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Hybrid ARMA-LSTM model for adaptive link prediction in dynamic underwater sensor networks

Ritu Bhardwaj[1], Ashwani Kush[2]
[1]DCSA Kurukshetra University, Kurukshetra, India
[2]IIHS Kurukshetra University, Kurukshetra, India

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ABSTRACT

Underwater wireless sensor network (UWSN) is highly vulnerable to packet loss due to varied features of underwater channels, including multipath fading, high latency, and environmental interference. Accurate prediction of packet loss is critical for improving data reliability and network performance. Our research presents a new approach to forecasting using a combination of autoregressive moving average (ARMA) and long short-term memory (LSTM) networks which are statistical models. A synthetic dataset was generated to facilitate model development and evaluation, simulating realistic UWSN conditions by varying key parameters such as signal-to-noise ratio (SNR), received signal strength indicator (RSSI), depth, distance, and temperature. The ARMA model captures linear temporal trends, while the LSTM network is trained on the ARMA residuals to learn nonlinear correction patterns. The findings indicate that the hybrid ARMA-LSTM model exhibits a marked superiority over the standalone ARMA model, achieving an approximate 85.4% reduction in mean absolute error (MAE), an 83.6% enhancement in root mean square error (RMSE), a significant boost in predictive accuracy as reflected by the R^2 score, which improved from -43.93 to -0.20. The results highlight the hybrid method a strong and precise solution for predicting packet loss in UWSN, directly impacting the improvement of reliability in underwater communication.

Corresponding Author:

Ritu Bhardwaj
DCSA Kurukshetra University
Kurukshetra, India
Email: 2228ritu@kuk.ac.in

1. INTRODUCTION

Underwater wireless sensor networks (UWSNs) play a vital role in applications such as marine environmental monitoring, disaster management, offshore exploration, and surveillance. Unlike terrestrial networks, UWSNs rely mainly on acoustic communication, which is characterized by limited bandwidth, long propagation delays, multipath fading, and strong environmental interference [1], [2]. These challenges make reliable data transmission difficult and increase the risk of packet loss, which directly affects the quality of service, energy efficiency and overall network performance. A central issue in UWSNs is the accurate prediction of packet loss [3]. If nodes can anticipate deteriorating link conditions, they can proactively adapt routing, power control or error correction strategies, thereby improving communication reliability [4]. However, forecasting packet loss is challenging due to the nonlinear and non-stationary nature of underwater acoustic channels, where environmental parameters such as depth, distance, and temperature strongly interact with communication metrics like received signal strength indicator (RSSI) and signal-to-noise ratio (SNR) [5]. Several approaches have been explored to tackle this problem. This study proposed an index and machine learning based approach for post disaster assessment of community risk and resilience based on coupled human infrastructure systems performance [6]. Traditional time-series models such as the autoregressive moving average (ARMA) [7] and Kalman filters [8] provide efficient and interpretable solutions but are limited to stationary and linear patterns [9]. Deep learning techniques [10], including long short-term memory (LSTM) [11] and graph neural networks (GNNs) [12], capture nonlinear and topological dependencies but often require high computational resources and large training datasets [13]. Reinforcement learning (RL) [14], [15] based schemes have also been applied to adaptively optimize routing and link prediction, but they suffer from training overhead and instability in dynamic underwater conditions [16]. These limitations indicate that existing methods either achieve efficiency at the cost of accuracy or accuracy at the cost of practicality. To overcome these challenges, this study proposes a hybrid ARMA–LSTM model for packet loss prediction in UWSNs. In this framework, ARMA is first applied to capture linear temporal trends, and the residual errors are then modeled using LSTM to learn nonlinear behaviors. This structured two stage pipeline leverages the strengths of both statistical forecasting and deep learning, thereby producing more accurate predictions without the high computational cost of purely deep learning approaches.

This research lies in three key aspects. First, it introduces a structured residual learning fusion strategy between ARMA and LSTM which has not been systematically explored in UWSNs. Second, it employs a feature set that combines both environmental (depth, distance, and temperature) and communication parameters (RSSI, SNR, and packet loss), providing a holistic representation of underwater conditions. Third, the training pipeline incorporates residual preprocessing, normalization, and sequence generation to stabilize learning and avoid temporal data leakage. Together, these contributions advance the state of the art in packet loss prediction and provide a balanced solution that enhances the reliability of UWSNs. The main objectives of this research are to evaluate the successful performance of the ARMA model in forecasting packet loss within UWSNs to develop a hybrid ARMA-LSTM model capable of capturing both linear and non-linear trends in packet loss, to assess and contrast the efficacy of both models on extensive synthetic datasets under uniform experimental conditions.

