Proceedings of the 7th International Conference on Asian and Pacific Coasts (APAC 2013) Bali, Indonesia, September 24-26, 2013

A SENSITIVITY STUDY OF REAL TIME STORM SURGE FORECAST MODEL TO METEOROLOGICAL AND HYDRODYNAMIC FIELDS ALONG THE SANIN COAST, JAPAN

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ABSTRACT: In the present study, the performance of the real time storm surge forecast model based on the neural network is examined by forecasting Typhoon Megi storm surge 2003 at Sakai, Japan in terms of a variety of the combinations of data obtained from Typhoons Songda 2004 and Maemi 2003. In the experiments, the data sets are trained with the meteorological data measured at five stations: the sea level pressure, the depression rate of the sea level pressure, the wind speed, the wind direction; the hydroulic data: the sea surface level and the storm surge at Sakai; the typhoon parameters: the typhoon position, the central pressure of the typhoon and the highest wind speed near the typhoon center. In addition, the forecast time spans of 01, 02, 03, 04, 05, 12 and 24 hours are investigated for all cases of the data sets. From the results, It is found that the performance of the real time forecast models shows best when training the neural network with the data set of the storm surge, the sea level pressure, the depression rates of the sea level pressure, the wind speed and the typhoon position at Sakai.

Keywords: Storm surge; real time forecast; artificial neural network

INTRODUCTION

Typhoons, which make landfall along the Sanin coast of Japan in the midlatitude (35° ~ 45°), induce abnormal storm surges at Sakai during the summer season. The maximum storm surge heights in the sea surface level are observed at Sakai with the time lags of approximately 14 ~ 17 hours after passing or making landfall. In addition, two peaks in the storm surge have been observed at landfall concurrently and with the time lag. For instance, one peak in the storm surge was observed at Sakai during Typhoon Maemi 2003, on the other hand, two peaks were measured during Typhoon Songda 2004. Along the Sanin coast, providing the accurate information of the storm surge to the residents in the local communities is important to prevent life and wealth from the natural disaster. In addition, the recent study (Yasuda et al., 2012) indicated that potential risks of storm surges in the East Asia are increased because the birth position of typhoons moves toward the east under the future climate change projection than the present climate circumstance.

To forecast the storm surge, a variety of methods have been taken to operate a real time forecast model. One of the conventional methods in the model is to operate a numerical storm surge model. In the numerical model, meteorological fields that 10m winds and sea level pressures are obtained from a parametric model or an atmospheric circulation model are essential to drive the storm surge. Those have occasionally been dealt with a parameter wind model.

Statistical formulae, which are obtained under specified conditions, have been operated to calculate the storm surge by taking determined factors.

An alternative forecast model is based on an artificial neural network. The meteorological and hydraulic information may train the artificial neural network for the corresponding storm surge at sites. Such information will be the wind speed, the wind direction, the sea level pressure, the depression rate of the sea level pressure, the tide, the residual surge and the position of the typhoon. The artificial neural network has been applied in the majority of the prediction models: the wave (Ota and Kimura, 1998), the storm surge (Yamashiro et al., 2010; Tseng et al., 2007) and the tsunami (Mase et al., 2011), for instance.

In the study, the performance of the artificial neural network was examined in order to forecast Typhoon Megi storm surge 2004 at Sakai Minato in terms of a variety of the combinations of the components gathered during Typhoon Songda 2004 and Maemi 2003. In the experiments, the neural network were trained by the data sets of the meteorological data measured at five stations: the sea level pressure, the central depression rates of the sea level pressure, the wind speed and the wind direction; the typhoon parameters: the typhoon position, the central sea level pressure and the highest wind speed near the typhoon center. In addition, the forecast time

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spans were investigated for all cases of the data sets; 01h, 02, 03h, 04h, 05h, 12h and 24h.

REAL TIME FORECAST MODEL

The artificial neural network in the present study consists of three layers: input, hidden and output layers. A log-sigmoid function is used between hidden and output layers. In the input layer, the parameters are taken as the input data set. The number of the hidden layer sets one layer and its neurons are identical to the number of components in the input data sets in the input layer. In the output layer, the storm surge is taken as the output set.

