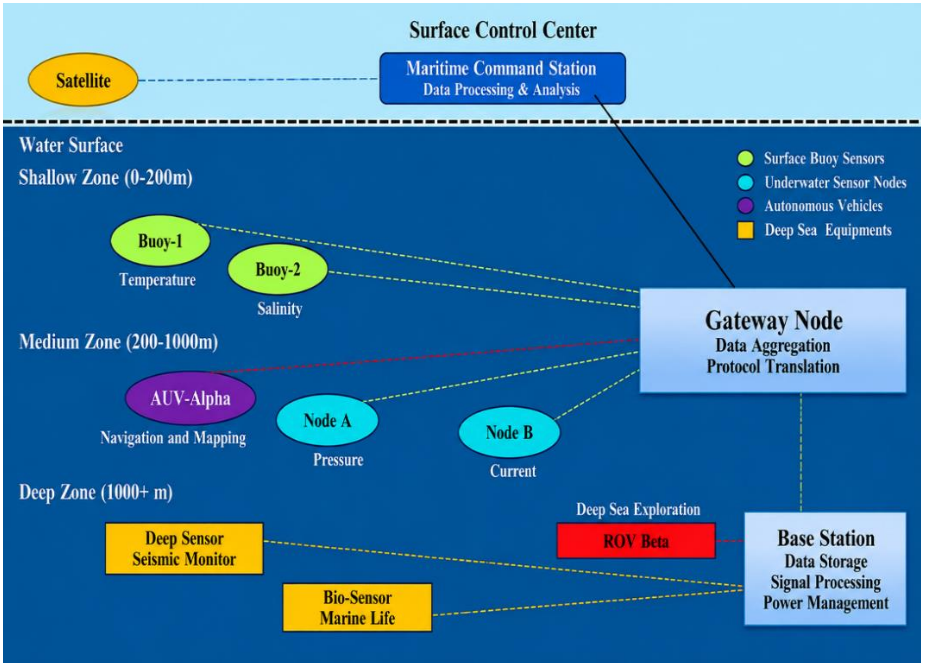

Fig. 1 Underwater wireless sensor network architecture

The intermediate zone comprises of underwater sensor nodes and Autonomous Underwater Vehicles (AUVs) for supporting sensing and data collection activities within the network. The sensor nodes obtain parameters like pressure and water current, and the AUV is employed for navigation, mapping and mobile data collection. The data collected is transmitted via underwater acoustics to the Gateway Node. These Nodes are used to relay between underwater devices and the surface network. It receives and collects data from various nodes, applies the relevant protocol conversion and sends the data to the surface network or underwater base station. Deep zone monitoring systems are implemented with a variety of sensors such as deep seismic monitoring sensors, marine bio-sensors and Remotely Operated Vehicles (ROVs).

These are the instruments which are employed to observe seismic activity, marine life and deep sea conditions. The information gathered is then stored, processed and managed in energy in the Base Station and then transmitted to the gateway [4]. Lastly, the gathered underwater data is transmitted from the gateway to the Maritime Command Station by inter-satellite communication. The data received can then be further analysed for monitoring and decision-making. This multi-layered structure helps in the management of devices in the underwater environment at different depths and to establish an effective communication infrastructure for underwater monitoring systems [2]. Underwater incident communications are more difficult. The network's topology can change abruptly, and nodes and links can fail, or packets can be lost or signal quality can degrade due to an event like an earthquake, tsunami, or underwater landslide. In such situations, conventional routing protocols such as AODV [5], LEACH [6] and DBR [7] might not function well as they consider only the latest information on the network when selecting the route for communications. Routes that are established at a time may be unstable shortly thereafter. This can result in multiple route discovery, higher delay, higher energy consumption and lower packet delivery rate. Although the reinforcement learning based routing approaches have improved the adaptability of UWSNs, the time taken by these approaches to learn and converge may be a problem during disaster in the case of frequent changes in the network parameters.

The changing state of networks can be predicted using deep learning methods. Graph Convolutional Networks (GCNs) [8] can be used to learn the spatial relationship between neighbouring sensor nodes; and Long Short-Term Memory (LSTM) networks [9, 10] can be used to learn the changes of network parameters over time. The advantages of the proposed framework are that, with the integration of both GCN and LSTM, both spatial and temporal information can be taken into account to predict future communication conditions. The parameters, such as Received Signal Strength Indicator (RSSI), Signal to Noise Ratio (SNR), traffic load, and residual energy, are parameters that can be predicted and used to make a routing decision. The information anticipated in the predicted information can assist the routing protocol to steer clear of links that could grow unstable and never have to resort to communication failure. This can minimize the amount of retransmissions and increase data transmission reliability.

In the literature, currently, there are a number of predictive routing approaches that have been developed, but without considering the severity of the disaster when making routing decisions [11]. The routing needs may not be the same when there is a disaster. But, when the network is working normally, it is more important to reduce the energy consumption since the network lifetime is to be increased. However, during a serious disaster like a Tsunami or undersea earthquake, it is important to get critical information to people quickly and reliably. Therefore, the routing strategy should be flexible for changing with the severity of the disaster. Among the most significant restrictions of the existing predictive routing techniques mentioned above, there is no adaptive mechanism [12].

However, existing predictive routing approaches mainly focus on predicting future network conditions and do not consider the severity of an ongoing disaster while making routing decisions. This creates a research gap because routing requirements can change from energy efficiency during normal conditions to reliable and fast communication during severe disasters. Therefore, an adaptive routing mechanism is needed that can adjust routing priorities according to the severity of the disaster. In order to address this issue, this paper introduces a Disaster Severity Weighted GCN-LSTM Routing Framework for UWSNs. The proposed framework first learns the spatial relationship between the neighbouring nodes of the sensors network through a Graph Convolutional Network (GCN).

The spatial features extracted by the GCN are passed to the LSTM network to learn the temporal variations in the underwater communication parameters. The Disaster Severity Weighting (DSW) mechanism is proposed based on the forecasted channel conditions and the information of the channel network to estimate the severity of the disaster. The packet loss, node and link failures, rate of the expected signal quality are all considered by the DSW. The disaster severity used in the routing cost function to alter the cost of reliability and energy efficiency.