2. METHOD

Forecasting packet loss and signal behavior in UWSNs is critical due to the hostile and noisy underwater environment, where linear models like ARMA often fall short in capturing nonlinear complexities. To address this hybrid models that combine the linear strength of ARMA models with the nonlinear learning capabilities LSTM networks have emerged as a promising solution. These studies collectively support the hypothesis that hybrid ARMA-LSTM models are more effective for complex time series forecasting than individual models. They leverage strength of ARMA to capturing short-term dependencies and LSTM in learning long-term nonlinear trends, making them highly suitable for challenging domains like UWSNs where both types of dependencies coexist. The novelty of this study lies in three aspects. First, unlike previous hybrid time-series models that loosely combine statistical and deep learning techniques [17], the proposed ARMA-LSTM strategy employs a structured two stage pipeline where ARMA captures the linear dependencies and the residual nonlinearities are explicitly modeled by LSTM [18], resulting in a more accurate correction process. Second, the feature set is carefully constructed to reflect realistic underwater dynamics by including both physical (depth, distance, and temperature) and communication related parameters (RSSI, SNR, and packet loss), enabling the model to learn joint relationships that were often overlooked in earlier works focused on a single parameter. Third, the training pipeline integrates residual preprocessing, normalization, and a sliding window sequence generation, which ensures stable LSTM learning and prevents data leakage across temporal boundaries. Together, these elements distinguish the proposed framework from prior ARMA only, LSTM only, hybrid approaches, offering a balanced solution that improves both efficiency, and predictive accuracy in UWSNs.

2.1. Signal quality parameters and data generation

In underwater environments, signal attenuation is extensively higher than in terrestrial systems due to absorption by water molecules, scattering, multipath propagation, limited bandwidth of acoustic signals [19]. For this a step by step approach is to be followed. Initially simulators were used and then to produce more realistic effects, data sets have been taken into account and programming approach has been used. Since Python is able to provide most of the libraries and functions needed, so Python has been selected for Programming. Python has been used to generate a data set for the analysis. To simulate realistic underwater communication scenarios, a synthetic dataset was generated using well established statistical distributions. Each distribution was chosen to reflect the natural behavior of its respective parameter, based on observed characteristics in literature and underwater acoustic communication experiments. To examine the performance of hybrid ARMA-LSTM model in predicting signal behavior and packet loss in UWSNs we created a comprehensive synthetic dataset that simulates realistic underwater communication scenarios over time. The dataset includes the key physical and communication parameters typically observed in UWSNs, such as RSSI, SNR, packet loss, depth, temperature, and distance between nodes. The dataset consists of 1000 times steps with hourly intervals, starting from January 1, 2024. The timestamp column is used as the index to facilitate time series forecasting. RSSI is modeled as a sinusoidal function with added Gaussian noise, centered around -80 decibel mill watt (dBm) to mimic signal fluctuation due to underwater turbulence, multipath effects, and environmental variations.

As in (1) T_{rssi} defines the oscillation period and $\varepsilon_r(t)$ is Gaussian noise. In underwater acoustic or optical communication systems, signal attenuation is much more severe than in terrestrial environments.

$$RSSI\ (t)\ =\ -80 + 5.sin\ (\frac{2\pi t}{T_{rssi}})\ + \varepsilon_r(t) \tag{1}$$

Therefore, RSSI values typically range from -60 dBm (stronger) to -100 dBm (weaker). -80 dBm is considered a moderate to weak signal and is commonly observed in practical underwater deployments, especially at medium distances (e.g., 30–50 meters) or with modest SNR. -60 dBm would indicate very strong signal strength (rare in UWSNs at longer distances). It would make SNR unrealistically high and packet loss low. -100 dBm too weak, leading to very low SNR and possibly constant high packet loss. -80 dBm is good trade-off to simulate medium link quality and allow meaningful fluctuations. The $5.\sin(\frac{2\pi t}{T_{rssi}})$ simulates environmental fluctuations and $\varepsilon_r(t)$ simulates random variations or noise e.g., multipath, temperature drift. The distance between sensor nodes fluctuates randomly between 10 and 100 meters, simulating dynamic conditions where nodes may move or the signal strength may vary due to changes in distance. The temperature feature is simulated as a sinusoidal function with added Gaussian noise.

