Prediction of short-term wind and wave conditions using Adaptive Network-based Fuzzy Inference System (ANFIS) for marine operations

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ABSTRACT: The paper focuses on prediction of short-term environmental conditions by using an improved ANFIS method for marine operations. The hindcast data used here consists of ten-year long one-hourly time series of mean wind speed U_w, significant wave height H_s and peak spectral wave period T_p at the North Sea Center. Before applying ANFIS models, a non-stationary decomposition technique is applied to the initial time series in order to extract the non-stationary character of the series and obtain the corresponding stationary part. Then both time series (initial and stationary one) are employed to establish ANFIS models for the prediction of future values of wind and wave parameters, respectively. The performance of forecasting models is assessed by means of error measures and uncertainty quantification. Results indicate that the short-term predictions based on the stationary time series produces better forecasts in both wave and wind characteristics and has a great application potential in marine operations.

1 INTRODUCTION

Short-term variation of wind and wave conditions has a great importance in planning and executing safe and efficient marine operations. Long-term statistical data of environmental conditions from measurements or hindcast models are useful for overall planning of marine operation activities. However, decision-making during the execution of marine operations requires more accurate and short-term prediction (forecast) of environmental conditions. For offshore wind turbines, the 6-hour forecasting is mainly used for on-site installation of bottom-fixed offshore wind turbines. The 1-3 days forecasting is, on the other hand, important for transportation of floating offshore wind turbines.

In order to predict the environmental conditions, several models such as empirical-based models, numerical-based models and soft-computing techniques have been developed during the last decades. In empirical-based models, waves can be predicted or forecasted with simple and fast methods (Wilson, 1965; Bretschneider, 1970; Hasselmann et al., 1973; Donelan, 1980), but these methods are only accurate in limited cases (Bishop et al, 1983). By means of the spectral energy or action balance equation, several numerical models (The WAMDI Group, 1988; Tolman, 1991; Booij et al., 1999) are employed to predict wave data with good spatial and time resolution. However, due to their complexity of numerical implementation, high CPU time required, and the need for accurate local bathymetric surveys, their implementation is not an easy task (Brown et al., 2007; Mahjoobi et al., 2008).

Recently, various soft-computing techniques have been used to predict wave parameters. The representative techniques include the Artificial Neural Networks (ANN) (Deo et al., 2001; Agrawal & Deo, 2002; Mandal et al, 2005; Jain & Deo, 2007), Fuzzy Inference System (FIS) (Kazeminezhad et al., 2005; Özger & Sen, 2007), and Adaptive Network-based Fuzzy Inference System (ANFIS) which is a combination of ANN and FIS. Kazeminezhad et al. (2005; 2007) and Mahjoobi et al. (2008) used ANFIS technique for the prediction of wave parameters and compared the results of the developed ANFIS with hindcasts of the Coastal Engineering Manual (CEM), ANN and FIS methods. Özger et al. (2007) and Akpınar et al. (2014) applied ANFIS to predict wave parameters and made a comparison with the results based on Auto Regressive Moving Average with exogenous input (ARMAX), Wilson, Shore Protection Manual (SPM), Jonswap, CEM methods. Malekmohamadi et al. (2011) investigated the efficacy of Support Vector Machines (SWMs), Bayesian Networks (BNs), ANNs, and ANFIS in wave height prediction. In most of the above studies, the non-stationarity is generally ignored, and the stationarity is sometimes stated as an unnecessary condition for the Fuzzy Time Series (FTS). In contrast, Stefanakos & Schinas (2015) and Duru et al. (2012) considered that before starting the fuzzy forecasting, the

non-stationarity should be removed from the initial time series. This procedure is especially important in time series of wind and wave parameters where the non-stationary character is inherent due to the seasonal effect. Based on this view, Stefanakos (2016a, 2016b; 2017) developed an ANFIS model with a non-stationary modelling for the prediction of wind and wave parameters, and more accurate forecasts were obtained.

The purpose of this paper is to develop an improved ANFIS method for forecasting short-term wind and wave conditions using in marine operations. Before an ANFIS model is established, two kinds of time series are considered. One is the initial, non-stationary one, and the other is the corresponding stationary one, which has been resulted by removing the non-stationary character using a decomposition procedure. Then, the ANFIS methods with initial and stationary time series are established, respectively. The proposed methods are utilized for the prediction of short-term mean wind speed U_w, significant wave height H_s and peak spectral wave period T_p through hindcast data in the North Sea Center datapoint. The prediction accuracies of the models are evaluated by means of several error measures. Besides, the model uncertainty in short-term weather forecasts during the all 10-year hindcast data is also investigated.