The feedforward neural network, which is a nonlinear function of its input set, is implemented into the real time forecast model. The information flows in the forward direction from the input to the output. The feedforward neural network was trained by Levenberg-Marquard method that it is one of the backpropagation algorithm. In order to improve accurate predictions in the storm surge forecast model, the number of hidden layers and iterations can be increased. In this improvement process, the Bayesian method was employed to avoid the meaningless process as if criteria are not assigned into the network.

As preprocesses of the input data sets, the input components were normalized by the constants of 1013 hPa for the sea level pressure, 100 hPa for the depression rate of the sea level pressure, 100 m/s for the wind speed, 360 degree for the wind direction, 100 cm for the sea surface level and the storm surge and, the longitude and the latitude at the Sakai for the typhoon position in order to have identical orders of magnitude. Then, the orders of components in the data set fall in the range of -1 to 1.

MEASUREMENT DATA

The study has attempted to develop the real time storm surge forecast model based on the artificial neural network trained by the local meteorological and hydrodynamic data around Sakai along the Sanin coast. Figure 1 shows the measurement stations of Hamada, Yonago, Matsue, Sakai, Ama and Saigo for the wind and the sea level pressure. The sea surface level and the storm surge are measured at Sakai.

Three typhoon events were selected to train and validate the artificial neural network in the real time storm surge forecast model; Typhoon Songda 2004 and Typhoon Maemi 2003 for the train, and Typhoon Megi 2003 for the validation. One peak in the storm surge was measured during Typhoons Maemi and Megi whereas two peaks were measured during Typhoon Songda.

The hourly data of the wind speed (m/s), the wind direction (degree), the sea level pressure (hPa), the sea surface level (m), the storm surge (m) were collected from the stations shown in Fig. 1. The typhoon parameters of the central position (degree), the central sea level pressure (hPa) and the maximum wind speed near the typhoon center were collected becasue those components are able to use directly as the input data set in the real time model without estimating the characteristic of the typhoon such as the distance to the maximum wind speed from the typhoon center and the maximum wind speed using an additional way of a parametric wind model.

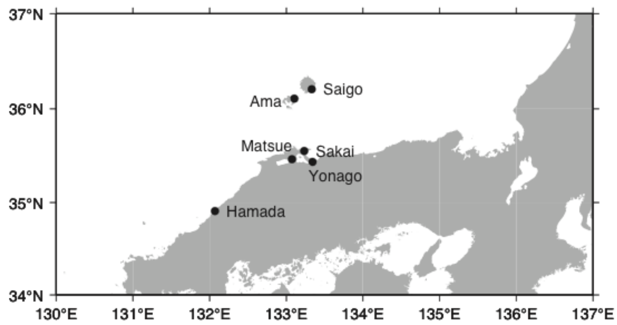

Fig. 1 Stations for the wind, the pressure and the sea surface level around Sakai.

EXPERIMENT OF THE FORECAST MODEL

As listed in Table 1, the experiment was designed to examine the sensitivity of the artificial neural network to the data sets in the storm surge forecast model. In order to train the artificial neural network, the components in the data sets collected during either the sole or blended typhoon events were taken into consideration. The storm surge was designated into the output data set. After the train, the network was validated by the Typhoon Megi storm surge.

In the forecast models of Case A1 - A4, the components gathered at one station during the sole typhoon of Songda were taken into consideration. The network was trained with the data sets consisting of the storm surge, the sea level pressure and the depression rate of the sea level pressure at one station. In the forecast model of Case A2, the tide measured at Sakai is added into the data set in Case A1. The wind speed is, then, made up of the data set in Case A3. In Case A4, the wind direction is supplied into the data set. In the forecast models of Case B1 - B4, the same components in the data sets as the Case A1 - A4 are taken but the components during two typhoon of Songda and Maemi are blended.

In Case C, the components of the wind and pressure from five stations are gathered during Typhoon Songda

The combinations of the components in Case C1 - C4 are identical to those in Case A1 - A4..