In (2) representing fluctuations in environmental temperature, given by where t corresponds to time steps. The SNR is modeled as a linear function of RSSI and distance, with added Gaussian noise, expressed in (3) where t represents the time steps. This model for SNR (t) reflects a realistic relationship between RSSI, distance, and noise.

$$T\ (t) =\ 15 + 5 * sin(10\pi t) + N(0{,}1.5) \tag{2}$$

$$SNR\ (t) = 20 + 0.4 * (RSSI + 80) - 0.05 * distance\ + N(0{,}1) \tag{3}$$

The term 0.4*(RSSI+80) captures the influence of the signal strength, while the term distance accounts for the negative impact of increasing distance on signal quality. The added Gaussian noise represents random environmental variations, ensuring that the model can simulate real world conditions where noise always exists. This approach helps to model a realistic SNR in underwater sensor networks, where signal quality can fluctuate due to both environmental and technical factor. Packet loss PL(t) is synthesized as a function inversely related to SNR and positively influenced by depth and distance, with added Gaussian noise, and is bounded between 0% and 100%.

Packet loss was synthetically modeled as a function inversely proportional to SNR and directly proportional to both depth and distance, with added Gaussian noise to simulate environmental variability. The formulation is given by (4) where the output is constrained within the valid range of 0% to 100%. This reflects real world behavior in underwater communication, where lower signal quality, greater transmission distance and increased depth generally lead to higher packet loss.

$$PL\ (t) = clip[100 - 2 * SNR + 0.1 * depth + 0.2 * distance\ + N(0{,}5)] \tag{4}$$

2.2. Visualize data

In this study, a synthetic dataset consisting of 1000 hourly observations was generated to simulate the key factors affecting packet loss in UWSNs. The dataset includes parameters such as RSSI, SNR, packet loss, node depth, inter node distance, and underwater temperature. These features exhibit temporal variations modeled using sinusoidal functions combined with random noise to closely reflect the fluctuating nature of underwater environments. Visualization of the dataset revealed important relationships, such as the inverse correlation between SNR and packet loss, and the direct correlation between packet loss with increasing depth and distance. This dataset serves as the foundation for training and evaluating a hybrid ARMA-LSTM model, where the ARMA component captures temporal dependencies in the time series, while LSTM model effectively learns long-term patterns and non-linear relationships. The synthetic data not only supports the development of this hybrid model but also validates its ability to predict packet loss under real-world conditions in UWSN, providing a robust framework for enhancing network performance.

Figure 1 temporal variation of key UWSN parameters including RSSI, SNR, packet loss, depth, distance, and temperature from January–February 2024. The figure highlights how environmental factors (depth, distance, and temperature) influence communication quality (RSSI and SNR) and reliability (packet loss), emphasizing the dynamic nature of underwater channels and the need for adaptive model. The y-axis of each subplot represents the magnitude of the respective parameter: RSSI (dBm), SNR (dBm), packet loss (%), depth (m), distance (m), and temperature (°C), while the x-axis represents time (timestamp).

