Ocean Engineering 122 (2016) 44–53

Contents lists available at ScienceDirect

Ocean Engineering

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

A real-time forecast model using artificial neural network for after-runner storm surges on the Tottori coast, Japan

Sooyoul Kim [a,*], Yoshiharu Matsumi [a], Shunqi Pan [b], Hajime Mase [c]

[a] Graduate School of Engineering, Tottori University, Koyama-cho Minami, Tottori 680-850, Japan
[b] School of Engineering, Cardiff University, The Parade, Cardiff CF24 3AA, UK
[c] Disaster Prevention Research Institute, Kyoto University, Gokasho, Kyoto, 611-0011, Japan

ARTICLE INFO

Article history:
Received 16 December 2015
Received in revised form
13 May 2016
Accepted 13 June 2016
Available online 23 June 2016

Keywords:
Storm surge forecasting
Artificial neural network
Typhoon
After-runner storm surge

ABSTRACT

The area of Sakai Minato on the Tottori coast, Japan, has suffered from water level increase between 15 and 18 h later after passing of typhoon (called as after-runner surge). To mitigate the impact of the extra water level rise, it requires a fast and accurate after-runner surge forecasting with a lead time of 24 h for the coastal community. The present study demonstrates the effect of selecting appropriate data sets for an artificial neural network-based after-runner surge forecast model on the accuracy of the surge predictions. In this study, 16 different data sets, consisting of the local meteorological and hydrodynamic parameters collected from local stations on the Tottori coast as well as the typhoon-characteristics, are applied to the newly-developed after-runner surge forecast model in Sakai Minato. The models results are carefully examined to determine the optimal data sets, which can yield accurate surge forecasting over a relatively long-lead time (e.g., 24 h). It was found that the combination of surge level, sea-level pressure, drop of sea-level pressure, longitude and latitude of typhoon, sea surface level, wind speed and wind direction are the optimal data sets for predicting the surge level with the lead time of 24 h.

1. Introduction

Storm surge forecasting is crucial to a decision-making process in the coastal management to reduce flooding risk in low-lying regions, and fast and accurate models are often desirable for forecasting the storm surge. A conventional method is to use process-based numerical prediction models, which are computationally expensive to run. An alternative method is to use advanced machine learning models such as artificial neural network that are driven by data from the relation between storm surge levels and corresponding information such as sea surface levels (=astronomic tide level+surge level), winds, sea level pressures and typhoon-characteristics (typhoon location, central atmospheric pressure, and maximum wind speeds near typhoon center). In comparison with conventional models, neural network-based models have advantages of fast computational time in a few tens of minutes to forecast output data, after the model is trained. The neural network-based models can be developed with any independent and dependent parameters (e.g., Tu, 1996). The neural network is like a set of equations with defined coefficients to detect relationships between output and input parameters. The development process of neural network-based models is empirical and many methodological issues remain to be solved, and the results are also difficult to use for gaining understanding of physics.

In the majority of studies, such alternative models were developed to predict the accurate value with a lead time before surge levels occur, using the artificial neural network (ANN) trained by observed data of surge, typhoon-induced meteorological and hydrodynamic parameters (e.g., Lee, 2006, 2008, 2009; Tseng et al., 2007). In these studies, the alternative models were aimed at predicting the surge levels up to six hours ahead. These studies showed that the use of the combination of typhoon-characteristics, local wind speeds, local wind directions, sea level pressures and storm surge levels is the best data set for forecasting the surge levels with a relatively short-lead time (up to six-hours ahead) in which their maximum surge levels usually coincide with typhoon landfalls on the Pacific Coast of Taiwan.

On the other hand, the historical record of storm surge along the Tottori coast, Japan, indicates that a sea level rise occurs 15–18 h later after typhoon passing (called as after-runner surge) as a result of Coriolis force (Kim et al., 2014). Therefore, the coastal managers in this region require accurate and rapid surge-level forecasting to provide the information on the after-runner surge at least 18 h in advance. However, in such a region, alternative models for surge level forecast with this lead time of 24 h have not

* Corresponding author.
E-mail address: sooyoul.kim@sse.tottori-u.ac.jp (S. Kim).

http://dx.doi.org/10.1016/j.oceaneng.2016.06.017
0029-8018/

been examined.

In the present study, we develop an alternative model to forecast the after-runner surge levels with the lead times of 5, 12 and 24 h that are trained by the combinations of parameters of hydrodynamic, meteorological and typhoon characteristics that were collected on the Tottori coast. Then, a series of numerical experiments is conducted to determine the optimal combinations of input parameters required by the ANN forecast model. The selection of the proper input data sets is crucial to the development of ANN forecast model on the Tottori coast, because once it is determined, essential data can be effectively collected and or, if necessary, reproduced using numerical surge simulations. To examine it, the sensitivity of the ANN forecast model to possible combinations of typhoon-related training data is investigated. From our results, for instance, it was found that a proper data set for the surge level forecast made in 24 h in advance should consist of surge level, sea-level pressure, drop of sea-level pressure, longitude and latitude of typhoon, sea surface level and wind speed and wind direction. Thus, it is believed that the characteristic of after-runner surge as described above might be important to select proper parameter sets model associated with the lead times in the ANN forecast. Therefore, optimizing the ANN forecast model with the appropriate training data is essential for the after-runner surge forecast with a relatively long-lead time on the Tottori coast.