During normal operation, the routing process will focus more on an energy-efficient path. The more serious the disaster, the more critical reliable and stable communication channels are given priority in the routing process. This means that the proposed framework has the ability to adjust its routing, depending on the differing disaster situations. A synthetic disaster-oriented underwater simulation environment is leveraged for the evaluation of the proposed framework. The simulation takes into account various network conditions, including channel fading, node mobility, random node failure and various disaster intensities. The effectiveness of the proposed technique is shown and analysed with some of the simulation parameters such as packet delivery ratio, end-to-end delay, and energy consumption, recovery time of the route and network lifetime in comparison with the conventional and learning-based routing methods. The results obtained confirm that it is possible to achieve better communication performances by implementing the proposed framework, in the case of underwater disasters with varying conditions.

2. Methodology

The complete methodology consists of six major stages: (1) Data Preprocessing, (2) Dynamic Graph Construction (3) GCN-LSTM based spatio-temporal prediction, (4) Disaster Severity Estimation (5) Adaptive Routing Cost Calculation, and (6) Optimal Path selection with energy and priority considerations. The energy consumption model and priority-aware loss function are incorporated within the routing and prediction stages. The output of each stage is used by the subsequent stage to support reliable and energy-efficient routing under varying underwater conditions.

2.1. Data Preprocessing

The synthetic dataset contains several underwater communication and environmental parameters, including RSSI, SNR, traffic load, residual energy, water depth, temperature, packet loss ratio, node failure ratio, link failure ratio, and transmission distance. Among these parameters, RSSI, SNR, traffic load, and residual energy are used as node-level input features for the GCN-LSTM prediction model.

The model is trained to predict the future values of RSSI, SNR, and traffic load, which are subsequently used to evaluate future communication conditions and support disaster-aware routing decisions. Residual energy is retained as an input feature to represent the energy condition of the sensor nodes, but it is not treated as a prediction output. The remaining parameters, including packet loss, node failure ratio, link failure ratio, water depth, temperature, and transmission distance, are used for network state representation, disaster severity estimation, and routing evaluation.

Underwater sensors operate in a constantly evolving world and can have missing values, noise or abnormal readings. Thus, the data need to be pre-processed before being fed into the prediction model. The first step is to remove unrealistic values from the data set, like when a RSSI value is higher than 0 dBm (Decibel-milliwatts) or an SNR value is lower than -50 dB (Decibel). This is followed by filling in missing values in various ways, depending on the type of parameter. Because of the nature of the parameters, they are usually assumed to be changing slowly with time; the values may be forward-filled interpolated [12]. If the number of missing values is not too large, the K-Nearest Neighbour (KNN) imputation method [13] is applied to estimate missing values for the parameters that can change more rapidly, such as RSSI, SNR and traffic load and residual energy. Also, abnormal observations in the dataset are checked with the Interquartile Range (IQR) methodology [14]. These abnormal values can be because of sensor error or temporary communication issues, and are eliminated prior to model training. Lastly, the features obtained from the processing are normalized between 0 and 1 using the Min-Max normalization [15] as shown in Equation (1) to ensure that all the parameters have a similar range for the training of the model.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

Where X is the original feature value, X_{min} is the minimum value of the feature in the training set. X_{max} is the largest value of the feature in the training set. The feature value, denoted as $X_{norm,}$ is the value of the feature after normalization**.** The normalization makes the communication parameters, including RSSI, SNR, traffic load, residual energy, temperature, and depth, have an equal role during the model training and makes the proposed framework more stable and faster to converge.

2.2. Dynamic Graph Construction

The UWSN is represented as a dynamic graph $G_t = (V, E_t, A_t)$ where V represents the sensor nodes, E_t represents the communication links, and A_t denotes the adjacency matrix at time t. Since the underwater network topology changes because of node mobility, water currents, acoustic fading, and disaster induced failures, the graph is updated for each time window. The initial adjacency matrix is constructed from the current communication conditions and connectivity between neighboring nodes. The GCN uses this graph together with the node feature matrix to learn spatial relationships among neighboring nodes. The subsequent GCN-LSTM model predicts future RSSI, SNR, and traffic load values. These predicted communication parameters are then used to update the link conditions and support the construction of the routing graph for the next decision interval. The normalized adjacency matrix is calculated as in Equation (2):

$$A_t^{norm} = D^{-\frac{1}{2}}(A_t + I)\, D^{-\frac{1}{2}} \tag{2}$$

Where A is adjacency matrix of the networks, I is identity matrix i.e. each node is connected to itself, D is Degree matrix or diagonal matrix, $D^{-\frac{1}{2}}$ normalization term i.e. scales nodes by their connectivity so highly connected nodes don’t dominate, A_t^{norm} is Symmetrically normalized adjacency matrix, often used in GCNs [16] or spectral graph analysis[17]. In a disaster situation e.g. earthquake, underwater landslide, tsunami debris, the network topology of UWSNs changes dynamically, Some links break due to obstruction, debris, or signal fading, some nodes fail due to pressure or battery drain, Communication becomes unreliable, and graph edges become sparse or unstable. If we directly use the adjacency A, nodes with high connectivity, like cluster heads or gateway nodes, dominate the learning. This bias is dangerous in disasters because high-degree nodes may suddenly fail, and isolated nodes still carry critical disaster data, e.g., seismic activity, sudden drop in pressure [18].

2.3. Prediction Model (GCN + LSTM)

The proposed model is designed to predict future underwater communication conditions by learning both spatial and temporal patterns in the UWSN. At time t, the node feature matrix $X_{t,}$ containing RSSI, SNR, traffic load, and is combined with the normalized adjacency matrix of the dynamic graph. First, the GCN extracts spatial features from the relationships among neighboring sensor nodes using $\boldsymbol{H_t = \sigma\left(A_t^{norm}\, X_t\, W_g\right)}$. The GCN layer applies a learnable weight matrix. $\boldsymbol{W_g}$ to the aggregated node features, followed by the ReLU activation function to introduce non-linearity. These spatial features are then provided to the LSTM, which learns the temporal dependencies and changes in the network conditions using $\boldsymbol{h_t, c_t = \mathrm{LSTM}(H_t, h_{t-1}, c_{t-1},)}$ = (H_t,h_{t-1},c_{t-1}) The trained GCN-LSTM model then predicts the future values of RSSI, SNR, and traffic load for the next H time steps. The prediction error is calculated using the priority-weighted loss function to improve the prediction of important network conditions. The predicted communication parameters are subsequently used to evaluate link reliability and link quality and are provided to the Disaster Severity Weighting mechanism for adaptive routing decisions. The predicted SNR at a future time step (t+h) is represented as in Equation (3):

$$\boldsymbol{SNR_{pre}^{h} = \widehat{SNR_{t+h}} \quad h = 1, 2, \dots, H} \tag{3}$$

Where SNR_{pre}^{h} represents the predicted SNR at the h future time step, denotes $\widehat{SNR_{t+h}}$ the SNR predicted by the GCN-LSTM model, and (H) represents the prediction horizon. For the immediate routing decision, the predicted SNR for the next time step is considered as $SNR_{pre} = \widehat{SNR_{t+1}}$. The obtained SNR_{pre} is then used in the DSI to determine the effect of network conditions on the routing decision.