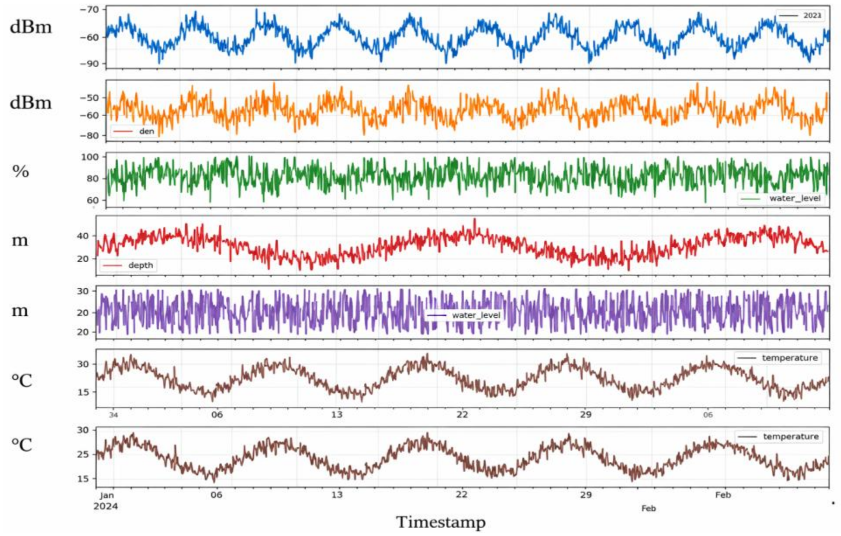

Figure 1. Temporal variation of UWSNs parameters from January to February 2024

2.3. Data correlation analysis

Figure 2 shows the Pearson correlation matrix for the synthetic UWSNs dataset variables like RSSI, SNR, packet loss, depth, distance, and temperature. Strong positive correlation 0.70 between RSSI and SNR confirms that higher signal strength improves signal quality. The strongest negative correlation –0.76 appears between SNR and packet loss, indicating that noisy channels sharply increase packet loss. Distance shows the strongest positive correlation with packet loss 0.79 and a negative correlation with SNR –0.59, highlighting the impact of attenuation over longer ranges. RSSI moderately correlates with packet loss –0.32, while depth exhibits only weak associations e.g., +0.12 with packet loss. Temperature correlations are negligible suggesting limited linear influence compared to dominant features like distance and SNR. These results emphasize the importance of integrating both physical (depth, distance, and temperature) and communication (RSSI, SNR, and packet loss) parameters for realistic UWSNs modeling.

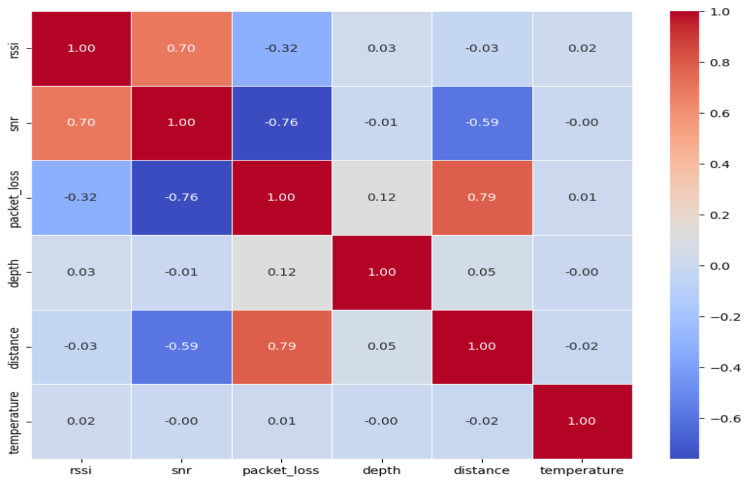

Figure 2. Correlation analysis

2.4. Data normalization

Data normalization is a critical pre-processing step in time series modelling, particularly when combining statistical models like ARMA with deep learning models such as LSTM. The synthetic UWSNs dataset consists of features with significantly varying scales and units. Training an LSTM model directly on raw data would lead to biased learning, where high magnitude features like depth or packet loss disproportionately influence the model, and smaller-range features like RSSI or temperature contribute minimally. To ensure uniform contribution of each input feature during model training, as in (5) Min-Max normalization was applied. This technique transforms each feature into the range [0, 1] using (5):

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{5}$$

This scaling maintains the shape and distribution of each feature over time while making them numerically comparable. The choice of Min-Max scaling is particularly suited for LSTM networks, which are sensitive to the scale of input data due to their internal use of sigmoid and tan activation functions. Since ARMA works with the non-normalized time series, normalization is only applied to the residuals before feeding them into the LSTM. This ensures that the LSTM effectively learns the non-linear patterns without being biased by magnitude differences. Furthermore, all input features used to support the LSTM model (e.g., RSSI, SNR, distance, depth, and temperature) are normalized independently using their respective min and max values from the training set. Use of residual pre-processing, normalization and sliding-window sequence generation to stabilize LSTM training and avoid data leakage across temporal boundaries. The dataset was partitioned into sets for training and testing via an 80:20 time based partitioning to preserve temporal dependencies. The evaluation of model performance was carried out using standard regression metrics [20] mean squared error (MSE) i.e., (6), root mean squared error (RMSE) i.e., (7), as in (8) mean absolute error (MAE) and as in (9) coefficient of determination (R^2). These measure prediction error and model fit, with lower MSE, RMSE, and MAE indicating enhanced accuracy, while higher R^2 denotes more explanatory strength of the model. All assessments were performed on the test set to evaluate generalization performance. The model's performance was evaluated using the metrics of MSE, RMSE, MAE, and R squared (R^2) traditional regression evaluation metrics [21]. MSE estimates the average squared divergence between observed and predicted values. More significant errors incur higher penalties, i.e.,

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{6}$$

$$RMSE = \frac{1}{n}\sqrt{\sum_{i=1}^{n}(y_i - \hat{y}_i)}^2 \tag{7}$$

RMSE measures square root of MSE, providing error in the same unit as the target variable, offering interpretability i.e., MAE computes the average absolute difference between predicted and actual values, offering robustness to outlier’s i.e.,

