A deep-sea ambient noise prediction method with few training samples based on VMD and LSTM

Guoli Song [1,2,3], Xinyi Guo [1,2,3], Qianchu Zhang[1,2], Jun Li[1,2], Qunyan Ren [1,2,3] and Li Ma

[1,2,3]

[1] Institute of Acoustics, Chinese Academy of Sciences, Beijing 100190, China
[2] Key Laboratory of Underwater Acoustic Environment, Chinese Academy of Sciences, Beijing 100190, China
[3] University of Chinese Academy of Sciences, Beijing 100190, China

* Correspondence: Guoli Song, songguoli@mail.ioa.ac.cn, No. 21 North 4th Ring Road, Haidian District, 100190 Beijing, China

Abstract: *Deep-sea ambient noise levels are an important factor affecting underwater target detection, underwater acoustic communications, as well as ocean ambient monitoring and animal protection. To predict the deep-sea ambient noise spectral level, a prediction method is established combined with Variational Mode Decomposition (VMD) and Long Short-Term Memory Networks (LSTM). It can predict the ambient noise level under the condition of few training samples in the frequency band of 20 Hz - 10 kHz. The test data verify that the level of the ambient noise in the next 7 days can be predicted by using the current 3 days of deep-sea ambient noise data. The frequency and time trends of the forecast results are consistent with the measured noise trends. The average of the root mean square error (RMSE) is less than 1 dB in both the prediction band and the prediction time.*

Keywords: *Deep-sea ambient noise, noise prediction, Variational Mode Decomposition, Long Short-Term Memory Networks, few training samples*

1. INTRODUCTION

Forecasting the temporal variations of ocean ambient noise enables the formulation of targeted strategies to mitigate its adverse impacts on marine organisms and ecosystems [1], while also enhancing the performance of sonar systems [2] and improving the safety of maritime search and rescue operations and navigation systems.

Ocean ambient noise is influenced by multiple natural factors, including wind speed, waves, ocean currents, temperature and so on, leading to significant temporal variability [3]. The interplay of these environmental parameters introduces high uncertainty and complexity into the generation and propagation of ocean ambient noise, posing challenges for temporal forecasting, particularly under limited sample conditions.

Conventional approaches to ambient noise intensity prediction primarily rely on physical sound field modelling and statistical empirical models. By integrating dynamic sound field modelling [4] with noise source analysis, it becomes feasible to forecast ocean ambient noise fields. In recent years, the development and application of deep learning technology in underwater acoustics have provided new approaches for ocean ambient noise forecasting. Currently, neural networks have made achievements in underwater noise classification [5-6], ship radiated noise identification [7-9], and sound source localization [10-11]. Ocean ambient noise forecasting with machine learning integration has also yielded preliminary successes. Song implemented a Long Short-Term Memory (LSTM)-based approach to predict deep-sea ambient noise, achieving a prediction error of <1 dB for the 20 Hz - 5 kHz frequency band using 2,712 samples with a 9:1 training-test split ratio [12]. Yuan developed a linear time-series model for long-term ambient noise prediction. Based on 20 days of measured data, they achieved wide-band ocean ambient noise prediction [13]. It should be specially noted that the two methods above rely on long-term training samples to achieve robust performance.

This paper proposes an ocean ambient noise spectral level (NL) forecasting method for deep-sea environments under limited training samples by integrating Variational Mode Decomposition (VMD) and LSTM networks. The method enables prediction of ambient noise intensity across the 20 Hz to10 kHz and has been validated through sea trials.

2. VARIATIONAL MODE DECOMPOSITION OF AMBIENT NOISE

Variational Mode Decomposition is a fully non-recursive and adaptive variational mode decomposition method. It determines the number of decomposed modes based on the intrinsic characteristics of the signal. It also optimally matches the central frequency and finite bandwidth for each mode adaptively, thus effectively decomposing the Intrinsic Mode Functions (IMFs). Here, VMD is primarily employed to decompose the ambient noise spectral level at a specific central frequency into subcomponents.

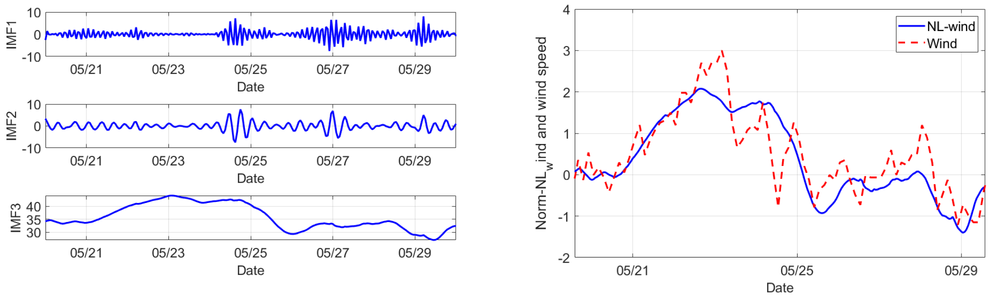

Fig.1: VMD decomposition results of NL and the trend of wind

As wind is one of the main factors of deep-sea ambient noise, the ambient noise spectral level time series is decomposed into two subcomponents - NL_wind and NL_other -via VMD, which means the wind-speed-related subcomponent and the composite subcomponent accounting for other environmental factors.