The forecast models of Case D1 - D4 are same with Case B1 - B4 but during the blended typhoons. In Case E, the central position of the typhoon is included in the data sets of Case D1 - D4. In the forecast models of Case F1 - F4, the component of the central sea level pressure is added into the data sets of Case E1 - E4. Finally, the forecast models of Case F1 - F4 are composed of the maximum wind speed near the center with the data sets in Case E1 - E4.

Table 1 Forecast models for the artificial neural network (SS: storm surge, SLP: sea level pressure, DRSLP: depression rate of sea level pressure, SSL: sea surface level, WS: wind speed, WD: wind direction, TP: typhoon position, CSLP: central sea level pressure, MWS: maximum wind speed near the center)

Case		Typhoon	Component	Station
A	1	Songda	SS + SLP + DRSLP	SLP: Ama
	2		SS + SLP + DRSLP + SSL	
	3		SS + SLP + DRSLP + SSL + WS	WS and WD: Saigo
	4		SS + SLP + DRSLP + SSL + WS + WD	
B	1	Songda + Maemi	SS + SLP + DRSLP	
	2		SS + SLP + DRSLP + SSL	
	3		SS + SLP + DRSLP + SSL + WS	
	4		SS + SLP + DRSLP + SSL + WS + WD	
C	1	Songda	SS + SLP + DRSLP	SLP, WS and WD: Ama, Saigo, Sakai, Yonago, Matsue and Hamada
	2		SS + SLP + DRSLP + SSL	
	3		SS + SLP + DRSLP + SSL + WS	
	4		SS + SLP + DRSLP + SSL + WS + WD	
D	1	Songda + Maemi	SS + SLP + DRSLP	
	2		SS + SLP + DRSLP + SSL	
	3		SS + SLP + DRSLP + SSL + WS	
	4		SS + SLP + DRSLP + SSL + WS + WD	
E	1		SS + SLP + DRSLP + TP	
	2		SS + SLP + DRSLP + SSL + TP	
	3		SS + SLP + DRSLP + SSL + WS + TP	
	4		SS + SLP + DRSLP + SSL + WS + WD + TP	
F	1		SS + SLP + DRSLP + TP + CSLP	
	2		SS + SLP + DRSLP + SSL + TP + CSLP	
	3		SS + SLP + DRSLP + SSL + WS + TP + CSLP	
	4		SS + SLP + DRSLP + SSL + WS + WD + TP + CSLP	
G	1		SS + SLP + DRSLP + TP + CSLP + MWS	
	2		SS + SLP + DRSLP + SSL + TP + CSLP+ MWS	
	3		SS + SLP + DRSLP + SSL + WS + TP + CSLP + MWS	
	4		SS + SLP + DRSLP + SSL + WS + WD + TP + CSLP + MWS	

The statistics of the relatively short term forecast models, which are 02h to 05h forecast time spans, indicate the values of RMSE around 0.2, on the other hand, the long term forecast models of 12h and 24h forecast time spans show a range from 0.2 - 0.4 for the values of RMSE and 1-CC. The forecast models of Case Bs trained by the data sets of the multiple typhoon event show the better prediction in the storm surge compared with Case As, which are trained by that of the sole event.

In addition to the forecast models composed of the majority of the combinations of the components, we examined a variety of forecast time spans: 01h, 02h, 03h, 04h, 05h, 12h and 24h. In the experiment of the forecast models, in total, 196 models were trained and validated.

RESULTS OF FORECAST EXPERIMENTS

To examine the sensitivity of the artificial neural network in the forecast model, we evaluate the forecasted storm surge by the statistical values of the root mean square error (RMSE) and the correlation coefficient (CC) in comparison with the observation at Sakai. The value of 1-CC is calculated to adjust for that of RMSE in the figure.