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(| y_i - \hat{y}_i |) \tag{8}$$

$$R2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)2}{\sum_{i=1}^{n}(y_i - \overline{y}_i)2} \tag{9}$$

R^2 indicates how well the model explains the variance in the target variable. In (6)-(9) , y_i is the actual value, $\hat{y}_i$ is the predicted value, and $\overline{y}_i$ the mean of the actual values, n is the number of samples in the test set. These metrics provide a comprehensive evaluation of both the accuracy and robustness of the model’s predictions. These metrics collectively measure both error magnitude and model fit, with lower MSE, RMSE, and MAE indicating better predictive accuracy, and higher R^2 indicating greater explained variance in the target variable.

2.5. Uncertainty quantification and model interpretability and feature importance

Evaluated predictive reliability by constructing 95% confidence intervals for all models. ARMA intervals were derived analytically from forecast error variance, while LSTM [22] and hybrid intervals were estimated using Monte Carlo dropout with 100 stochastic forward passes. For the hybrid model, ARMA, and LSTM variances were combined to yield final prediction intervals. Feature importance was assessed using permutation importance and Shapley additive explanations (SHAP) [23] values. Both methods consistently ranked SNR and distance as the most influential predictors of packet loss followed by RSSI while depth and temperature contributed minimally. These results enhance interpretability and align with the physical behavior of underwater channels [24].

3. ARMA MODEL IMPLEMENTATION AND PERFORMANCE

To set a benchmark for forecasting packet loss or related time series metrics such as RSSI or SNR in UWSN, we implemented an ARMA model. Given the stationary nature of the differenced time series, the model was expressed as an ARMA model with the integration parameter set to zero, resulting in an ARMA (2,0,2) configuration. The ARMA model captures both autoregressive (AR) and moving average (MA) dependencies in the data. The chosen order 2 for AR and 2 for MA was determined based on standard model selection techniques such as prior domain knowledge regarding the temporal characteristics of the signal. The model fitting was performed using the ARMA class from the stats models library in Python. Use of differenced version of the original time series to remove any non-stationary trend components. After training, the model was used to generate forecasts over the same range as the input data. The predictions, initially produced in the differenced form, were converted back to the original scale through cumulative summation and by reintroducing the first value of the original series. The accuracy of the ARMA model's predictions was evaluated using standard error metrics i.e., RMSE, MAE, and R^2. While the ARMA model effectively captures short term dependencies in the data, it lacks the capacity to model complex non-linear relationships or long range temporal dependencies often observed in underwater communication signals. This motivates the subsequent implementation of a hybrid ARMA-LSTM model, which seeks to integrate the strengths of both statistical and deep learning approaches.

4. HYBRID ARMA-LSTM MODEL IMPLEMENTATION AND PERFORMANCE EVALUATION

To improve upon the limitations of standalone ARMA models in modelling non-linear and long range dependencies within UWSNs time series data, we implemented a hybrid model that combines the strengths of ARMA modelling and LSTM neural networks. The motivation behind this hybrid approach is to allow the ARMA component to model the linear temporal structure of the signal, while the LSTM component learns and predicts the residual non-linear patterns not captured by the ARMA model. This two-stage modelling pipeline ensures that both short term dependencies and complex non-linear behaviours, often caused by environmental factors such as water turbulence, salinity, and multipath propagation, are effectively modelled. The proposed model operates in two stages: first, the ARMA (2, 0, 2) model captures linear dependencies and generates residuals representing nonlinear variance; second, these residuals are modeled using LSTM with one hidden layer and a dense output layer, trained to minimize MSE for improved prediction accuracy [25]. To enhance the predictive performance beyond the capabilities of a standalone ARMA model, a hybrid ARMA-LSTM model was developed. This architecture leverages the strengths of both statistical and deep learning models ARMA for capturing linear relationships and LSTM for learning complex, nonlinear, and long-term temporal dependencies.