2.4. Disaster Severity Weighting

To enable adaptive routing under dynamic underwater conditions, a DSW mechanism is incorporated into the proposed framework. The DSW module estimates the current intensity of an underwater disaster by considering multiple network indicators that reflect communication reliability and network stability. Specifically, the Disaster Severity Index (DSI) is computed using the Packet Loss ratio (PL), Node Failure ratio (NF), Link Failure ratio (LF), and the degradation in the predicted SNR. Before calculating the DSI, PL, NF , LF and predicted SNR component are normalized to the range [0, 1]. The normalized values are then combined using the predefined weights w_1, w_2, w_3, and w_4. The resulting DSI lies within the range [0, 1], where a higher value represents a more severe disaster condition.

The DSI is calculated as in Equation (4):

$$\mathrm{DSI} = w_1\mathrm{PL} + w_2\mathrm{NF} + w_3\mathrm{LF} + w_4\,(1 - \mathrm{SNR}_{pre}) \quad (4)$$

Where w_1, w_2, w_3, and w_4 are weighting coefficients assigned to each parameter, satisfying the constraint ($w_1 + w_2 + w_3 + w_4 = 1$). The calculated DSI value lies between 0 and 1, where a higher value shows more severe underwater network conditions. The disaster condition is classified into four levels, based on the DSI value. A DSI of between 0 and 0.25 indicates normal conditions (not much communication problem in the network). This range of values 0.25 to 0.50 is considered to be in a mild disaster condition, where some channel quality changes and occasional link failures may be expected. The DSI value between 0.50 and 0.75 is for moderate disaster conditions, where the amount of packet loss rises, links become unstable, and communication reliability lowers.

If the DSI value is 0.75 and higher, the condition is deemed to be severe with high channel degradation, frequent link failure, node failure and communication interruptions. The severity of the disaster is then calculated and used to route through the communication paths to find appropriate ones.

The routing algorithm under normal conditions mainly concerns with saving energy and prolonging network life. With the escalation of the disaster, more emphasis is placed on the reliability of the links, stability of nodes, and predicted channel conditions. The routing process is thus dynamically adjusted based on the existing disaster situation, thereby ensuring stable data transmission in the critical underwater disaster environment and optimizing energy consumption in the normal network.

2.5. Adaptive Routing Cost Function

The proposed routing framework uses an adaptive routing cost function that enables energy efficiency and communication reliability to be dynamically adjusted based on the estimated disaster's severity. The proposed routing method would adjust the disaster intensity-dependent routing priorities, in contrast to traditional routing methods, where the weights are fixed regardless of the disaster situation.

Therefore, the routing strategy can choose the optimal path according to the energy consumption in the common network, and can select highly reliable communication path in the case of severe disaster. The transmission energy required for sending a packet of size (k) over a communication distance (d) is calculated using the underwater acoustic energy model as in Equation (5):

$$E_{tx}\,(k,d) = E_{elec}\,.\,k + E_{amp}\,.\,k\,.\,d^{\gamma} \quad (5)$$

Where E_{elec} represents the electronic energy consumed per transmitted bit, $E_{amp}$is the acoustic amplifier coefficient, (d) denotes the transmission distance, and γ is the underwater acoustic path-loss exponent. Similarly, the reception energy is expressed as E_{rx} (k)= E_{elec}·k, which represents the energy required to receive a packet of size (k).To incorporate disaster awareness into the routing process, the routing cost for each communication link (i,j) is formulated as in Equation (6):

$$C_{ij} = \alpha\,(\mathrm{DSI})\frac{E_{tx}}{E_{residuals}} + \beta\,(DSI)\left(1 - R_{ij}\right) + \gamma\,(\mathrm{DSI})\,\left(1 - LQ_{ij}\right) \quad (6)$$

In the proposed routing model, The routing cost C_{ij} is calculated for each communication link between sensor nodes i and j by considering the estimated disaster severity, link reliability, and predicted link quality. The coefficient α (DSI) represents the disaster-dependent routing component, while β (DSI) controls the importance of communication reliability. Similarly γ (DSI) controls the importance of the predicted link quality.

The coefficients are dynamically adjusted according to the estimated disaster severity, allowing the routing strategy to give greater importance to energy-efficient operation under normal conditions and to reliable and high-quality communication links during severe disaster conditions. The routing coefficients are dynamically adjusted according to the estimated DSI. The energy-related coefficient is defined as $\alpha(DSI) = 1 - DSI,$ which decreases as disaster severity increases. The reliability coefficient is defined as $\beta(DSI) = 0.5 + 0.5\,DSI,$ which increases with disaster severity, thereby giving greater importance to reliable communication links under severe conditions.

Similarly, the predicted link-quality coefficient is defined as $\gamma(DSI) = DSI,$ which increases as the disaster becomes more severe and gives greater importance to the predicted quality of the communication link. Therefore, under normal network conditions, where DSI is low, the routing process gives relatively greater importance to energy efficiency. As disaster severity increases, the contribution of the energy-related component decreases, while the importance of link reliability and predicted link quality increases.

This adaptive adjustment enables the proposed routing framework to change its routing priorities according to the severity of the disaster. where R_{ij} represents the reliability of the communication link between sensor nodes i and j. It is calculated from the predicted SNR as $R_{i,j} =$

$\frac{\{SNR_{i,j}^{pre} - SNR_{\{min\}}\}}{SNR_{\{max\}} - SNR_{\{min\}}}$, where $SNR_{i,j}^{pre}$ is the SNR predicted by the GCN-LSTM model for the link between nodes i and j, while $SNR_{\{min\}}$ and $SNR_{\{max\}}$ represent the minimum and maximum reference SNR values, respectively. The value of $R_{i,j}$ is normalized between 0 and 1, where a higher value indicates a more reliable communication link. A higher value of R_{ij} indicates a more reliable link, while $1 - R_{ij}$ represents the corresponding link unreliability penalty in the routing cost. LQ_{ij} represents the predicted link quality between sensor nodes i and j.

