Sound Velocity Profiles Time Series Prediction Method Based on EMD-NARX Model

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Introduction

- Some deep-sea measurements need continuous operations in specific sea areas when the time-series variation of the SVP has a non-negligible impact on the accuracy of the measurement results. The SVP of the deep ocean have certain time-series variation characteristics with time changes, and the time-series variation of sound velocity can be understood as a complex nonlinear relationship.
- Neural networks have been increasingly applied to marine prediction problems because of their self-learning, self-organizing, and self-adaptive characteristics[1-3].
- In this paper, we propose a method to predict the time series of SVP by combining EMD (Empirical mode decomposition) and NARX (Nonlinear autoregressive neural network with external input)[4], and through the process of decomposing and then superimposing the sound velocity time series signal, we achieve the prediction of the time series variation of deep ocean sound velocity, which can provide a reference for related scientific research and practical settlement.

Methods

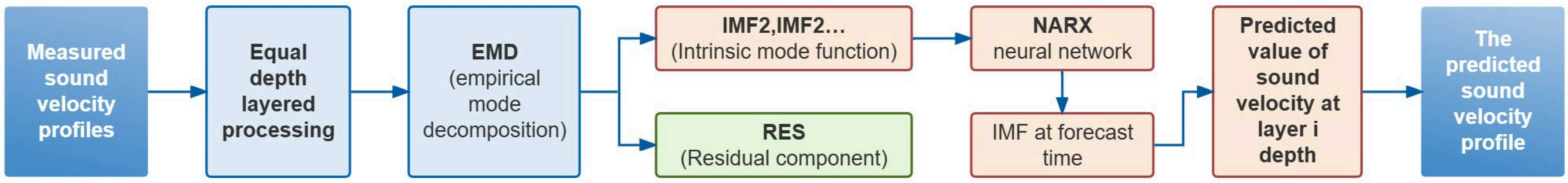

Figure 1. Flow chart of EMD-NARX SVP time series prediction.

Results

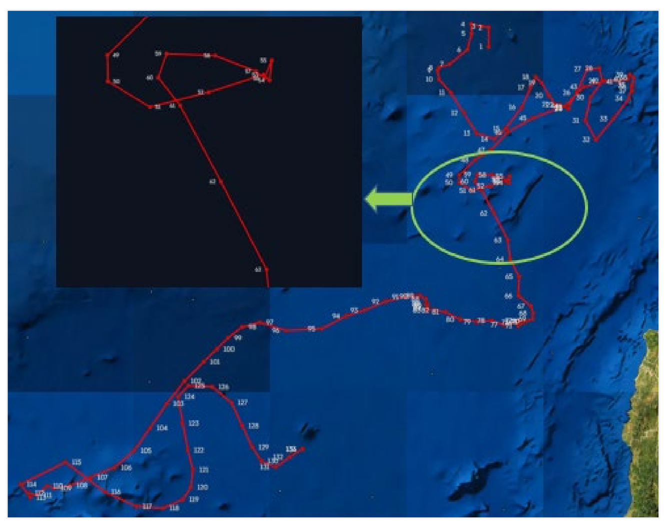

Figure 2. Location map of Argo buoys data.

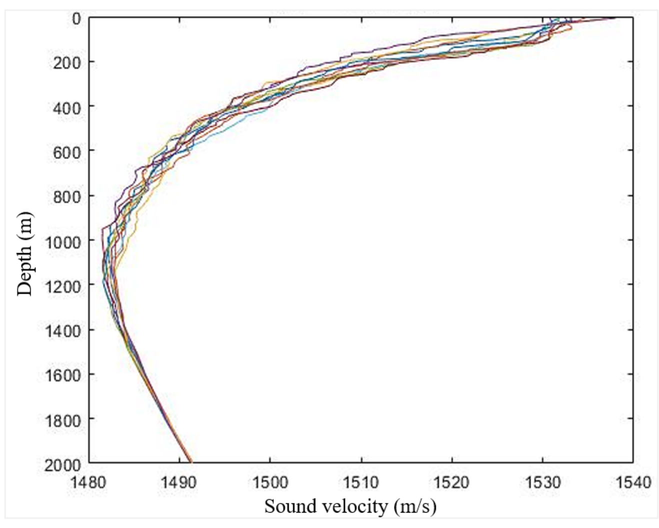

Figure 3. Experimental SVP.