Fig. 1 displays the three subcomponents derived from VMD decomposition of the ambient noise spectral level at 10 kHz. Analytical results indicate that IMF3 exhibits long-term trend alignment with wind speed, therefore IMF3 is denoted as NL_wind, whereas the remaining components (IMF1, IMF2, and the residual) are summed to form NL_other.

3. VMD-LSTM-BASED AMBIENT NOISE PREDICTION METHOD

Building upon the decomposition of ambient noise subcomponents, the LSTM network is integrated to predict ambient noise intensity.

Let the two decomposed subcomponents of the noise spectral level at a specific central frequency f_c be denoted as $NL\_wind_{f_c} = \left\{NL\_wind_{f_c t}\right\}, t = 1,2,\ldots,n$ and $NL\_other_{f_c} = \left\{NL\_other_{f_c t}\right\}, t = 1,2,\ldots,n$. The two time-series subcomponents are used as inputs to the network and output the noise spectral level through the forecasting model. Specifically, the network utilizes two historical subcomponent sequences $NL\_wind_{f_c t}$ and $NL\_other_{f_c t}$ over a temporal window L=1 to predict $NL_{f_c(t+L)}$ .Then ,the predicted $NL_{f_c(t+L)}$ is decomposed via VMD into updated subcomponents $NL\_wind_{f_c(t+L)}$ and $NL\_other_{f_c t}$. These updated subcomponents are then fed back into the LSTM to predict $NL_{f_c(t+L+1)}$. This iterative process enables extended forecasting of spectral level across the frequency range of 20 Hz to 10 kHz, so that the variation curve of NL with frequency is obtained.

Fig. 2 illustrates the architecture of the deep-sea ambient noise intelligent learning and forecasting model, which comprises an input layer, LSTM layer, fully connected layer, and output layer. A dropout layer is incorporated between the LSTM layer and the fully connected layer to mitigate overfitting. The model is constructed with the following hyperparameters: 128 hidden neurons, dropout rate of 0.2, and initial learning rate of 0.0005.

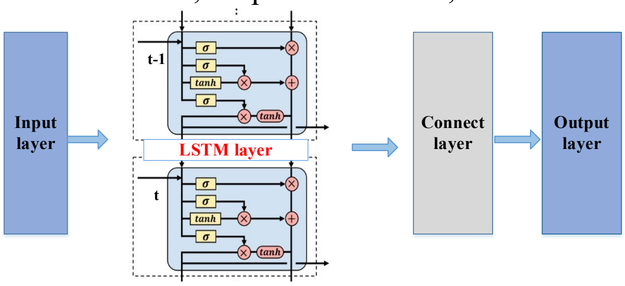

Fig.2: The prediction network of ambient noise intensity.

To assess the performance of the forecasting model, two mean root-mean-square errors (RMSEs) are defined in the frequency domain and time domain, respectively:

- Frequency-Averaged RMSE (denoted as $\overline{RMSE\_F}$): The RMSE between predicted and ground-truth NL is averaged over N frequency bands across the entire forecasting duration.

$$\overline{RMSE\_F} = 1/N \sum_{i=1}^{N} \sqrt{\sum_{j=1}^{T} \left(NL_{pre}(i,j) - NL_{true}(i,j)\right)^2 / T} \tag{1}$$

- Time-Averaged RMSE (denoted as $\overline{RMSE\_T}$): The RMSE between predicted and ground-truth NL is averaged over T forecasting time steps across the entire frequency band.

$$\overline{RMSE\_T} = 1/T\sum_{j=1}^{T}\sqrt{\sum_{i=1}^{N}\left(NL_{pre}\left(i,j\right)-NL_{true}\left(i,j\right)\right)^{2}_{i}/N} \tag{2}$$

Where $NL_{pre}\left(i,j\right)$ is the predicted noise spectral level at the $i-th$ frequency band and $j-th$ time step, and $NL_{true}\left(i,j\right)$ is the measured noise spectral level at the $i-th$ frequency band and $j-th$ time step,

4. RESULTS AND ANALYSIS

4.1 Data Acquisition and Processing

The ambient noise data utilized in this study were collected in a deep-sea region using a subsurface hydrophone deployed at a depth of 2,672 meters. The system operated at a sampling rate of 64 kHz from 00:00 May 20 to 00:00 May 30, yielding 240 hours of valid data. Synchronous meteorological parameters (e.g., wind speed, temperature) were measured using meteorological sensors during the noise acquisition period.