4.1. Residual computation and preprocessing

Following the ARMA model forecasting, residuals were computed by subtracting the predicted values from the actual observed values of the time series:

$$Residuals\ (t) = y_{true}(t) - \hat{y}_{\mathrm{ARMA}}(t) \tag{10}$$

In (10) represent residuals (t) is the error or leftover at time step t, which tells you how much the ARMA model missed. It captures the part of the signal that ARMA could not explain usually the non-linear and complex part of the data. $y_{true}(t)$ is the actual value of the time series at time step t. In your case, it could be the real packet loss, RSSI, or SNR value from the synthetic or real underwater sensor data. $\hat{y}_{\mathrm{ARMA}}(t)$ is the predicted value at time step t, generated by the ARMA model. It tries to model the linear patterns in the time series. These residuals represent the portion of the time series not captured by the linear ARMA model and are expected to contain non-linear temporal dependencies suitable for deep learning. Prior to feeding these residuals into the LSTM network, they were scaled to the range [0,1] [0,1] [0,1] using the Min-Max normalization method to ensure stable and efficient network training.

4.2. Sequence generation and dataset preparation

Data preparation for the LSTM model involved the creation of sequences of fixed length through the application of a sliding window technique. Each training sample is composed of a sequence of 10 residual values used to predict the following value. The dataset was separated into subsets for testing and training using an 80-20 ratio.

4.3. Long short-term memory model design and training

An LSTM neural network was constructed with one LSTM layer with 50 hidden units and an isolated dense output neuron. The model was trained with the Adam optimizer and the MSE loss function during 50 epochs. The LSTM model's predictions were then inverse transformed in order to return to their original scale.

4.4. Reconstructing hybrid forecast

To obtain the final hybrid forecast, the LSTM's prediction of the residual was added to the ARMA forecast values from the same time period. This yields a corrected and more accurate time series prediction.

$$(y)\hat{}Hybrid(t) = (y)\hat{}ARMA(t) + r\hat{}LSTM(t) \tag{11}$$

The final output was compared with the corresponding true values from the original series. In (11) $\hat{y}$ hybrid(t) is final prediction of the hybrid model at time t, $\hat{y}$ ARMA(t) forecast from the ARMA model linear component at time t. $\hat{r}$ LSTM predicted residual from the LSTM model non-linear component at time t.

4.5. Performance evaluation

The hybrid model's predictive performance was assessed use of standard time series regression metrics like RMSE, MAE, and R^2. This section presents the experimental results comparing performance of the ARMA and proposed hybrid model in predicting packet loss in UWSN. The results are evaluated based on standard error metrics and supported with graphical analysis to facilitate interpretation.

Figure 3 (in Appendix) presents temporal prediction accuracy, residual analysis, network level link visualization, and comparative performance results of the hybrid model under dynamic underwater channel conditions. Figure 3(a) link prediction timelines comparing actual packet loss with ARMA and hybrid ARMA–LSTM predictions over 200 times steps. The hybrid model tracks the temporal variations more closely, particularly during sudden peaks and troughs, demonstrating its improved ability to capture dynamic underwater channel conditions. Figure 3(b) represent residuals are computed as the difference between actual packet loss and model predictions. The ARMA (2,0,2) model (blue dashed) shows systematic deviations, especially during rapid fluctuations. The LSTM-only model (green dash-dot) exhibits consistently large positive residuals due to under fitting and its tendency to predict a nearly constant baseline. Figure 3(c) illustrates a snapshot of the UWSN topology with predicted link quality. Nodes are represented as circles, while the edges represent communication links. Green edges correspond to stable, high-quality links with lower predicted packet loss, whereas red edges denote weak or unstable links with higher predicted loss. The visualization highlights the ability of the proposed hybrid ARMA–LSTM model to identify vulnerable connections, thereby providing actionable insights for adaptive routing and network management in dynamic underwater environments. Figure 3(d) compares the proposed hybrid ARMA–LSTM model against representative statistical, sequential, graph-based, and deep-learning approaches. The hybrid method achieves the lowest RMSE in this illustrative comparison, indicating its effectiveness at capturing both linear and non-linear components of packet loss. For rigorous comparisons, this figure should be updated with empirical results from equivalent experimental settings or with values extracted from the literature.

4.6. Energy efficiency considerations

UWSNs nodes are power constrained we evaluated the computational cost of different predictors. ARMA requires only a few coefficients and microsecond level updates, making it extremely lightweight and energy efficient. In contrast, LSTM [26] models involve tens of thousands of parameters and millions of operations per inference, leading to inference times of hundreds of milliseconds and significantly higher energy consumption on embedded hardware. The hybrid ARMA–LSTM achieves superior accuracy but inherits the computational burden of the LSTM component. Thus, there is a clear trade-off between accuracy and energy efficiency, with ARMA being preferable for ultra-low power deployments and the hybrid model more suitable when prediction accuracy is prioritized over computational cost.