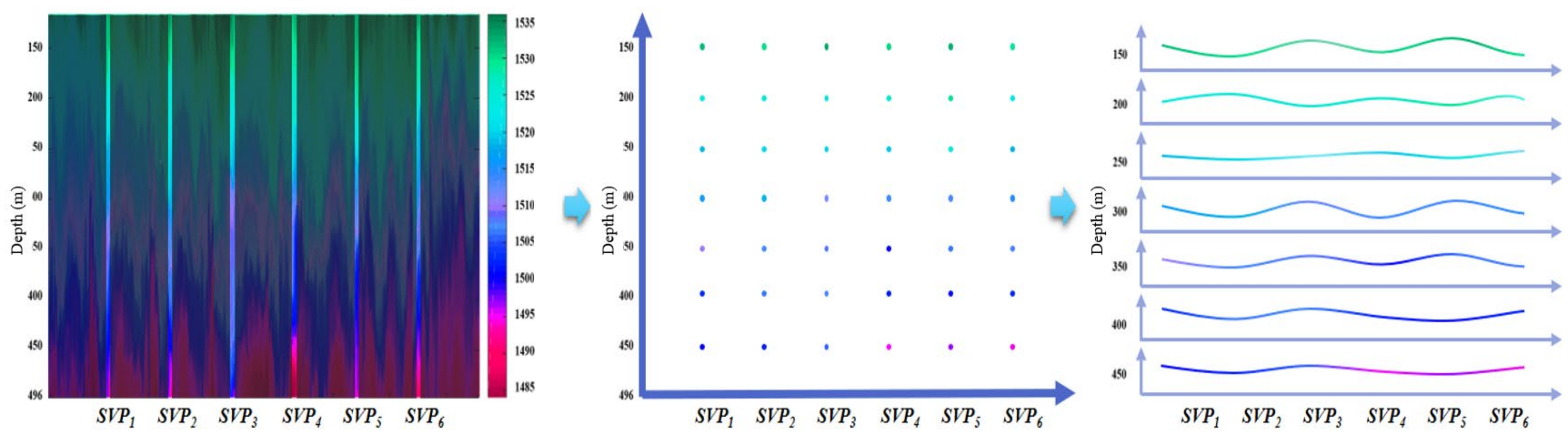

Figure 4. Time series sound velocity curves extracted from the SVP. (a) Velocity profile of sound collected in actual operation. (b) Velocity values at different depths. (c) Timing processing of sound velocity values at different depths.

Table 1. Precision indicators of the three models.

Predicted SVP	Methods	RMSE	MAE	R2
SVP-11	Polynomial	3.7637	2.2647	0.941
	NARX	1.8799	1.1931	0.9844
	EMD-NARX	1.3114	0.9457	0.9924
SVP-12	Polynomial	9.3917	5.8681	0.7357
	NARX	3.0197	2.0879	0.9626
	EMD-NARX	1.6025	1.1557	0.9884
SVP-13	Polynomial	17.8791	11.5491	0.4848
	NARX	6.9436	4.0363	0.8353
	EMD-NARX	2.5731	1.5325	0.9676

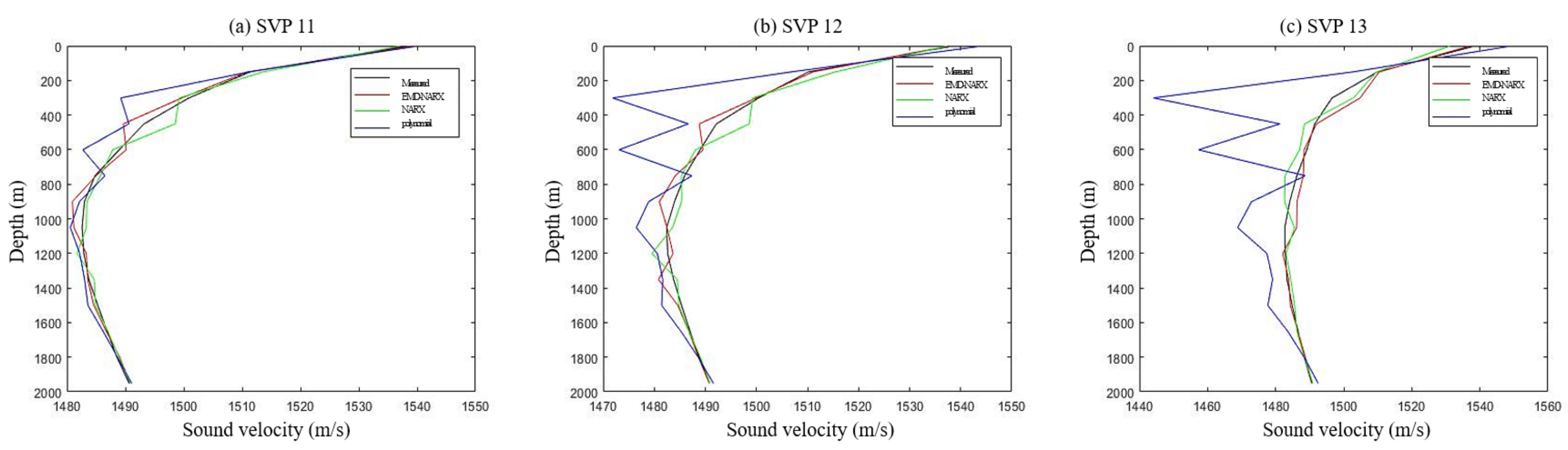

Figure 5. SVP predicted by three models. The first 10 SVP of the time series were brought into the model as known quantities, and the 11th, 12th, and 13th SVP were predicted.

Conclusion

- The prediction accuracy of all three models decreases with time, among which the EMD-NARX time series prediction model has the most stable performance. The EMD-NARX prediction model can fit the time-series sound velocity data well, and the correlation coefficient R of each data set is close to 1.
- Compared with the traditional polynomial fitting projection and the NARX, The EMD-NARX sound velocity time series prediction model can better predict the deep-sea sound velocity profile, which not only improves the prediction accuracy of the sound velocity profile but also sorts out the relationship between the deep-sea sound velocity profile and the time series variation more clearly.

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