Oceanologia (2017) 59, 331—349

Available online at www.sciencedirect.com

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ORIGINAL RESEARCH ARTICLE

Application of neural networks and support vector machine for significant wave height prediction

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Received 14 July 2016; accepted 18 March 2017
Available online 19 April 2017

KEYWORDS
Significant wave height;
Wave prediction;
Machine learning;
ANN;
SVM

Summary For the purposes of planning and operation of maritime activities, information about wave height dynamics is of great importance. In the paper, real-time prediction of significant wave heights for the following 0.5—5.5 h is provided, using information from 3 or more time points. In the first stage, predictions are made by varying the quantity of significant wave heights from previous time points and various ways of using data are discussed. Afterwards, in the best model, according to the criteria of practicality and accuracy, the influence of wind is taken into account. Predictions are made using two machine learning methods — artificial neural networks (ANN) and support vector machine (SVM). The models were built using the built-in functions of software Weka, developed by Waikato University, New Zealand.
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1. Introduction

Information about wave height is of great importance for the design and planning of different sea-related activities in maritime structures (Deo and Naidu, 1999). For the design purposes, long-term prediction of wave height is usually made to provide information about rare events with a return period from 5 to 100 years. Operational activity planning requires real time and short-term prediction of wave height to gauge sea conditions during the following hours and next few days. The process of energy transference from wind to waves and consequent generation of wave spectra has not yet been fully resolved. The general theoretical level related to the generation of waves was established by Lamb (1932), Phillips (1957) and Miles (1957). The pioneering numerical implementation of the theoretical basis set was defined by Donelan (1977), while Schwab et al. (1984) formed the semi-empirical parameter model, the so-called 1st generation model. From then until today, important contributions have been made by Cavaleri and Malanotte-Rizzoli (1981), Janssen (1989, 1991,

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Peer review under the responsibility of Institute of Oceanology of the Polish Academy of Sciences.

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http://dx.doi.org/10.1016/j.oceano.2017.03.007
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1992, 1998) and Johnson (1998), Johnson and Kofoed-Hansen (2000). The 3rd generation model is currently in use. Commonly used numerical methods (NM) with parametrically based equations or differential equations include a hint of uncertainty in converting wind energy into wave energy, and are mostly computationally exhausting (Herbich and Bretschneider, 1990). Mentioned fact implies and imposes the interesting idea of application of a computationally less expensive machine learning (ML) approach for short-term prediction of sea waves. On the other hand, the numerical approach has the ability to estimate wave characteristics for a whole area, while the ML approach tends to be used for specific locations, that is points with installed wavegraph. NM use measurements from specific locations for results verification, while the ML approach demands measured data in the sense of inputs (wave height, period, wind velocities, fetch, air pressures, temperatures etc.) and desired output (wave height, wave period etc.) for model building (e.g. see articles cited in next paragraph). Theoretically, ML could be used (without NM) for a wider area: in the presence of enough wavegraphs or for building models based on NM input and NM output, in situations when there is a lack of time, since ML models are less computationally expensive.

Although ANN are commonly used for wave height forecasting and are hugely popular (i.e. researches of Balas et al., 2004; Deo et al., 2001; Deo and Naidu, 1999; Mahjoobi and Mosabbeb, 2009; Makarynskyy, 2004; Tsai et al., 2002 etc.), efficiency and accuracy also encourage the usage of support vector machine (i.e. Fernandez et al., 2015; Mahjoobi and Mosabbeb, 2009; Malekmohamadi et al., 2011), *knn* nearest neighbours (i.e. Zamani et al., 2008), genetic programming (i.e. Nitsure et al., 2012), model trees (i.e. Etemad-Shahidi and Mahjoobi, 2009), rough set theory (i.e. Abed-Elmdoust and Kerachian, 2012), fuzzy logics (Sylaios et al., 2009), Kalman Filtering (Altunkaynak and Wang, 2012) and so on. Sometimes the performance of ANNs is improved through the usage of genetic algorithm (Altunkaynak, 2013), discrete wavelet transformation (Chandra et al., 2012), fuzzy interference (Malekmohamadi et al., 2011) or even combined with physically based models (Reikard et al., 2011).