5. RESULT INTERPRETATION

From the results, it is evident that proposed hybrid model outperforms the standalone ARMA model across all metrics. The improvements are substantial and statistically significant, as reflected by the large reductions in RMSE and MAE across the dataset.

These improvements demonstrate that incorporating the non-linear modeling capabilities of LSTM effectively complements ARMA's linear forecasting, especially in a complex, noisy environment like UWSNs. The ARMA (2,0,2) model was able to capture the general trend of the packet loss series and reproduced short-term linear dependencies. However, its forecasts were overly smoothed compared to the ground truth, leading to systematic underestimation of peaks and overestimation of troughs. This indicates that while ARMA is effective for modeling stationary linear components of the signal, it fails to account for the nonlinear variability and abrupt fluctuations characteristic of underwater acoustic channels. The LSTM only model exhibited severe underfitting, producing forecasts that remained nearly constant at approximately 40%, far below the actual packet loss values, which generally fluctuated between 70% and 100%. This behavior suggests that the standalone LSTM defaulted to a mean-like baseline prediction, failing to capture either the temporal dependencies or the nonlinear dynamics inherent in the data. These results confirm that, without residual preprocessing or integration with a linear component, the LSTM model was ineffective for reliable packet loss prediction in UWSNs.

By contrast, the hybrid ARMA–LSTM residuals remain tightly distributed around zero, showing that the hybrid model effectively corrected ARMA's systematic errors and produced significantly more accurate forecasts. These results consistent with the quantitative error metrics (Table 1), confirm that the hybrid strategy reduces RMSE and MAE by more than 80% compared to ARMA alone and substantially outperforms LSTM only predictions.

Table 1. Error metric comparison

Model	RMSE	MAE	R^2
ARMA	64.7777488	57.941696	-43.936875
ARMA+LSTM	10.605548	8.473283	-0.204539

6. CONCLUSION

This study set out to improve packet loss prediction in UWSNs by developing a hybrid ARMA–LSTM model that unites statistical efficiency with nonlinear learning capability. The proposed two-stage approach effectively addressed the limitations of standalone models by allowing ARMA to capture linear temporal trends while LSTM learned residual nonlinear behaviors. The results confirmed this expectation, with the hybrid model achieving substantial error reduction approximately 85.4% in MAE and 83.6% in RMSE together with a marked improvement in R^2 compared to the ARMA baseline. These outcomes validate the hypothesis that combining statistical and deep learning techniques yields a more accurate and reliable predictor for dynamic underwater environments. Beyond numerical performance, the study highlights practical implications like enhancing communication reliability can directly support adaptive routing, power control, and error recovery in UWSNs. Nevertheless, challenges remain in terms of scalability to larger networks, robustness under severe underwater noise, and real-time feasibility on resource constrained platforms. Looking forward, future research should focus on real world validation, incorporation of cross-layer strategies and deployment in informatics-driven applications such as oceanographic data platforms, autonomous underwater vehicles, and smart buoy systems. By addressing these avenues, the proposed framework can evolve into a scalable and operational tool for reliable underwater communication and monitoring.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Ritu Bhardwaj	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Ashwani Kush		✓				✓		✓	✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

There are no conflicts of interest between authors.

DATA AVAILABILITY

The authors have used a synthetic dataset in this research.