A higher value of LQ_{ij} indicates better communication quality, while $1 - LQ_{ij}$ represents the corresponding link-quality penalty in the routing cost. The predicted link quality LQ_{ij} is obtained using the predicted RSSI and SNR values. It is defined as $LQ_{ij} = \frac{RSSI_{i,j}^{norm} + SNR_{i,j}^{norm}}{2}$ where $RSSI_{i,j}^{norm} = \frac{RSSI_{\{ij\}} - RSSI_{\{min\}}}{RSSI_{\{max\}} - RSSI_{\{min\}}}$ and $SNR_{i,j}^{norm} = \frac{SNR_{\{ij\}} - SNR_{\{min\}}}{SNR_{\{max\}} - SNR_{\{min\}}}$ are the normalized predicted RSSI and SNR values, respectively.

Thus, LQ_{ij} also lies between 0 and 1, with a higher value indicating better communication quality. The terms $1 - R_{ij}$ and $1 - LQ_{ij}$ represent the reliability and link-quality penalties, respectively, used in the adaptive routing cost function.

2.6. Priority-Aware Routing Strategy

During disasters, timely delivery of critical data is essential. To achieve this, need to be design a priority weighted loss function in Equation (7):

$$L = \frac{1}{N}\left(y_{true} - y_{pred}\right)^2 . w_p \tag{7}$$

Where w_p represents the priority weight of packets. Routing decisions are made by balancing predicted energy consumption and link stability (RSSI, SNR).

For high-priority packets, paths with higher stability are selected even at higher energy cost. For low-priority packets, energy-efficient routes are preferred.

2.7. Algorithm

The complete process is summarized in Algorithm 1.

Input: Dynamic network graph (G(V,E)), packet size (k), source node (S), destination node (D), node feature matrix (X_t), trained GCN-LSTM prediction model (M), disaster weighting parameters w_1,w_2,w_3,w_4.

Output: Optimal routing path P* and adaptive transmission

Step 1: Data Preprocessing Remove invalid values (e.g., RSSI > 0, SNR < −50). Apply imputation for missing values and outlier filtering.

Step 2: At time t, construct node feature matrix X_t including RSSI, SNR, traffic load, and residual energy.

Build the Dynamic Graph $G_t = (V,E_t,A_t)$ and compute the normalized adjacency matrix.

$$A_t^{norm} = D^{-\frac{1}{2}}(A_t + I)\, D^{-\frac{1}{2}}$$

Step3. First, spatial features are extracted using a Graph Convolutional Network (GCN):

$$H_t = \sigma\left(A_t^{norm}\, X_t\, W_g\right)$$

Where, A_t^{norm} is the normalized adjacency matrix, W_g is the GCN weight matrix, and σ is the activation function. Next, temporal dependencies are learned using an LSTM network:

$$h_t, c_t = \mathrm{LSTM}\left(H_t, h_{t-1}, c_{t-1}\right)$$

For each node i, use M to predict $\hat{y}_i$ = (RSSI, SNR, Traffic). Compute prediction loss with priority weighting:

$$L = \frac{1}{N}\left(y_{true} - y_{pred}\right)^2 . w_p$$

Step 4: Energy Model For each link (i, j) ∈ E, compute transmission energy:

$$E_{tx}(k,d) = E_{elec} . k + E_{amp} . k . d^{\gamma}$$

Step 5: Calculate the DSI using packet loss, node failure, link failure, and predicted SNR. Update the adaptive coefficients α(DSI), β(DSI), and γ(DSI).

$$\mathrm{DSI} = w_1\mathrm{PL} + w_2\mathrm{NF} + w_3\mathrm{LF} + w_4\left(1 - \mathrm{SNR}_{pre}\right)$$

Update the adaptive routing coefficient.

α (DSI) =1−DSI, β (DSI)=0.5+0.5DSI, γ(DSI)=DSI

Step 6: For each communication link (i,j), calculate the routing cost using Cij, the estimated disaster severity, link reliability R_{ij}, and predicted link quality LQ_{ij}.

$$C_{ij} = \alpha\,(\mathrm{DSI})\frac{E_{tx}}{E_{residuals}} + \beta\,(DSI)\left(1 - R_{ij}\right) + \gamma\,(\mathrm{DSI})\left(1 - LQ_{ij}\right)$$

where $R_{i,j}$ represents the reliability of the link between nodes i and j based on the predicted communication conditions, and $LQ_{i,j}$ represents the predicted link quality. The coefficients α(DSI), β(DSI), and γ(DSI) are dynamically determined according to the estimated disaster severity.

Step 7: For each candidate neighboring node, compare the calculated routing cost. Cij and select the next-hop node with the minimum routing cost.

Step 8: Forward the packet through the selected next-hop node according to its assigned priority.

3. Result and Discussion

This section presents the performance evaluation of the proposed GCN-LSTM based disaster-aware energy-efficient routing scheme for underwater wireless sensor networks. The proposed routing framework is evaluated against LEACH, DBR, EEDBR, and the conventional GCN-LSTM routing framework under the same network and channel conditions. The comparison is performed using packet delivery ratio, end-to-end delay, energy consumption, network lifetime, and routing recovery performance. The conventional GCN-LSTM framework is used as the primary learning-based baseline to evaluate the additional contribution of the proposed mechanism.

3.1. Dataset Generation and Experimental Configuration

The proposed framework is tested using a synthetic UWSNs dataset that represents different underwater communication conditions in both normal and disaster situations. Real-world underwater datasets for disaster events are difficult to collect because underwater deployment requires high cost and proper access to the sensing environment. Therefore, a simulation-based method is used to generate the required dataset. The generated data represent important changes that can occur in an underwater network, such as node movement, channel variations, packet loss, link failures, and changes in network topology during a disaster.

For the simulation, a three-dimensional underwater network with 100 sensor nodes is considered. The nodes are randomly placed in a 1000 m × 1000 m × 500 m underwater area. The sensor nodes communicate using acoustic links and periodically send the collected information towards the surface sink node. To make the simulation closer to actual underwater conditions, the position of the nodes is changed according to the effect of underwater currents.

The communication links are also affected by propagation delay, signal attenuation, ambient noise, and random packet losses. During each communication interval, different network parameters are collected, including RSSI, SNR, traffic load, residual energy, packet loss ratio, node failure ratio, link failure ratio, water depth, water temperature, and transmission distance. Different disaster situations are also included in the dataset to study the behaviour of the network under changing conditions. Four types of underwater disasters are considered, namely underwater earthquakes, tsunamis, submarine landslides, and severe storms.