2 METHODOLOGY

2.1 *Study Area and Data Set*

Figure 1. the study area and the locations of site

The North Sea area is concerned in this study. The dataset used here comprises of hindcast data based on a high-resolution regional atmospheric model (SKIRON) and an ocean wave model (WAM), and locations of the provided sites are shown in Figure 1. At each site, the mean wind speed at a height of 10m above the mean sea level is produced by the atmospheric model and it then will be used as the input for the wave model to obtain wave properties. After that one-hourly time series of mean wind speed U_w, significant wave height H_s and peak spectral wave period T_p are obtained. The period covered is from January 2001 to December 2010. For more details, see Li et al. (2015).

The data set used in this study comprises of wind and wave data at the North Sea Center (site 15, Figure 1). This site is a shallow shelf sea adjacent to the North Atlantic with a mean water depth of 29 meters and distance to shore of 300 kilometers. During the mentioned period, the 50-year return period wind speed and significant wave height are 27.2 m/s and 8.66 m respectively, and the mean value of peak spectral wave period is 6.93s.

2.2 *Model Setup*

2.2.1 *Data Pre-processing Technique*

A many-year long time series of waves and wind data is a nonlinear, non-stationary and seasonal time series. It can be decomposed into a seasonal mean value and a residual stationary time series multiplied by a seasonal standard deviation (Athanassoulis & Stefanakos, 1995). For a multi-variate time series, the decomposition procedure (Stefanakos & Schinas, 2014) can be shown as

$$\underset{(N\times 1)}{\mathbf{Y}(t)} = \underset{(N\times 1)}{\mathbf{M}(t)} + \underset{(N\times N)}{\boldsymbol{\Sigma}(t)}\ \underset{(N\times 1)}{\mathbf{W}(t)} \tag{1}$$

or, in matrix notation

$$\begin{bmatrix} Y_1(t) \\ Y_2(t) \\ \vdots \\ Y_n(t) \\ \vdots \\ Y_N(t) \end{bmatrix} = \begin{bmatrix} M_1(t) \\ M_2(t) \\ \vdots \\ M_n(t) \\ \vdots \\ M_N(t) \end{bmatrix} + \begin{bmatrix} \Sigma_{11}(t) & \Sigma_{12}(t) & \dots & \Sigma_{1N}(t) \\ \Sigma_{21}(t) & \Sigma_{22}(t) & \dots & \Sigma_{2N}(t) \\ \vdots & \vdots & \vdots & \vdots \\ \Sigma_{n1}(t) & \Sigma_{n2}(t) & \dots & \Sigma_{nN}(t) \\ \vdots & \vdots & \vdots & \vdots \\ \Sigma_{N1}(t) & \Sigma_{N2}(t) & \dots & \Sigma_{NN}(t) \end{bmatrix} \begin{bmatrix} W_1(t) \\ W_2(t) \\ \vdots \\ W_n(t) \\ \vdots \\ W_N(t) \end{bmatrix} \tag{2}$$

where N is the number of time series. $\mathbf{M}(t)$ is the monthly mean value vector and $\boldsymbol{\Sigma}(t)$ is the monthly covariance matrix which are deterministic periodic functions with period of one year. They describe the exhibited seasonal patterns. $\mathbf{W}(t)$ is a vector zero-mean, stationary, stochastic process.

The seasonal patterns (mean value vector and covariance matrix) are estimated by averaging the time series of monthly mean values $M_{3,n}(j,m)$ and covariance matrix $S_{3,nl}(j,m)$

$$\tilde{M}_{3,n}(m) = \frac{1}{J}\sum_{j=1}^{J} M_{3,n}(j,m) = \frac{1}{J}\sum_{j=1}^{J}\frac{1}{K_m}\sum_{k=1}^{K_m} Y_n(j,m,\tau_k) \tag{3}$$

$$\tilde{S}_{3,nl}(m) = \frac{1}{J}\sum_{j=1}^{J} S_{3,nl}(j,m)$$

$$= \frac{1}{J}\sum_{j=1}^{J}\sqrt{\frac{1}{K_m}\sum_{k=1}^{K_m}[Y_n(j,m,\tau_k) - M_{3,n}(j,m)][Y_l(j,m,\tau_k) - M_{3,l}(j,m)]} \quad (4)$$

$$n,l = 1,\ldots,N$$

where J is the number of years, K_m is the number of observations within the *m-th* month, and $Y_n(j,m,\tau_k)$ is a re-parametrization of $Y(t)$

$$\left\{ Y_n(j,m,\tau_k), \quad \begin{matrix} j=1,\ldots,J \\ m=1,\ldots,12 \\ k=1,\ldots,K_m \end{matrix} \right\}, \qquad \mathrm{n} = 1,\ldots,\mathrm{N}, \quad (5)$$

where j is the year index, m is the month index and τ_k represents the monthly time.

