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Real-time forecasting of wave heights using EOF – wavelet – neural network hybrid model

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ABSTRACT

Recently, along with the development of data-driven models, artificial neural networks (ANN) have been used in ocean wave forecasting models. Hybridization of ANN with wavelet analysis or fuzzy logic approach has also been used. The wavelet and neural network hybrid models (WNN models) show better performance than ANN models. However, their accuracy decreases with increasing lead time because they do not consider the relation between wave and meteorological variables. Moreover, the WNN model has been developed to forecast the wave height at a single location where the past wave height data are available. To resolve these problems, in this paper, a hybrid model is developed by combining the empirical orthogonal function analysis and wavelet analysis with the neural network (abbreviated as EOFWNN model). The past wave height data at multiple locations and the past and future meteorological data in the surrounding area including the wave stations are used as input data. The model then forecasts the wave heights at the locations for various lead times. The developed model is employed to forecast the wave heights at eight wave observation stations in the coastal waters around the East/Japan Sea. The EOFWNN model is shown to perform better compared with the WNN model for all lead times regardless of the decomposition level of wavelet analysis. The EOFWNN model is proven to be a promising tool for forecasting wave heights at multiple locations where the past wave height data and the past and future meteorological data in the surrounding area are available.

1. Introduction

Real-time forecasting of wind-generated waves over a period of a few hours or a few days at a specific location is required for ocean and coastal engineering operations. Since the physical process of wave generation by wind is basically uncertain, complex, non-linear, and non-stationary, it is not fully understood yet. Despite of considerable advances in computational techniques, the solutions obtained by numerically solving the equations of wave growth are neither exact nor uniformly applicable at all sites and at all times due to the complexity and uncertainty of the wave generation phenomenon (Deo et al., 2001).

Since the last decade, an alternative approach based on the use of data-driven models such as artificial neural networks (ANN) has been developed by many researchers to forecast ocean waves (Deo et al., 2001; Londhe and Panchang, 2006; Makarynskyy et al., 2005; Zamani et al., 2008). An ANN is suitable for partially understood underlying physical processes such as wind-wave relationship. A major issue in this type of forecasting is the selection of appropriate input data patterns that are likely to influence the desired output. Even though the ANN has flexibility, it may not be able to cope with non-stationary data without preprocessing the input and output data (Cannas et al., 2006). In recent years, hybridization of ANN with other techniques has been used in wave height forecasting to overcome the limitation of ANN and to provide effective modelling. Özger (2010) proposed the combination of wavelet and fuzzy logic approaches to forecast wave heights up to 48-h lead time. The correlation coefficients between observed and forecasted wave heights were between 0.647 and 0.745, which were larger than those of auto-regressive moving average (ARMA), ANN, and fuzzy logic models. Deka and Prahlada (2012) and Prahlada and Deka (2015) used a wavelet and neural network (WNN) model to forecast significant wave heights up to 48-h lead time using 3 hourly wave height observation data. Their results showed good predictions at shorter lead times but lower accuracies at longer lead times. Dixit and Londhe (2016) also used WNN technique to predict extreme wave heights up to 36-h lead time for five major hurricanes. Shahabi et al. (2017) developed genetic programming based wavelet transform to forecast significant wave heights up to 48-h lead time. The WNN hybrid model showed better prediction performance than the ANN model but some deviation was observed at longer lead

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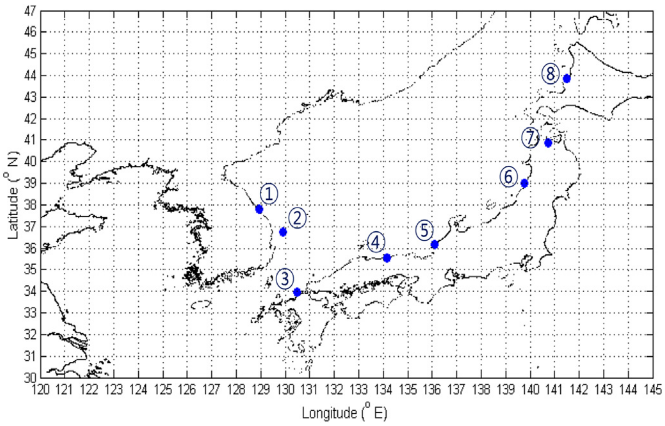

Fig. 1. Wave measurement locations.

Table 1
Information on wave measurement stations and statistical properties of wave data at each station.