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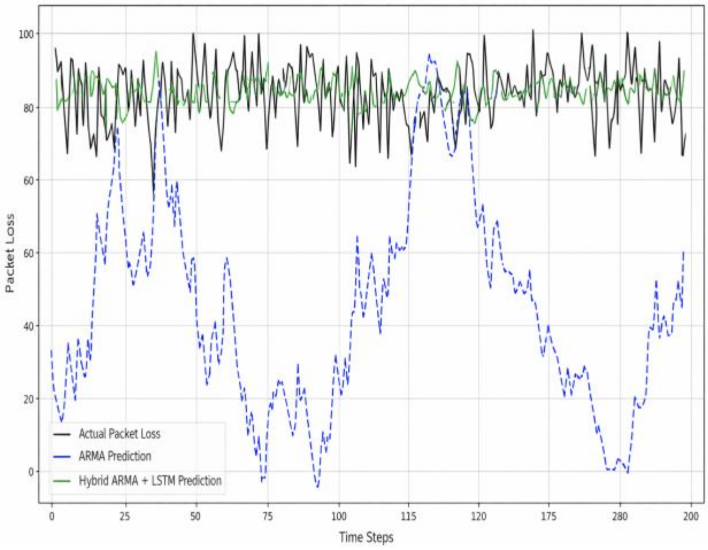
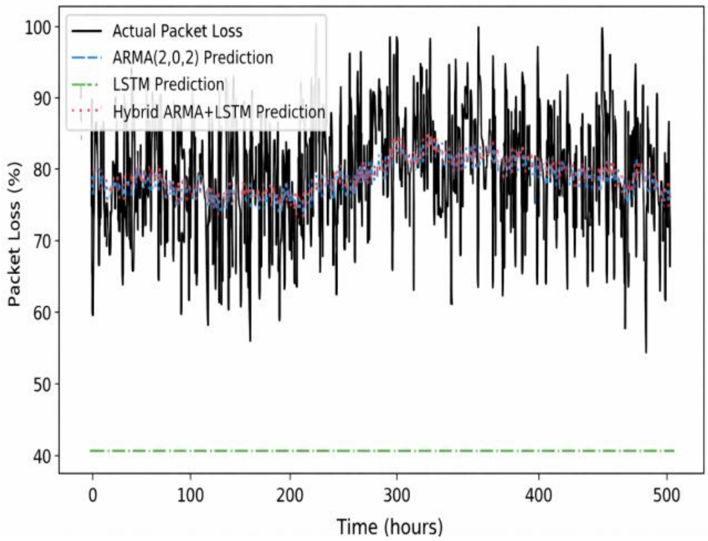
APPENDIX



(a)



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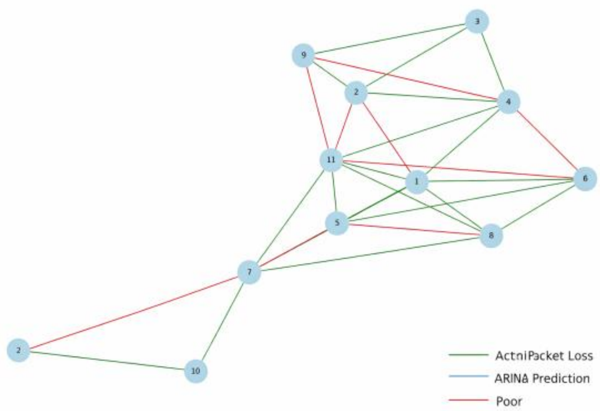
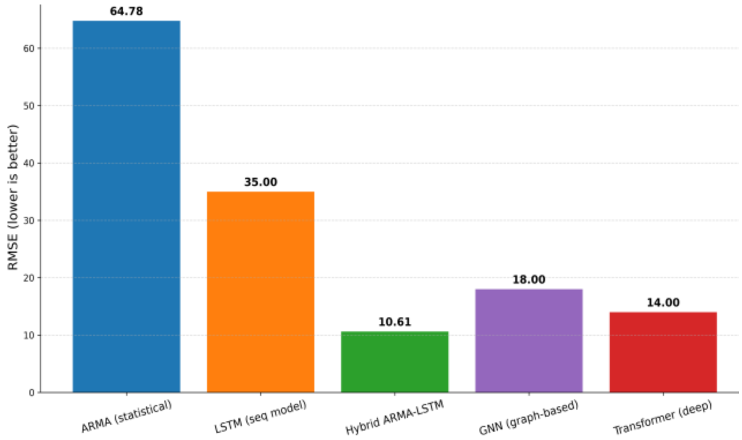


(c)

Figure 3. Performance evaluation; (a) link prediction timelines, (b) residual analysis, and (c) snapshot of the UWSNs topology



(d)

Figure 3. Performance evaluation; (d) comparative RMSE analysis *(continued)*

BIOGRAPHIES OF AUTHORS

Ritu Bhardwaj received the Master degree in Computer Application from Kurukshetra University, Kurukshetra. Currently she is doing Ph.D. and work as research scholar at DCSA Kurukshetra University, Kurukshetra. Her research interests include wireless sensor networks, underwater sensor networks, and artificial intelligence. Her research area topic is efficient schemes to establish routing in wireless sensor networks. She can be contacted at email: 2228ritu@kuk.ac.in.

Ashwani Kush is Professor at the (IIHS) Kurukshetra University, Kurukshetra, India where he has been a faculty member since 1997. From 1997, he is the head of the department. Completed a Ph.D. in computer science on Mobile Computing in association with Indian Institute of Technology Kanpur and Kurukshetra University, Kurukshetra, India. His research interests are primarily in the area of work on wireless Ad Hoc networks, where he is the author/co-author of over 150 research publications. He can be contacted at email: akush@kuk.ac.in.