It has been shown that periodic extensions of the quantities $\tilde{M}_{3,n}(m)$ and $\tilde{S}_{3,nl}(m)$ are good estimates of $M_n(t)$ and $\sum_{nl}(t)$, respectively (Stefanakos & Athanassoulis, 2002).

In our case, we have the initial joint long-term time series of three wind and wave parameters, i.e. mean wind speed U_w, significant wave height H_s and peak spectral wave period T_p. By using Eq.(2)-(4), the initial time series can be decomposed to obtain the stationary part $\mathbf{W}(t)$ and the deterministic seasonal patterns $[\mathbf{M}(t), \mathbf{\Sigma}(t)]$.

2.2.2 FIS/ANFIS

Fuzzy inference system (FIS) starts with the concept of a fuzzy set. A fuzzy set is an extension of a classical set whose elements can be a member of more than one set and take membership degrees between 0 and 1. The degree of membership of a given element is defined by the membership functions (MFs). MFs is a curve which can transform verbal data to numerical data. For example, if X is an universe of discourse (like H_s) and x is a particular element of X, then a fuzzy set O (like 'high') on X can be described as:

$$O = \{(x, \mu_O(x), x \in X\} \quad (6)$$

where $\mu_O(x)$ is the membership function, which provides a measure of the degree of similarity of x to the fuzzy set O ('H_s is high').

A Fuzzy Inference System (FIS) is a nonlinear method presented within the context of fuzzy set theory mapping from a given set of input variables to an output by means of a list of fuzzy statements or called IF-THEN rules. IF-THEN rules are expressions of the form 'If A Then B' to infer a fuzzy output based on fuzzy inputs, where A and B are labels of fuzzy sets characterized by certain MFs. Normally, the IF part is called premise and the THEN part is called consequent. A FIS consists of the following four functional blocks:

1. Fuzzifier. Fuzzification of the input variables into fuzzy input using the MFs stored in the fuzzy knowledge base.
2. Fuzzy knowledge base. It is composed of the data base and rule base, which containing the MFs of the fuzzy sets and IF-THEN rules, respectively.
3. Inference engine. Mapping the set of fuzzy input to fuzzy output by means of IF-THEN rules.
4. Defuzzifier. Defuzzify the fuzzy output to a crisp output.

The most important two types of fuzzy inference method are Mamdani (Mamdani, 1974) and Takagi-Sugeno (Takagi & Sugeno, 1985) fuzzy inference methods, which have different defuzzification schemes. In TS method, outcome of each IF-THEN fuzzy rule is a scalar rather than a fuzzy set for the output variable of the form:

R_r: IF x_1 is $S_r^{(1)}$, x_2 is $S_r^{(2)}$, ... , x_n is $S_r^{(n)}$

THEN $y_r = p_r x_1 + q_r x_2 + \ldots + t_r x_n$ (7)

where $S_r^{(i)}$ is a linguistic value (like 'low' and 'high' for H_s) which is represented by fuzzy sets and p_r, q_r, t_r are parameters to be defined.

The main problem with TS fuzzy inference method is the selection of parameters. Traditionally, the parameters are determined through the experience of experts or past available data of the system. Besides, it is also difficult to determine which shape of MFs has the best performance in FIS. Thus, the Adapted Network-based Fuzzy Inference System (ANFIS) was first proposed by Jang (1993) and is applied to optimize the premise and consequent parameters based on the available datasets by using a hybrid learning algorithm. Specifically, parameters of membership functions are trained using a back-propagation learning algorithm, while parameters of IF-THEN rules are adjusted by the least square method. To illustrate the procedure, a simple structure of ANFIS consisting of two input x_1 and x_2 and one output y is shown in Figure 2.

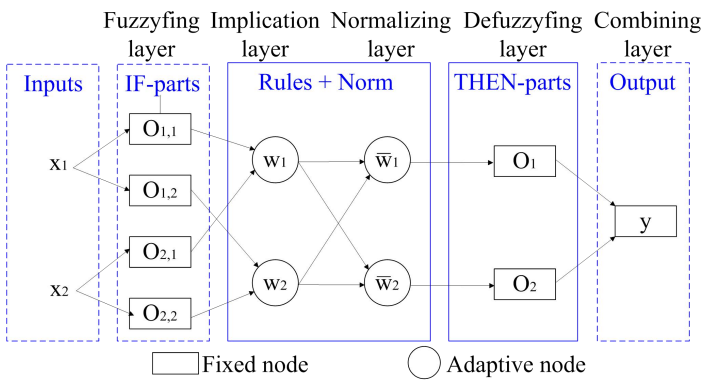


Figure 2. ANFIS architecture

In this ANFIS structure, the first layer is fuzzifying layer, in which the inputs x_i are fuzzified to the membership values based on the MFs of linguistic labels, as shown in Eq.(8). The second and third