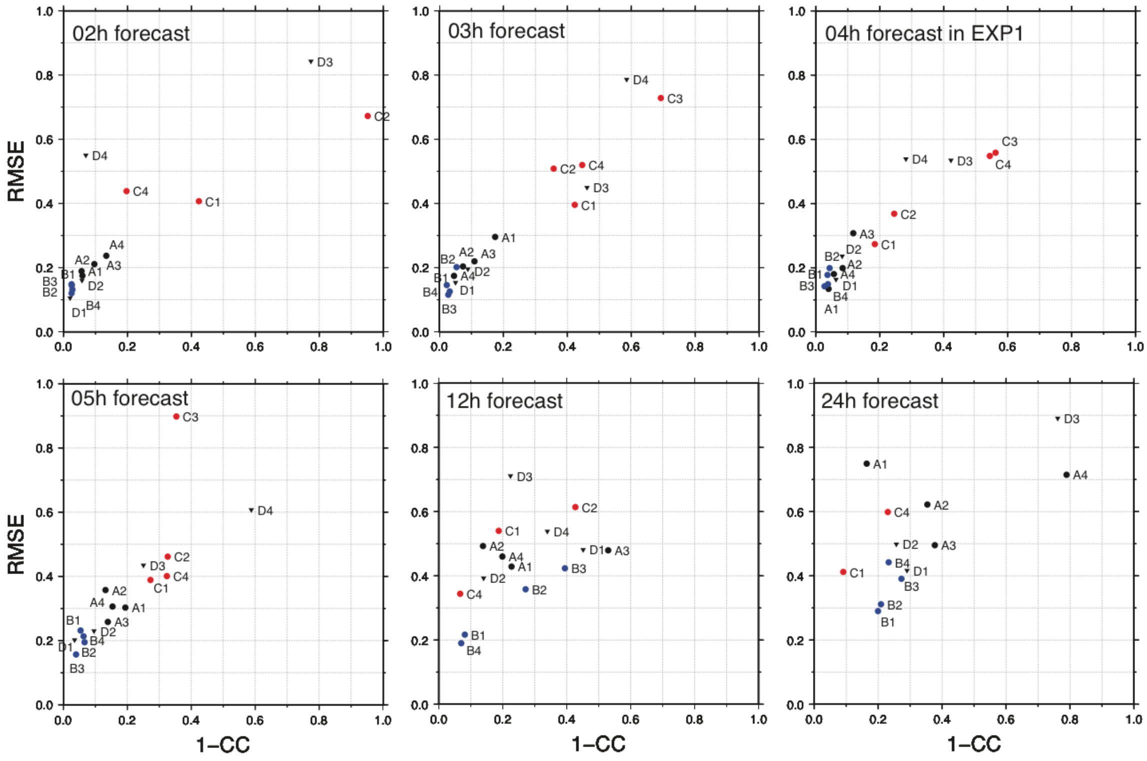

Fig. 2 The statistics of RMSE and 1-CC calculated between the forecast and the observation in the forecast models of Cases As, Bs, Cs and Ds with the forecast time spans of 02h, 03h, 04h, 05h, 12h and 24h

Effect of the number of components in the data set

The effect of the number of typhoon events in the data set on the accuracy in the forecasted storm surge was evaluated as shown in Fig. 2.

In the figure, the results of the forecast models for Case A1 - A4 correspond to the sole typhoon event those of Case B1 - B4 are, however, a match for the blended event. The statistics of RMSE and 1-CC show lower values in the forecast models of Case Bs than those from the Case As (the results of 01h no appear).

In the study, when taking the components in the data sets from one station in the forecast models of Case Bs, the statistical values are lower rather than when taking the components at five stations in the models of Case Ds. This tendency becomes significant in the case of the 24h forecast models. Overall, the forecast models of Case Bs show that the statistical values are lower in all the forecast time spans. However, the most accurate forecast models vary with the condition of the forecast time span. For example, the statistical values indicate that the most improved forecast models are Case D1, B3, A1, B3, B4, and B1 for 02h, 03h, 04h, 05h, 12h and 24h forecasts, respectively.

In addition, the forecast results indicate that as the forecast time span is long, the prediction accuracy in the long term forecast models becomes lower than in the short term models of 02h, 03h, 04h and 05h forecasts.