The effect of these disasters is represented by increasing node failures, communication interference, channel attenuation, and packet loss. According to the changes in these parameters, the network condition is divided into four levels: Normal, Mild, Moderate, and Severe. A total of 50,000 communication samples are produced for the experiments. For the proposed GCN-LSTM prediction model, the entire dataset is split into 70% training, 15% validation, and 15% testing data for training and testing the model.

The dataset generated has various network conditions and disaster level, providing support for the evaluation of the proposed routing framework when considering various underwater conditions. The effectiveness of underwater disaster routing framework for the proposed DSW-GCN-LSTM algorithm is verified under various disaster scenarios in the underwater environment.

The proposed routing method is evaluated with some of the existing routing protocols like LEACH, DBR, EEDBR and GCN-LSTM routing model without DSW mechanism. Parameters used to make the comparison include packet delivery ratio, energy consumption, network lifetime, and routing robustness. These are metrics to look at the communication health after a network change due to a disaster is applied to the suggested method. The experiments are repeated several times to minimize the impact of random noise, and average performance across the various simulation run is used for each experiment.

3.2. Dataset Validation

A validation process was carried out prior to model training to assess the quality and suitability of the synthetic dataset. The proposed model predicts the temporal variations of traffic load, RSSI, and SNR, which are used to assess the communication conditions and support disaster-aware routing decisions. The generated data were processed to maintain consistency, and invalid samples were eliminated during the Preprocessing stage. Next, descriptive statistical analysis was performed by calculating the mean, standard deviation, minimum, and maximum values for each feature. This analysis was used to examine the distribution and variation of the generated parameters under different underwater network conditions.

Correlation analysis was then conducted to examine the relationships among the communication parameters. RSSI and SNR showed a positive correlation, while packet loss showed a negative correlation with RSSI and SNR. Similarly, an increase in transmission distance and the number of node or link failures resulted in an increase in packet loss. These relationships are consistent with the expected behaviour of underwater communication networks. The generated dataset was then divided into training (70%), validation (15%), and testing (15%) sets. The training set was used to optimize the parameters of the GCN-LSTM model, while the validation set was used for hyper-parameter tuning and early stopping to reduce the possibility of overfitting. The testing set was reserved for the final evaluation of the prediction performance. The predictive performance of the GCN-LSTM model was evaluated using MAE, RMSE, and R^2.

Table 1. Validation results of the GCN-LSTM prediction model

Metric	Training	Validation	Testing
MAE	0.041	0.045	0.048
RMSE	0.058	0.063	0.067
R^2	0.972	0.964	0.958

The testing results produced an MAE of 0.048, an RMSE of 0.067, and an R^2 value of 0.958. These results indicate that the model can accurately learn and predict the selected underwater communication parameters from the generated data. The close performance across the training, validation, and testing sets also indicates that the model does not exhibit substantial overfitting. Therefore, the generated dataset provides a suitable simulated environment for evaluating the proposed disaster-aware routing framework.

Overall, the results show that the GCN-LSTM model provides stable prediction performance across the training, validation, and testing datasets. The small difference between the obtained errors indicates that the model maintains consistent performance on unseen data. The high R^2 value indicates that the model effectively captures the variations in the selected underwater communication parameters. Hence, the validated synthetic dataset can be effectively used for further evaluation.

3.3. Packet Delivery Ratio

UWSNs have many important performance metrics, such as Packet Delivery Ratio (PDR), which is utilized to assess the reliability of communication. Under increasing disaster severity, as shown in Figure 2, different routing protocols achieved PDR as follows. The proposed framework can consistently achieve the best packet delivery ratio in all disaster scenarios. All routing protocols perform the same in normal operation, as communication links do not change significantly. As the extent of disaster grows, however, conventional routing protocols suffer greatly from packet delivery as the links frequently fail, nodes move around, and the channels degrade severely.

The proposed framework, on the other hand, leverages forecasts of RSSI and SNR values along with the DSW mechanism to identify unstable communication links in advance and choose more reliable communication routes prior to the occurrence of a disaster. Under the overall performance comparison, the proposed framework achieves a PDR of 96.8%. When evaluated according to disaster severity, the PDR ranges from 97.5% under normal conditions to 94.0% under severe disaster conditions. These results indicate that the proposed DSW mechanism maintains reliable communication as disaster severity increases.

3.4. End-to-End Delay

Figure 4 presents the average end-to-end delay of the evaluated routing protocols. As disaster intensity increases, communication interruptions and repeated route discoveries significantly increase transmission latency in conventional routing algorithms. The proposed framework substantially reduces the average end-to-end delay by predicting future channel conditions and dynamically selecting reliable forwarding paths before communication failures occur.

Furthermore, the adaptive weighting mechanism increases the importance of link reliability during severe disaster conditions, thereby minimizing retransmissions and route reconstruction overhead. As a result, the proposed routing framework achieves an average delay of approximately 185 ms, which is considerably lower than the comparison methods.

3.5. Energy Consumption

The average energy use of various routing protocols is compared in Figure 3. One of the key issues in UWSNs is energy efficiency since underwater sensor nodes are battery limited and battery replacement in UWSNs is unfeasible. Routers often waste energy by re-transmitting packets and by performing a route discovery every time a communication fails when using conventional routing protocols.

The proposed DSW routing strategy optimizes the use of unnecessary transmissions by proactively selecting stable communication paths in advance, based on the forecasted channel conditions. In normal operation, the routing algorithm mainly aims to transmit energy efficiently, and in severe disaster state, it gradually focuses on the communication reliability. This adaptive behaviour leads to the average energy consumption of around 0.82J, which is a very significant improvement over the existing routing protocols.

3.6. Network Lifetime

Figure 5 shows the network lifetime obtained by different routing protocols. The proposed framework performs better because it distributes the network traffic among different reliable paths instead of depending too much on a single node or route.

This helps to avoid high energy consumption at individual nodes. The proposed routing method also reduces unnecessary retransmissions and distributes the forwarding work among the available nodes, which helps in delaying node failures caused by battery depletion.