For processing, the raw ambient noise data were segmented into 1-hour intervals. Spectral levels were computed for 1/3-octave bands within the 20 Hz -10 kHz frequency range, generating a 240-hour time series of noise spectral levels. Then it was decomposed into two subcomponents NL_wind and NL_other.

4.2 Prediction Results Analysis

The two subcomponents (NL_wind and NL_other) were partitioned into a training set (30%, 72 samples) and a test set (70%, 168 sample points). These subcomponents served as inputs to the LSTM network, generating forecasts of the ambient noise spectral level (denoted as the VMD-based method). For comparison, a baseline model using the ambient noise spectral level (NL) as input was also evaluated (denoted as the NL-based method).

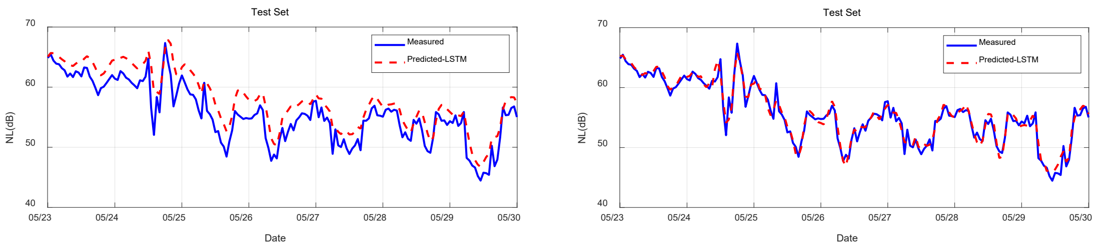

Fig.3: Comparison of Ambient Noise Spectral Level Predictions at Representative Frequencies (Left: NL-based method | Right: VMD-based method).

The Fig. 3 depicts the predicted noise intensity profiles obtained from the NL-based (left panels) and VMD-based (right panels) methods at 1 kHz. As can be seen from the figure, the VMD-based method significantly outperforms the NL-based approach.

Predictions were generated for all 1/3-octave bands within the 20 Hz -10 kHz range. The RMSEs between predicted and ground-truth values were analyzed, yielding frequency-dependent RMSE profiles shown in Fig. 4. Overall, the VMD-based method outperforms the NL-based approach. The frequency-averaged RMSE $\overline{RMSE\_F}$ for the two methods are 2.23 dB (NL-based) and 0.96 dB (VMD-based), respectively.

Fig. 5 compares measured and predicted frequency-dependent noise spectral levels at hour 168 of the test set. The solid blue line represents the measured NL, and the dotted red line represents the predicted NL. The VMD-based predictions (fright figure) exhibit closer alignment with measured spectral trends across frequencies. At hour 168, the NL-based method has a RMSE of 1.94 dB, while the VMD-based method's RMSE is 1.07 dB.

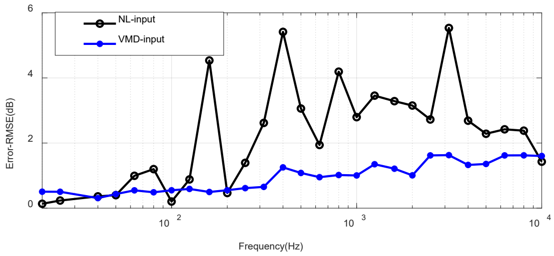

Fig.4: Frequency variation curve of RMSE for ambient noise forecasting.

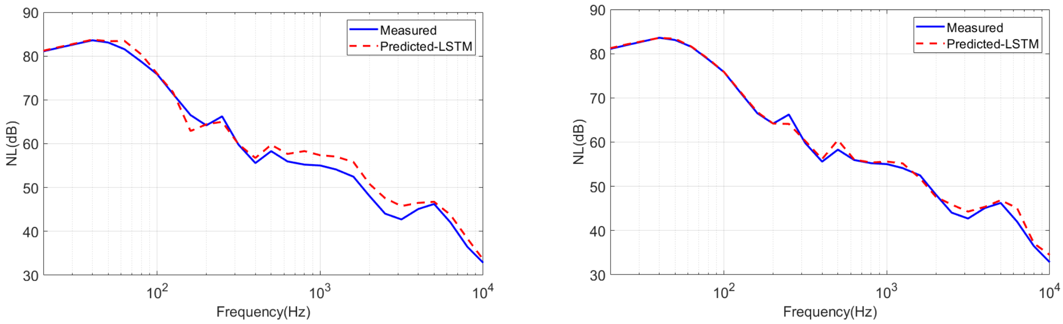

Fig.5: Frequency variation curves of forecasted ambient noise spectral level and the truth (Left: NL-based method | Right: VMD-based method).