In Fig. 3, the differences of the maximum sea surface levels between the prediction and the observation and of the times when measuring the maximum in the observation and the prediction are shown. Both of the differences were divided by the maximum of the observation for the difference of the maximums and 24h for the difference of the generation times to normalize them. Those differences are an important factor for the real time storm surge forecast at Sakai, because the maximum of the storm surge at Sakai is independent of landfall of the typhoon, while that in general concur with landfall. Within the errors from -0.2 to 0.2 in both the differences, the normalized differences show that the short term forecast models of Case A and B, which are 02h - 05h time spans, have similar errors in the accuracy. But the differences for the 12h and 24h time spans indicate lower errors in the Case Bs than in the Case As. In comparison with the forecast models of Case Bs, through the whole experimental cases, the better values no appear in the forecast models of Case Ds.

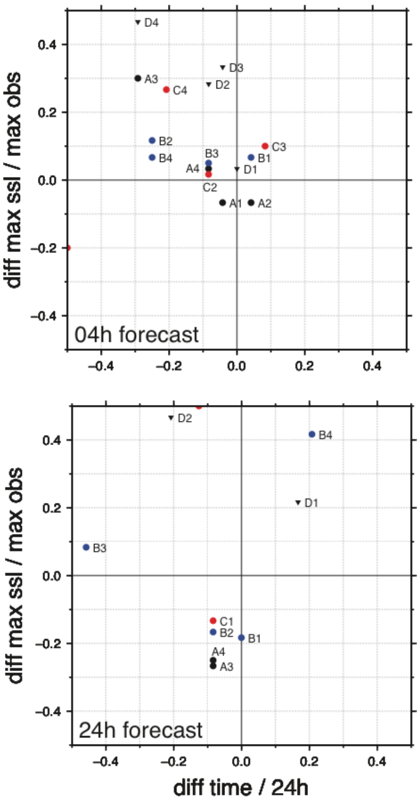

Fig. 3 Differences of the maximum sea surface levels between the prediction and the observation and of the times when measuring the maximum in the observation in the forecast models of Case As, Bs, Cs and Ds.

Effect of the class of the components in the data set

In the section, we have investigated how the combinations of the components in the data set influences on the accuracy of the forecast model. The statistical values of RMSE and 1-CC calculated from the forecast models of Case Ds, Es, Fs and Gs are shown in Fig. 4. The statistics of the whole models vary with the condition of the combination of the components and the forecast time spans. In the short term forecast models of 02h, 03h, 04 and 05h time spans, the statistical values of the Case D1 are best in the range of 0 to 0.2. In the long term forecast models of 12h time span, the RMSE and 1-CC values of Cases F2 indicate that the forecast model trained by the combined data set of the storm surge, the sea level pressure, the depression rate of the sea level pressure, the tide, the typhoon position and the central sea level pressure show the best performance. In the case of 24h time span, the forecast model of Case E1 obtained the lowest values in the statistics when training it with the data set blended by the storm surge, the sea level pressure, the depression rate of the sea level pressure and the typhoon position.