Station	No.	Location	Waver depth (m)	Min (m)	Max (m)	Mean (m)
Gangneung	1	128° 55′ 43.2″ E, 37° 47′ 50.8″ N	15.0	0.05	5.65	0.79
Wangdolcho	2	129° 43′ 52.9″ E, 36° 43′ 10.3″ N	15.3	0.06	5.89	1.10
Genkainada	3	130° 28′ 05″ E, 33° 56′ 02″ N	39.5	0.16	5.76	1.34
Tottori	4	134° 09′ 41″ E, 35° 33′ 16″ N	30.9	0.13	5.12	1.61
Fukui	5	136° 04′ 30″ E, 36° 09′ 50″ N	36.7	0.13	6.75	1.83
Sakata	6	139° 46′ 45″ E, 39° 00′ 31″ N	45.9	0.14	8.64	1.87
Aomori	7	140° 44′ 21″ E, 40° 51′ 10″ N	24.9	0.09	1.89	0.32
Rumoi	8	141° 28′ 07″ E, 43° 51′ 59″ N	49.8	0.12	5.74	1.46

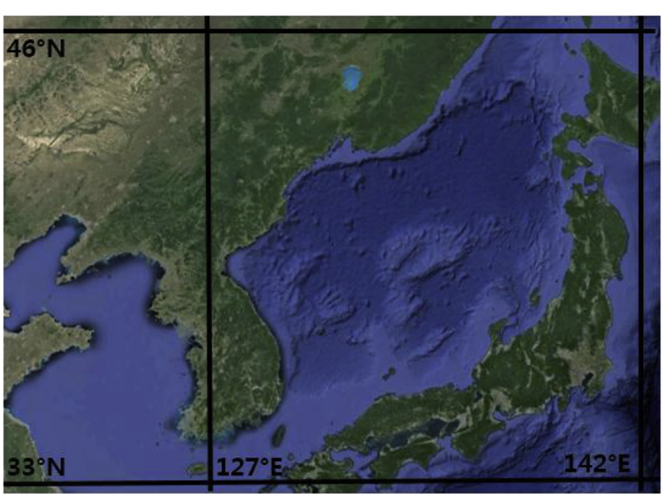

Fig. 2. Region of meteorological data.

times.

In many hybrid models for forecasting wave heights, only wave height data have been used as the input data. The dominance of persistence in the wave height time series should be considered in wave forecasting models. However, the dominance of persistence decreases as the lag time increases. Therefore, considering the relationship between wave and meteorological variables becomes more important as the lead time increases. However, it is difficult to interpret the relationship between spatially distributed meteorological and wave data using an ANN or WNN model. Moreover, there is a limitation in using ANN or WNN model in that the model cannot forecast spatially distributed wave heights together. In other words, it is necessary to develop and run the model for each location separately.

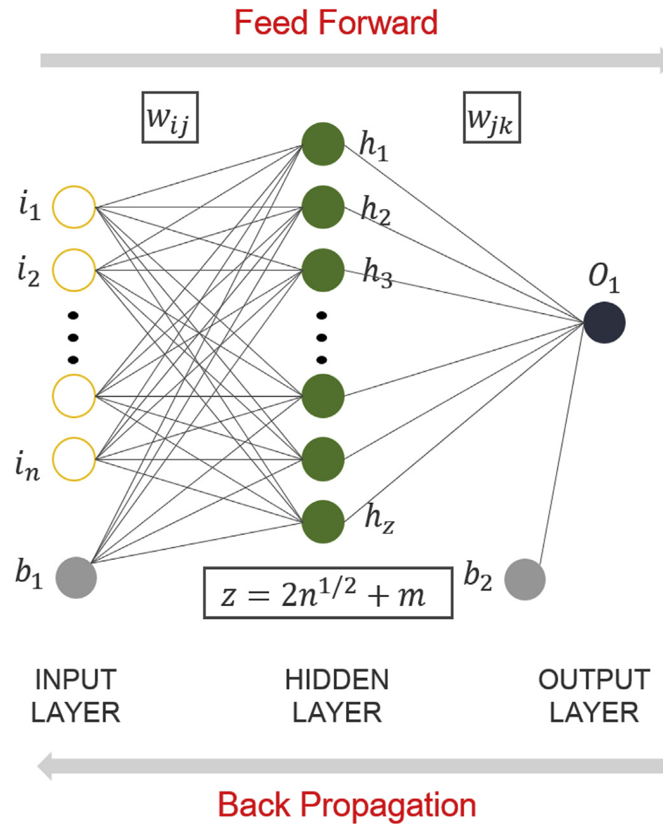

Fig. 3. ANN structure.

In this study, an EOFWNN model is developed by combining the empirical orthogonal function (EOF) analysis and wavelet analysis with the neural network to forecast significant wave heights in multiple locations simultaneously. The input data of the model are the past wave height data and the past and future meteorological reanalysis data in the surrounding area including the wave stations. The model then calculates the wave heights in the locations simultaneously for various lead times. The developed model is employed to forecast significant wave heights in eight wave observation stations in the coastal waters around the East/Japan Sea.

2. Description of data

The significant wave height data were obtained at two wave stations (Gangneung and Wangdolcho) operated by KIOST (Korea Institute of Ocean Science and Technology) and at six different locations (Genkainada, Tottori, Fukui, Sakata, Aomori and Rumoi) of NOWPHAS (Nationwide Ocean Wave information network for Ports and HArbourS). Fig. 1 shows the locations of wave measurement, and Table 1 presents the information on the wave stations and the statistical properties of wave data at each station. The stations are located along the coast of the East/Japan Sea. Even though they are far from one another, the entire area in the East/Japan Sea is governed by an identical meteorological system. Therefore, it is assumed that the wave data at different stations show similar physical processes. The wave data of KIOST were obtained every