Fig. 6 shows the RMSE variation over time across the entire frequency band. Overall, the VMD-based method outperforms the NL-based method. The time-averaged RMSE $\overline{RMSE\_T}$ of the two methods are 2.50 dB and 0.93 dB, respectively.

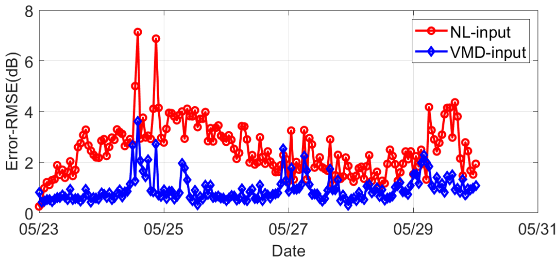

Fig.6: Time variation curve of RMSE for ambient noise forecasting.

In summary, the VMD-based method exhibits enhanced performance in terms of frequency-domain errors as well as temporal errors under the condition of small-samples compared to the NL-based baseline.

5. CONCLUSIONS

This study proposes a VMD-LSTM integrated method for forecasting deep-sea ambient noise spectral level, validated using 240 hours of field-measured marine data. The forecasting performance of the VMD-based and NL-based methods was comparatively analyzed across two dimensions: temporal variations at individual frequencies as well as frequency-dependent variations across the 20 Hz - 10 kHz band under limited training samples. Results show that the VMD-based method demonstrates superior performance with limited training data. Under a 3:7 training-test split ratio (i.e., using 3-day historical data to forecast the next 7 days), the model achieves:

- Frequency-averaged RMSE: 0.96 dB (across the entire forecasting duration).

- Time-averaged RMSE: 0.93 dB (across the 20 Hz -10 kHz band).

Both RMSE metrics are below 1 dB, underscoring the method's reliability for practical applications.

6. ACKNOWLEDGEMENTS

This research was funded by National Natural Science Foundation of China, grant number 12474445 and Basic and Frontier Exploration Project Independently Deployed by Institute of Acoustics, Chinese Academy of Sciences, grant number JCQY202408.

REFERENCES

[1] **L. S. Lemos, J. H. Haxel, A. Olsen**, Effects of vessel traffic and ocean noise on gray whale stress hormones, *Sci. Rep.*, volume (12), pp. 18580, 2022.

[2] **Z. Zhao**, Analysis and application of spatio-temporal correlation characteristics of measured ocean ambient noise, *Applied Acoustics*, volume (214), pp. 109653, 2023.

[3] **F. Li, D. Xu, J. Wang**, et al., Observations of wind-generated noise by the tropical cyclone, *J. Acoust. Soc. Am.*, 143(6), pp. 3312-3324, 2018.

[4] **L. Pang**, Methodology study on the fluctuations prediction of the acoustic filed in the sophisticated oceanographic environment, Beijing：University of Chinese Academy of Sciences,2019.

[5] **G. Song, X. Guo**, Underwater Noise Modeling and Its Application in Noise Classification with Small-Sized Samples, Electronics, volume (12), pp. 1-17, 2023.

[6] **G. Song, X. Guo**, **W. Wang**, Underwater Noise Classification based on Support Vector Machine, *IEEE/OES China Ocean Acoustics Conference COA 2021*, China, 14–17 July, 2021.

[7] **Z. Shan**, High Signal-to-Noise Ratio MEMS Noise Listener for Ship Noise Detection, Remote Sensing, volume (15), pp. 777, 2023.

[8] **S. Liu**, A fine-grained ship-radiated noise recognition system using deep hybrid neural networks with multi-scale features, Remote Sensing, volume (15), pp. 2068, 2023.

[9] **W. Fan, H. Yao, H. Wang**, Recognizing the State of Motion by Ship-Radiated Noise Using Time-Frequency Swin-Transformer, IEEE Journal of Oceanic Engineering, volume (15), pp. 2068, 2024.

[10] **C. Li, Z. Huang, J. Xu, X. Guo**, Multi-channel underwater target recognition using deep learning, ACTA ACOUSTICS, volume (45), pp. 506-514, 2020.

[11] **H. Niu, Z. Gong** Deep learning source localization using multi-frequency magnitude-only data, J. Acoust. Soc. Am., volume (146), pp. 211-222, 2019.

[12] **G. Song, X. Guo, L. Ma**, A Prediction Method for Deep Sea Ambient Noise Intensity Based on LSTM, IEEE/OES China Ocean Acoustics Conference COA 2024, 29-31 May, 2024.

[13] **B. Yuan, L. Lu**, Prediction of Full-Frequency Deep-Sea Noise Based on Sea Surface Wind Speed and Real-Time Noise Data, Remote Sensing, volume (17), pp.101, 2025.