Some of the first research in this area was provided by Deo and Naidu (1999) and consisted of ANN applied for real-time wave forecasting in the upcoming 3—24 h using wave characteristics exclusively as input parameters. The research provided more accurate results than the previously used stochastic autoregressive models. By applying ANN without wave information, Deo et al. (2001) had used data on wind velocities and fetch for the prediction of significant wave heights and average wave periods. Usage of the data from three wavegraph stations resulted in imprecise results for one station, most probably because of the excessive distance of the location where wind characteristics were measured and the influence of wave deformations in shallow sea depth. Tsai et al. (2002) used ANN for short-term prediction of wave heights and periods on the basis of data from three wavegraph stations in surroundings with various physical characteristics. The assumption that there exists a good correlation between significant wave height and one-tenth, maximum and average wave height was used (Goda, 2000). Two approaches, one with only significant wave heights, the second with other characteristical heights included, did not result in notable accuracy difference, except the fact that when 8 inputs were used it was only necessary to use data from the previous 15 days for training to achieve satisfactory results with ANN. An analogous procedure was given for predicting wave periods using the inputs from the last 30 days and predicting the outputs for next 60 days resulting in slightly lower accuracy than wave height prediction. Makarynskyy (2004) used ANN for significant wave height and periods forecasting for the following 1—24 h. After splitting the data into three equal non-overlapping parts, for training network, calibration and validation, ANN was trained using the assumption that information from the previous 48 h (48 inputs) was sufficient to predict the following 24 h (24 outputs). Then the correction was done on the information from the obtained forecast only (as 24 inputs) and observed waves (24 outputs). The third approach included forecasts from the first and second one (as 48 inputs) for estimating the possibility of predicted waves accuracy increasing (24 outputs). Remarks on the paper include the fact that data was split into three equal parts without considering seasonality (Medina, 2005). Balas et al. (2004) compared the ANN and Elman's type ANN with the stochastic autoregressive model (AR) and the same model with exogenous input (ARX) for the estimation of missing values of wave heights, periods and directions. The Elman recurrent network is, unlike usual statical ANNs, a dynamic system with the ability to learn the instant state of timely dependable variables. The first approach included available input variables from the previous time step for ANN, one wave height for height prediction and thus one previous period for period prediction with AR. The second approach included wind velocities from the last 8 time steps, but the ARX model was used instead of AR. Elman's ANN gave slightly more accurate results than ANN, while the autoregressive models gave less accurate results. A comparison between *knn* nearest neighbours and locally weighted regression with ANN for the purpose of wave height prediction using the data of previous wave heights, wind velocities and directions was provided by Zamani et al. (2008). The ANN gave better results for prediction of wave height in several upcoming time steps, while the other two methods resulted in more accurate prediction for the first subsequent time step. Mahjoobi and Mosabbeb (2009) forecasted wave heights using wind characteristics as inputs in ANN and SVM. They highlighted the smaller number of parameters and simplicity of the SVM method. Malekmohamadi et al. (2011) provided a comparison between ANN, Bayes networks (BN), SVM, adaptive neuro-fuzzy interference system (ANFIS) for prediction of wave heights from the wind velocity. Their conclusion was that BN and SVM can give useful information about input and output data reliability. A genetic programming technique (GP) was used by Nitsure et al. (2012) in extensive research aimed at finding the best model for the prediction of wave height for the following 12 and 24 h using the information about wind velocities and directions. The results were satisfactory with the recommendation of further research into a more accurate way of predicting extreme values.

For applying ML, simply described as the learning of patterns in data, data is scheduled in instances (number of examples for training) and attributes (values which describe the problem). So the training has to be performed on a certain number of inputs and outputs. Most researchers have tended to use a minimal number of inputs (up to 1, 2, 3 or more) and rarely larger number like 24 and 48 in (Makarynskyy, 2004

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