Expert Systems with Applications 39 (2012) 2549–2559

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Estimation of significant wave height in shallow lakes using the expert system techniques

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ARTICLE INFO

Keywords:
Artificial Neural Network
Kalman Filtering
Genetic Algorithms
Stochastic
Dynamic model
Significant wave height

ABSTRACT

Significant wave height is an important hydrodynamic variable for the design application and environmental evaluation in coastal and lake environments. Accurate prediction of significant wave height can assist the planning and analysis of lake and coastal projects. In this study, the Genetic Algorithm (GA) is used as the optimization technique to better predict model parameters. Also, Kalman Filtering (KF) is used for prediction of significant wave height from wind speed. KF technique makes predictions based on stochastic and dynamic structures. The integrated Geno Kalman Filtering (GKF) technique is applied to develop predictive models for estimation of significant wave height at stations LZ40, L006, L005 and L001 in Lake Okeechobee, Florida. The results show that the GKF methodology can perform very well in predicting the significant wave height and produce lower mean relative error and mean-square error than those from Artificial Neural Network (ANN) model. The superiority of GKF method over ANN is presented with comparisons of predicted and observed significant wave heights.

1. Introduction

Prediction of significant wave height traditionally is very important to the applications of coastal and ocean engineering, especially in the design, analysis, and determination of the economical life of coastal and offshore structures. For the study of a large lake, wind waves induced resuspension of bottom sediments and accompanying water quality problems can be of major concerns. Reddy, Sheng, and Jones (1995) stated that internal phosphorus loads associated with resuspended bottom sediments in Lake Okeechobee are approximately the same in magnitude as external loads. The bottom stresses resulting from wind generated surface waves are the major causes of sediment resuspension and transport. Therefore, accurate prediction of significant wave height can also assist greatly the prediction of resuspended sediment concentration in the water column.

Wind speed is one of the major inputs in numerical wind wave models for predicting significant wave height. For operational wave forecasting, these are derived from atmospheric models starting with the pressure fields. Wind measurements may be used in establishing the pressure fields and special cases for local site specific wave models. In terms of the factor of wind, researchers have tried to establish relationships with empirical formulations between significant wave height and wind speed (Bishop, 1983; Bretschneider, 1970; Donelan, Hamilton, & Hui, 1985; Hasselmann et al., 1973). Numerical models based on solving the energy transfer equations have also been proposed by various researchers (Barnett, 1968; Booij, Ris, & Holthuijsen, 1999; Chen, Zhao, Hu, & Douglass, 2005; Hasselmann, 1962; Ris, Holthuijsen, & Booij, 1999) to perform improved spatial and temporal predictions of wind waves. Jin and Wang (1998) developed a two-dimensional nonlinear shallow-water wave model to predict time variation of significant wave heights in Lake Okeechobee. Generally, a comprehensive wind wave model needs high speed computers and a variety of input data, which make it unattractive for practical uses (Goda, 2003). Although those models can provide detailed temporal and spatial variation of wind induced wave elevations, they may not be efficient in terms of economic point of view for preliminary or even final design in some cases (Goda, 2003). Therefore, simplified wave prediction methods are frequently required for practical applications and for the cases that quick evaluation and low cost estimates are needed.

Modern modeling techniques have been used for the simple wave predictions during recent years. Deo, Jha, Chaphekar, and Ravikant (2001), Agrawal and Deo (2002) and Tsai, Lin, and Shen (2002) have used Artificial Neural Network (ANN) for forecasting wave parameters. Makarynskyy (2004) applied the ANN technique to predict significant wave heights and zero-up-crossing wave periods. Kazeminezhad, Etemad-Shahidi, and Mousavi (2005) established fuzzy logic model based on fetch length and

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doi:10.1016/j.eswa.2011.08.106

meteorological variables such as wind speed and duration. Also, Özger and Şen (2007) used fuzzy logic approach to forecast the wave parameters. Kalra and Deo (2007) estimated significant wave heights, average wave period, and wind speed at a coastal site using ANN based on TOPEX satellite data recorded at 19 offshore locations. Spatial wave predictions were investigated by Altunkaynak (2005) and Altunkaynak and Özger (2005). They also employed Kalman Filtering (KF) technique for wave estimations in deep sea conditions (Altunkaynak, 2008; Altunkaynak & Özger, 2004).

In this study, we present models for predicting significant wave heights at four stations in Lake Okeechobee, Florida using the concept of a combined Genetic Algorithm and Kalman Filtering (GKF) approach. For performance comparisons, an established ANN model is also applied for the predictions of significant wave height in Lake Okeechobee. So far, the adopted GKF approach has not yet been applied to the study of wind induced waves in lakes. The use of Genetic Algorithm (GA) (Altunkaynak, 2008, 2009; Buckles & Petry, 1994) that is an optimizing technique to determine the model parameters can remove the dependence of some mathematical solving difficulties, such as derivative, initial values, and boundary conditions that are required in analytical and numerical solutions. In addition, the KF approach has the advantage of providing adaptive corrections for the values predicted from system equations with minimized errors. The models of GKF and ANN are first calibrated with training (or calibration) data then applied for predictions of significant wave height. The results from GKF based stochastic dynamic models are presented and the comparisons are made with those from ANN and the test data.