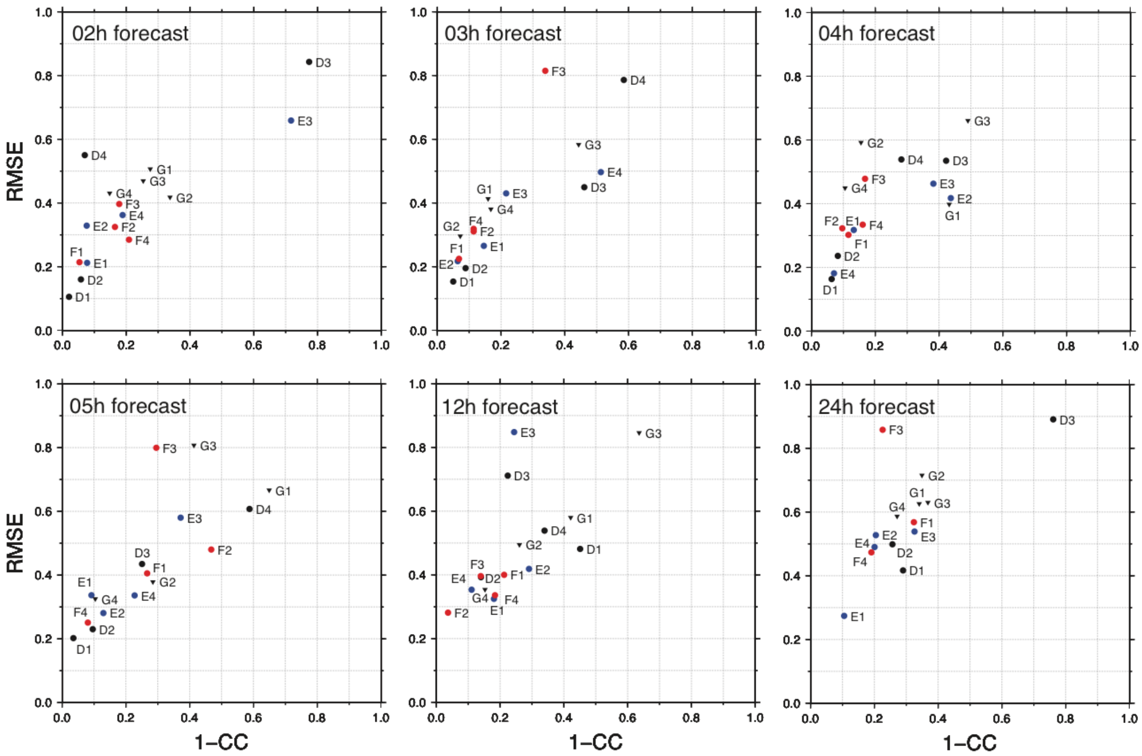

Fig. 4 The statistics of RMSE and 1-CC calculated between the forecast and the observation in the forecast models of Cases Ds, Es, Fs and Gs with the forecast lead times of 02h, 03h, 04h, 05h, 12h and 24h

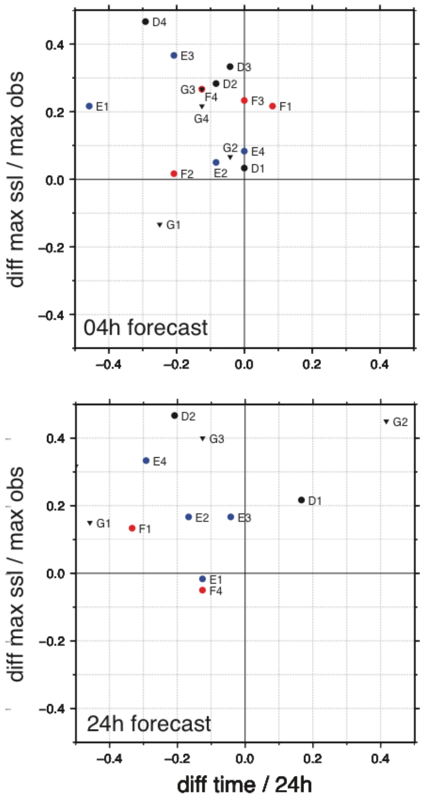

Fig. 5 Differences of the maximum sea surface levels between the prediction and the observation and of the times when measuring the maximum in the observation in the forecast models of Case Ds, Es, Fs and Gs

Next, the concurrence of the predicted maximum storm surge with the observed maximum is examined from the forecast models of Case Ds - Gs. Figure 5 shows the two values; the difference of the maximum storm surges between the prediction and the observation; the difference of the generation times between the maximums. The majority of the forecast models falling into the range of -0.2 - 0.2 in both differences are necessarily not equivalent to the results of the statistics in all cases. For example, in the 04h time span, the forecast models of F2, G2, G4 and F1 show a good performance in the difference of the maximum but the models of G2 and E2 indicate the large values of RMSE and 1-CC. In the case of the 24h time span, the values of the differences are widely scattered in comparison with the results of the short term forecast models. As a result, it is found that when the data set is combined with the typhoon position (Case E2, E3 and E1), the forecast model of 24h time span predicts the observation at Sakai.

CONCULSIONS

In the study, the sensitivity of the real time forecast model to the combination of the input data is investigated at Sakai at the Sanin coast, Japan. It is found that the performance of the real time forecast model shows best when training the neural network with the input data set of the storm surge, the sea level pressure, the depression rates of the sea level pressure, the wind speed and the typhoon position.

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