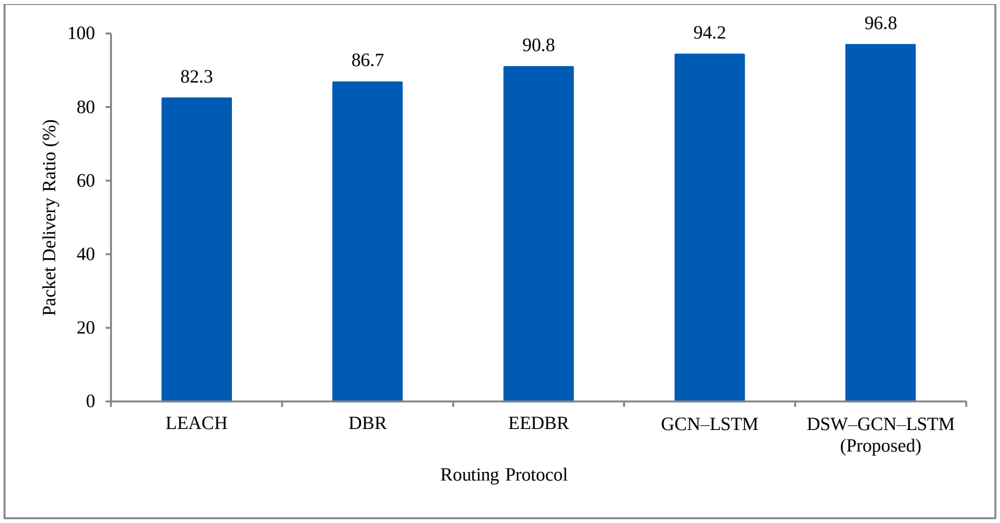

Fig. 2 Packet delivery ratio comparison

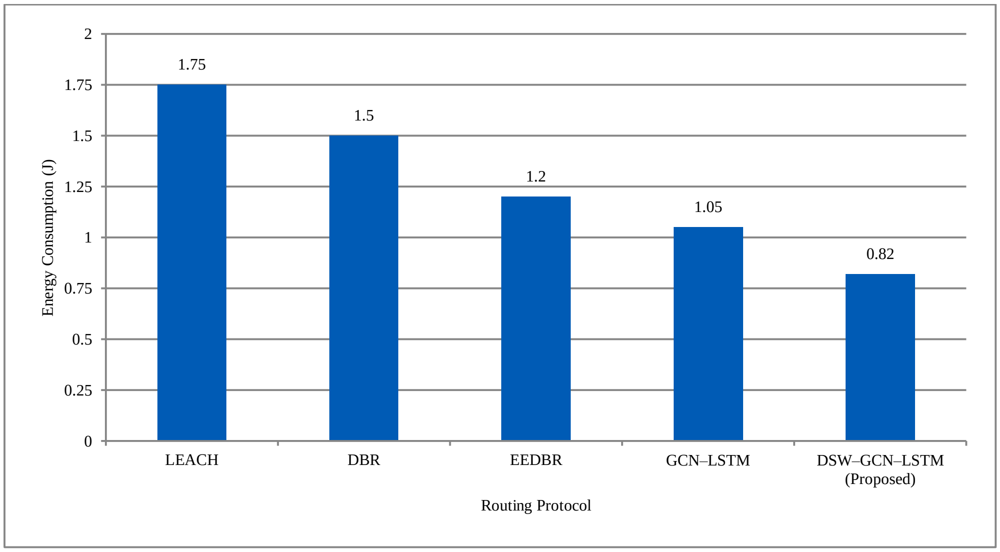

Fig. 3 Energy consumption comparison

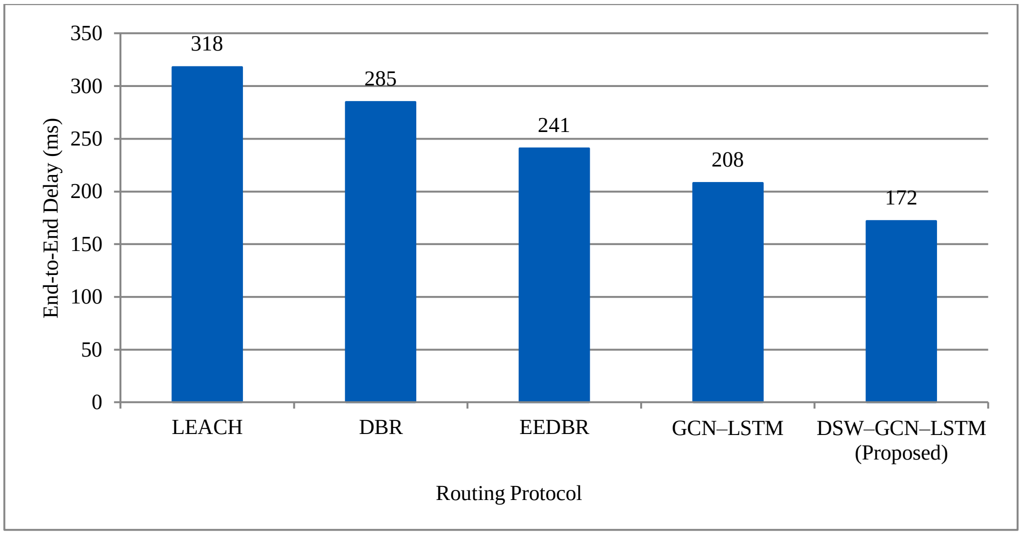

Fig. 4 End-to-End delay comparison

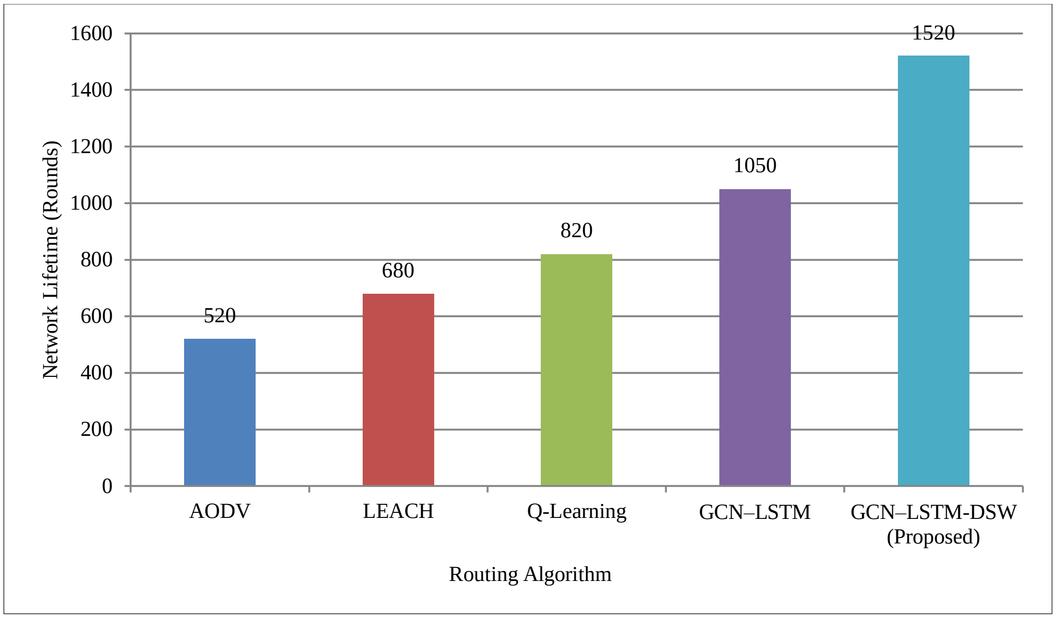

Fig. 5 Network lifetime comparison

As a result, the proposed framework improves the network lifetime by approximately 12.6% compared with the baseline GCN-LSTM model and performs better than the conventional routing protocols under disaster conditions. The obtained results show that the combination of GCN, LSTM, and the proposed Disaster Severity Weighted mechanism improves the overall performance of underwater communication. Traditional routing protocols mainly make decisions using the current network condition, whereas the proposed framework also considers the predicted future channel condition and changes the routing priority according to the disaster severity. This allows the routing process to identify and avoid unstable links before they fail. It also helps to reduce retransmissions and save energy when the network is in normal condition, while during severe disaster conditions; more importance is given to reliable communication.

3.7. Performance Evaluation

Further experiments were conducted under a new disaster severity degree level. Through the results obtained, it is found that the underwater communication system using the proposed technique has better overall performance. The traditional routing protocols take into account only the current network condition, while the proposed framework also takes into account the predicted future channel condition and changes the routing priority depending on the severity of the disaster. This permits the routing process to recognize and steer clear of unstable links even in the event of their failure. It also decreases retransmission and energy consumption in normal times, and takes more consideration for reliable communication in severe disaster times. Overall, the proposed framework has advantages such as better packet delivery, lower end-to-end delay, lower energy usage, faster recovery of the route, and longer network life, demonstrating its applicability for reliable communication in disaster-stricken UWSN. Further experiments were conducted under a new disaster severity degree level (Normal, Mild, Moderate and Severe) to analyze the adaptability of the proposed routing framework. This table could be helpful when demonstrating how more valuable the DSW mechanism becomes as the underwater disaster gets worse. The performance of the conventional GCN-LSTM routing framework is compared with the proposed GCN-LSTM integrated with DSW mechanism in Table 2. The results show that the DSW module can effectively improve the reliability of communication, energy efficiency and resilience of the underwater network in the face of a dynamic underwater disaster. The proposed framework achieves a PDR of 96.8% while the conventional GCN-LSTM model achieves 94.0%, which is an increase of 2.8%.

The improved performance is said to be due to the adaptive routing strategy, which relies on the DSI to detect the unstable communication links and dynamically re-route traffic to more stable ones before the links fail. As a result, less data packets are wasted during data transmission, especially in severe disaster situations. There is also a significant decrease in the communication latency. The proposed method has an average reduction in end-to-end delay of 185ms from 210ms, which gives a reduction of 11.9%. The routing algorithm proactively predicts the degradation of the channel and avoids using an unreliable channel in the routing process, thereby significantly reducing the number of retransmissions and the route reconstruction process, which leads to faster delivery of packets. Likewise, the proposed framework enhances the energy efficiency by decreasing the average energy consumption from 0.90 J to 0.82 J, which is an 8.9% decrease.