2. Kalman Filtering formulations

As described above, the Kalman Filtering (KF) technique (Gelb, 1974; Kalman, 1960) is utilized to perform the computations of significant wave height with inputs of wind speed. KF is a set of mathematical equations that provides an adaptive modeling of state variables in a way that minimizes the squared error. This technique is capable of making estimations of past, present and even future states. There are two phases in this approach including system and measurement modeling. By taking into account the serial correlation between variables of measured past and present values, the first step is to construct the system equation, which is given as

$$X_k = \Phi_{k/k-1} X_{k-1} + \varepsilon_{k-1} \tag{1}$$

where $X_k = \begin{bmatrix} H \\ W \end{bmatrix}_k$ is current state variable vector, X_{k-1} represents previous state variable vector, and $\varepsilon_{k-1} = \begin{bmatrix} \varepsilon_H \\ \varepsilon_W \end{bmatrix}_{k-1}$ is error vector. Here, H = significant wave height and W = wind speed. $\Phi_{k/k-1} = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$ is a (2×2) transition matrix that converts state variable at previous time ($k-1$ time level) to the state variable at the present time (k time level). The optimized elements of the transition matrix in the system equation are determined in the training stage using the Genetic Algorithm, in which the coefficients are found automatically by examining the generated coefficients in chromosome structure that minimize the mean square error between observations and computed values.

The second step is to establish the measurement equation to transform the state vector X_k into a measurement vector, Z_k

$$Z_k = G_k X_k + \eta_k \tag{2}$$

where the (1×2) matrix $G_k = [0,1]$ in the measurement equation relates the state vectors to the measurement at time k and η_k is measurement noise vector of dimension $(m \times 1)$. Eq. (2) provides the procedure to relate the wind speed of present state to the significant wave height of present state. The system and measurement noises are assumed to be independent of each other. It is also assumed that each noise variable has a normal probability distribution. System and measurement errors have zero means and finite variances, defined as Q_k and R_k, respectively. Generally, the Q_k and R_k covariance matrices might change with each measurement at every time step, however here they are assumed to be constant.

The predictions are obtained by using system and measurement equations in a recursive manner. The projected $\underset{k/k-1}{\hat{X}}$ at time step k is obtained by solving the system Eq. (1) using the information from time step $k-1$ assuming zero error vector. Then this prediction is substituted into Eq. (2) for measurement error calculation as $Z_k - G_k \underset{k/k-1}{\hat{X}}$. In this study, $Z_k = W_k$. The final prediction is determined by combining the $\underset{k/k-1}{\hat{X}}$ with a Kalman gain vector, K_g as

$$\hat{X}_{k/k} = \hat{X}_{k/k-1} + K_g(Z_k - G_k \hat{X}_{k/k-1}) \tag{3}$$

The formulation of Kalman gain K_g, a (2×1) matrix determined by the procedure of minimizing mean square error of $X_k - \hat{X}_{k/k}$, can be found in Kalman (1960).

3. Determination of Kalman Filtering model parameters by Genetic Algorithms

Genetic Algorithms (GAs) approach is an optimum solution seeking technique by generating numbers randomly for a field in which the solution range is well-known. The advantages of using GAs to determine the model parameters have been addressed in the literature (Buckles & Petry, 1994; Sen, 2004; Altunkaynak, 2008, 2009, 2010). Some of the key advantages separating GAs from the statistical method can be summarized in the following.

1. The GAs procedure does not involve solving complex equations and the continuous condition of the variables or data is not required.
2. All arithmetical operations in GAs are based on probability and stochastic processes and the optimum transition matrix can be determined very practically.
3. The GAs can generate many solution points for the selection of the optimum solution.
4. The GAs can search solution points in a wide solution space.

The GAs are generally coded by binary system (0,1) due the ease of calculations. To proceed the GAs procedure, first, a group of numbers that belong to decision variables is chosen randomly. Those numbers formed with a sequence of binary codes are called chromosomes. The chromosome structure in binary system of the transition matrix elements (a,b,c, and d) is shown in Fig. 1. After coding the matrix elements, the robustness of each chromosome in the society can be calculated separately. Robustness criteria of a chromosome are determined according to the mean square error between observed and predicted values. Desired solution is the point that makes the mean square error the smallest. This corresponds to the optimum solution point. Maintaining the life of the chromosomes or disconnection from the society depends on their robustness. The cross-over process in the GAs plays an important role to result in more robust members in the society. Probability of maintaining the life is higher in members who have higher robustness degree and vice versa. Available generations are diversified by using GAs operators that are cross-over and mutation. It allows the decision procedure moves more effectively to reach the solution by participation of new members.