Cluster analysis is effective to look for appropriate data sets to be used in ANN by discovering a similarity between parameters in a data set (e.g., Dreyfus, 2002). One of the clustering methods is a dendrogram, which estimates a distance (the similarity is higher if the distance is closer) between parameters and then, groups associated parameters into a set. However, the appropriate data sets for the 24 h-lead time surge forecast obtained from the selection method used in the present study are different from those grouped by the dendrogram; for instance, the present selection method shows that the appropriate data set for it is the combination of surge level, sea level pressure, drop of sea-level pressure, typhoon location (longitude and latitude), wind speed and wind direction, while the dendrogram illustrates that individuals are separated into the different groups (see, Fig. 9), which will be discussed in Section 5.

The present study demonstrates the selection of the appropriate combination of input parameters for the surge level forecast with the lead times of 5, 12 and 24 h in the ANN models in Section 2. In Section 3, we provide the explanation of collected data for training, validating and testing for the ANN models, and a series of experiments. Then, results are given in Section 4. In addition, discussion is done in Section 5. Finally, the conclusions are given in Section 6.

2. Storm surge prediction model using artificial neural network

2.1. Overview of artificial neural network

Artificial Neural Network (ANN) is one of the data processing techniques. In the majority of studies, ANNs have been applied with significant emphasis on the predictions of: tides (e.g., Deo and Chaudhari, 1998; Lee et al., 2002; Lee, 2004), sea surface levels (Sztobryn, 2003; Makarynskyy et al., 2004; Makarynska and Makarynskyy, 2008), waves (Deo and Naidu, 1999; Deo et al., 2001), tsunamis (Mase et al., 2011), storm surges (Lee, 2006, 2008, 2009; Tseng et al., 2007), breakwaters (Mase et al., 1995; Mase and Kitano, 1999; Mase et al., 2007).

ANNs can be classified into feedforward (static) networks and feedback (recurrent or dynamic) networks (e.g., Dreyfus, 2002). A feedforward neural network implements nonlinear functions of their inputs. Those nonlinear functions are neurons, which are defined by nonlinear, weighted and biases functions. Therefore, the feedforward neural network is represented as a set of neurons connected together, in which the information flows in the forward direction from the inputs to the outputs. On the other hand, a feedback neural network is governed by nonlinear discrete-time recurrent equations.

In the present study, the feedforward neural network with a single layer of input, hidden neuron and output is used as shown in Fig. 1. The back-propagation optimization technique was employed to train the network in this study. The back-propagation algorithm is a popular, computationally economical method for computing gradients of cost functions (e.g., Dreyfus, 2002). We used the Levenberg–Marquardt algorithm that has advantage in terms of the reduction of computational time among several back-propagation algorithms of the conjugate gradient method, the scaled conjugate gradient method, the Broyden–Fletcher–Goldfarb–Shanno method and the Levenberg–Marquardt method. The parameters of the Levenberg–Marquardt method are given in Table 1. As described by Mase et al. (2011) and Dreyfus (2002), the feedforward neural network should not only fit training data sets, but also generalize to provide satisfactory results for surge level forecasts. If the feedforward neural network uses too many weights and trained too strict, outputs would be of high accuracy, but it might involve a large number of less meaningful computations for non-trained data. On the other hand, if it uses too few weights, it is not able to learn from the training data efficiently. Here, we use the regularization method of early stopping before the performance function reaches a pre-defined threshold (for example 10^{-6} m) of the mean squared error between the observed and predicted surge levels. The iteration number for training was 10,000 at maximum. The functions of hyperbolic tangent sigmoid transfer and linear transfer are used in the hidden and output layers, respectively. The phases of training and validating are taken for surge level forecasts with relatively long-lead times of 5, 12 and 24 h. All collected data from one event were used for the training phase. In the validation phase, the trained model is applied to one typhoon event to forecast a time series of surge levels with a given lead time. The test phase is done by one event as done in the validation phase. The detailed description for the data taken in the present study will be given in Sections 2.2 and 2.3.

2.2. Input parameters

In the conventional method, a process-based numerical storm surge prediction model is driven by typhoon-induced wind and pressure fields, which are generally estimated from either a parametric wind and pressure model or an atmospheric general circulation model. Consequently, the accuracy of storm surge predictions is significantly dependent on the quality of the meteorological data, and in general there is a significant level of uncertainty of the estimated meteorological data. In the present study, to minimize such an uncertainty in the ANN forecast model for the surge level with the given lead time, we gathered the hourly measured meteorological and hydrodynamic data remotely delivered to an operating system from the observation stations on the Tottori coast. We selected five local meteorological stations at Hamada, Matsue, Yonago, Ama and Saigo, and one hydrographic station at Sakai Minato, as shown in Fig. 2(b), operated by Japan Meteorological Agency. In addition, typhoon characteristics such as typhoon position (longitude and latitude), central atmospheric pressure and highest wind speed near the typhoon center are collected.

According to Hiyajo et al. (2011), the surge level of 100 year return period at Sakai Minato is approximately 0.63 m, estimated