The adaptive routing cost gives higher priority to energy conservativeness during normal operation and gradually switches the routing preference to communication reliability during severe disaster conditions. This adaptive behavior avoids useless packet re-transmission and can help to distribute energy consumption among sensor nodes.

Table 2. Performance comparison

Metric	GCN-LSTM	GCN-LSTM-DSW	Improvement
PDR(%)	94.0	96.8	+2.8%
End-to-End Delay (ms)	210	185	−11.9%
Energy Consumption (J)	0.90	0.82	−8.9%
Network Lifetime (Rounds)	1050	1520	+44.7%
Route Recovery Time (s)	2.3	1.5	−34.8%
Link Failure Rate (%)	10.2	6.8	−33.3%

In addition, the network lifetime is significantly boosted from 1050 rounds to 1520 rounds, representing an improvement of approximately 44.7%. The balanced energy usage and lower communication overheads lead to increased lifetime, since the battery is not drained out in a hurry, and the operational life of the underwater sensor network is extended. The DSW is also proposed to improve network recovery after a communication disruption. The route recovery time is improved on average from 2.3 s to 1.5 s, which is an improvement of 34.8%. This reduction is possible because the routing protocol can anticipate the failure of an individual link and can create other communication paths before the link fails.

Moreover, the failure rate of the link drops from 10.2% to 6.8%, which is 33.3% reduction. The GCN-LSTM model continuously predicts traffic load, RSSI, and SNR for the network nodes. These predicted parameters are subsequently used to evaluate link conditions and adapt routing decisions according to the estimated disaster severity. In general, the experimental results validate that routing based on the Disaster Severity Weighting mechanism and the underwater condition prediction model based on the GCN-LSTM model can adapt to the underwater environment. The approach proposed here differs from the traditional GCN-LSTM architecture by using variable routing priorities depending on the severity of the disaster, estimating the situation. This adaptive decision-making capability results in increased packet delivery, reduced communication delay, energy saving, longer network life, quicker route recovery, and enhanced resilience in an underwater network in the event of disasters.

3.8. Performance under Different Disaster Severity Levels

Experiments were performed for the proposed routing framework to assess its adaptability to different levels of disaster severity -Normal, Mild, Moderate, and Severe. The results of the conventional GCN-LSTM model and the proposed GCN-LSTM integrated with the DSW mechanism are shown in Table 3. Both models perform well with similar performance under normal network conditions, where the PDR of the conventional GCN-LSTM model is 97.0%, and the proposed model is 97.5%. The improvement is on the low end, as the communication links are not changing, and there is little need for extensive routing adaptation. Under mild disaster conditions, the proposed model yields a PDR of up to 96.8%, which shows that the proposed DSW mechanism starts to detect the breaking links and adjust the routes before the communication quality becomes too poor. The benefit of the proposed approach becomes more apparent as the disaster severity escalates to a moderate level. The packet drop ratio improves from 94.0% to 95.8%, showing the effectiveness of the adaptive routing based on the DSW to decrease the packet drop rate due to node failures and changing channel conditions. The best improvement occurs under severe disaster conditions, when the conventional GCN-LSTM model has a PDR of 88.0% while the proposed framework has 94.0% or a 6 percentage point relative improvement of 6.8%.

Table 3. Performance comparison under underwater disaster severity

Disaster Severity	GCN-LSTM	GCN-LSTM + DSW
Normal	97%	97.5%
Mild	96%	96.8%
Moderate	94%	95.8%
Severe	88%	94.0%

This is a very important achievement as it shows that the DSW mechanism effectively redirects the routing from energy conservation to communication reliability when network conditions are extremely unstable. Overall, the results indicate that the proposed DSW mechanism offers minimal intervention when there is little or no disaster events, hence maintaining energy efficiency, but starts to take effect as the disaster increases in severity. This adaptive routing mechanism ensures proper communication, minimizes packet losses, and enhances network robustness under critical underwater disaster situations. As can be seen from the results, the difference between the conventional GCN-LSTM model and the proposed framework becomes larger with the increase of disaster severity. The trend shows that the routing strategy described in this paper is not only efficient in normal scenarios but also has the ability to meet the requirements of underwater communication during disasters. The proposed routing framework dynamically changes the routing cost based on the Disaster Severity Index and proactively finds a reliable communication path before a failure occurs, and thus, in a challenging underwater environment, the packet delivery is always higher. The above superior demonstrated in severe disaster conditions confirms the effectiveness of combining disaster-aware adaptive weighting and spatio-temporal channel prediction. The experimental results show that the proposed Disaster Severity Weighted approach is able to appropriately change the routing priorities according to the network's changing condition.

In the normal operating mode, energy conservation is the main goal, leading to fair use of the batteries and long network lifetime. When the disaster grows in severity, the adaptive routing cost gradually tends to focus more on communication reliability and predicted channel quality, which allows the routing protocol to keep stable communication even in the face of frequent node failures and degrading underwater channel conditions. Table 3 shows the comparison of the conventional GCN-LSTM model and the GCN-LSTM-DSW routing model for dynamic underwater disaster scenarios.

This adaptive behavior results in a substantial reduction in the amount of packets lost, and an increase in the delivery of packets during critical disaster events, and it also decreases the communication delay. The performance comparison between the conventional GCN-LSTM framework and the proposed GCN-LSTM-DSW routing framework is given under dynamic underwater disaster scenarios in Table 3. The proposed method achieves consistently better PDR across all disaster severity levels, which shows the effectiveness of the adaptive disaster-aware routing strategy.

Table 4. Comparative prediction performance model using regression evaluation metrics

Model	MAE	RMSE	R^2
LSTM	0.086	0.121	0.891
GCN	0.071	0.099	0.917
GCN-LSTM-DSW	0.048	0.067	0.958

The experimental results show that the proposed Disaster Severity Weighted mechanism is able to adapt the routing priorities as per the varying network conditions. In normal working, the energy saving is still the main goal, and the utilization of the battery is balanced, and the life of the network is longer. As the disaster increases, the adaptive routing cost gradually changes its focus to communication reliability and predicted channel quality, which allows the routing protocol to keep communication stable under the frequent failure of nodes and the poor underwater channel situation. This adaptive behaviour can decrease the communication delay and packet loss during a critical disaster event, and it can effectively enhance the packet delivery. The proposed method consistently outperforms the baseline in the reported routing performance metrics, which shows the effectiveness of the adaptive disaster-aware routing scheme. The testing dataset was used to test the predictive capability of the proposed GCN-LSTM model by employing the Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and coefficient of determination (R^2) as standard regression metrics. Table 4 shows that the model has an MAE of 0.048, an RMSE of 0.067 and R^2 value of 0.958 on the testing dataset. Low value of MAE and RMSE shows that the value of the communication parameters predicted by the model is very close to the value of the target communication parameters, and the high value of R^2 shows that the proposed prediction model explains the variance of 95.8% of the observed one. The results validate the effectiveness of the underwater communication characteristics captured by these results and serve as a suitable dataset for training and evaluating the proposed underwater Disaster Severity Weighted GCN-LSTM routing framework.

4. Conclusion

This paper proposed a Disaster Severity Weighted GCN-LSTM routing scheme to enhance the reliability of communication and save energy in UWSN under a dynamic disaster environment. The proposed framework combines a GCN to learn the spatial relationship between the sensor nodes, an LSTM network to predict the time-varying underwater communication parameters, and a novel Disaster Severity Weighting (DSW) mechanism that adaptively adjusts the routing decisions based on the estimated severity of the underwater disaster. Unlike conventional routing methods, which rely on fixed routing priorities, the proposed method dynamically optimizes the energy, link reliability and channel quality to make proactive decisions on which routes to use under changing network conditions.

The simulation results showed that the proposed framework achieved superior performance in terms of various performance metrics in comparison with the traditional GCN-LSTM routing model. In particular, the proposed approach achieved an overall Packet Delivery Ratio of 96.8%, decreased the average end-to-end delay from 210 ms to 185 ms, reduced the energy consumption from 0.90 J to 0.82 J. The network lifetime improves from 1050 rounds for the conventional GCN-LSTM approach to 1520 rounds for the propose framework, and reduced the link failure rate from 10.2% to 6.8%. Under different disaster severity levels, the proposed framework achieved PDR values ranging from 94.0% under severe conditions to 97.5% under normal conditions, demonstrating its ability to adapt routing priorities according to changing disaster conditions.

The results show that the proposed spatio-temporal channel prediction combined with an adaptive disaster-aware routing approach can effectively improve the robustness and resilience of underwater communication networks. The proposed framework dynamically changes the routing priority according to the estimation of the disaster level, which helps minimize packet loss, the interruption of communication, and optimize network performance, ensuring efficient energy consumption during disasters. The proposed framework is able to exhibit good performance, but the procedure adopted in this study is simulated underwater. Future work involves testing the proposed routing framework with either Aqua-Sim NG or NS-3 underwater network simulator, and adding to the models more realistic underwater acoustic propagation models, node mobility patterns and environmental factors. Furthermore, the combination of reinforcement learning/transformer-based prediction models and the proposed disaster-aware routing mechanism could further enhance the adaptability and communication reliability of large-scale underwater monitoring systems. In summary, the proposed Disaster Severity Weighted GCN-LSTM framework can be used to enhance the reliability, energy efficiency and disaster-resilience of communication in UWSNs, which is suitable for underwater environmental monitoring, offshore infrastructure monitoring and underwater disaster early-warning applications.

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