layers are implication and normalizing layer respectively. In these two layers, the firing strength w_j for each rule and the corresponding normalized firing strength are calculated by Eq.(9)-(10). Then the outcome O_i of each rule can be calculated in the defuzzifying layer using the corresponding IF-THEN rules, as shown in Eq.(11). Based on the weighted average of all IF-THEN rules outcomes, the overall output y can finally be estimated by Eq.(12). It should be noted that in the ANFIS architecture, the FIS model is optimized by using adaptive neutral network. On one hand, by fixing the premise parameters in IF part (fuzzifying layer), the information is propagated forward to defuzzifying layer and the consequent parameters are identified using the least square method. On the other hand, by fixing the consequent parameters in THEN part (defuzzifying layer), the error is propagated back to fuzzifying layer and the premise parameters are modified and the optimal values are determined. Therefore, it can be seen that the only information need to be specified is the number and the type of MFs for each input variables.

$$O_{i,j} = \mu_j(x_i),\ for\ i,j = 1,2 \tag{8}$$

$$w_j = \prod_i \mu_{ij}(x), for\ i,j = 1,2 \tag{9}$$

$$\overline{w}_j = \frac{w_j}{\sum_i w_i}, for\ i,j = 1,2 \tag{10}$$

$$O_i = \overline{w}_i \cdot y_i = \overline{w}_i \cdot (p_i x_1 + q_i x_2 + r_i), for\ i = 1,2 \tag{11}$$

$$y = \sum_i \overline{w}_i \cdot y_i \tag{12}$$

In this study, three ANFIS models are developed to predict mean wind speed U_w, significant wave height H_s and peak spectral wave period T_p. For the prediction of each environmental parameter, the following ANFIS systems are considered:

(a) mean wind speed U_w:

$$U_w(t+1) = f_1(U_w(t)) \tag{13}$$

(b) significant wave height H_s:

$$H_s(t+1) = f_2(U_w(t), H_s(t)) \tag{14}$$

(c) peak spectral wave period T_p:

$$T_p(t+1) = f_3(U_w(t), H_s(t), T_p(t)) \tag{15}$$

where f function in each system includes n IF-THEN rules. The number n depends on the the number of fuzzy sets for each input variable. It can be seen that in this study, the prediction is a recursive process, that is the one-hour ahead forecasts only depend on the weather conditions of the previous hour.

By using the following forecasting method, two kinds of simulated time series $\tilde{Y}(t)$ and $\tilde{W}(t)$ are obtained:

(i) Applying ANFIS to the initial non-stationary $Y(t)$ to obtain the forecast $\tilde{Y}(t)$. The obtained series is referred to as 'initial time series' and the corresponding method is called 'initial-method'.

(ii) Applying ANFIS to the stationary-part $W(t)$ to obtain the forecast $\tilde{W}(t)$. Then, $\tilde{W}(t)$ should be combined with the seasonal patterns to get the simulated version of the initial non-stationary $Y(t)$. The obtained series and method are referred to as 'stationary time series' and 'stationary-method' respectively.

2.3 *Measuring Forecasting Quality*

In order to evaluate the short-term forecasting performance, the following four error measures are used:

(a) Root Mean Square Error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{I}\sum_{i=1}^{I} |e(t_i)|^2} \tag{16}$$

where I is the total number of testing data, and the forecasting error at time t_i is the difference between forecasts $f(t_i)$ and actual values $a(t_i)$: $e(t_i) = a(t_i) - f(t_i)$

(b) Bias

$$Bias = \frac{1}{I}\sum_{i=1}^{I}(-e(t_i)) \tag{17}$$

(c) Scatter Index (SI)

$$SI = \frac{RMSE}{\overline{a}} \tag{18}$$

where $\overline{a}$ is defined as the mean value of $a(t_i)$

$$\overline{a} = \frac{1}{I}\sum_{i=1}^{I} a(t_i) \tag{19}$$

(d) Correlation coefficient (R^2)

$$R^2 = \frac{\sum_{i=1}^{I}(f(t_i) - \overline{a})(a(t_i) - \overline{a})}{\sqrt{\sum_{i=1}^{I}(f(t_i) - \overline{a})^2 \sum_{i=1}^{I}(a(t_i) - \overline{a})^2}} \tag{20}$$

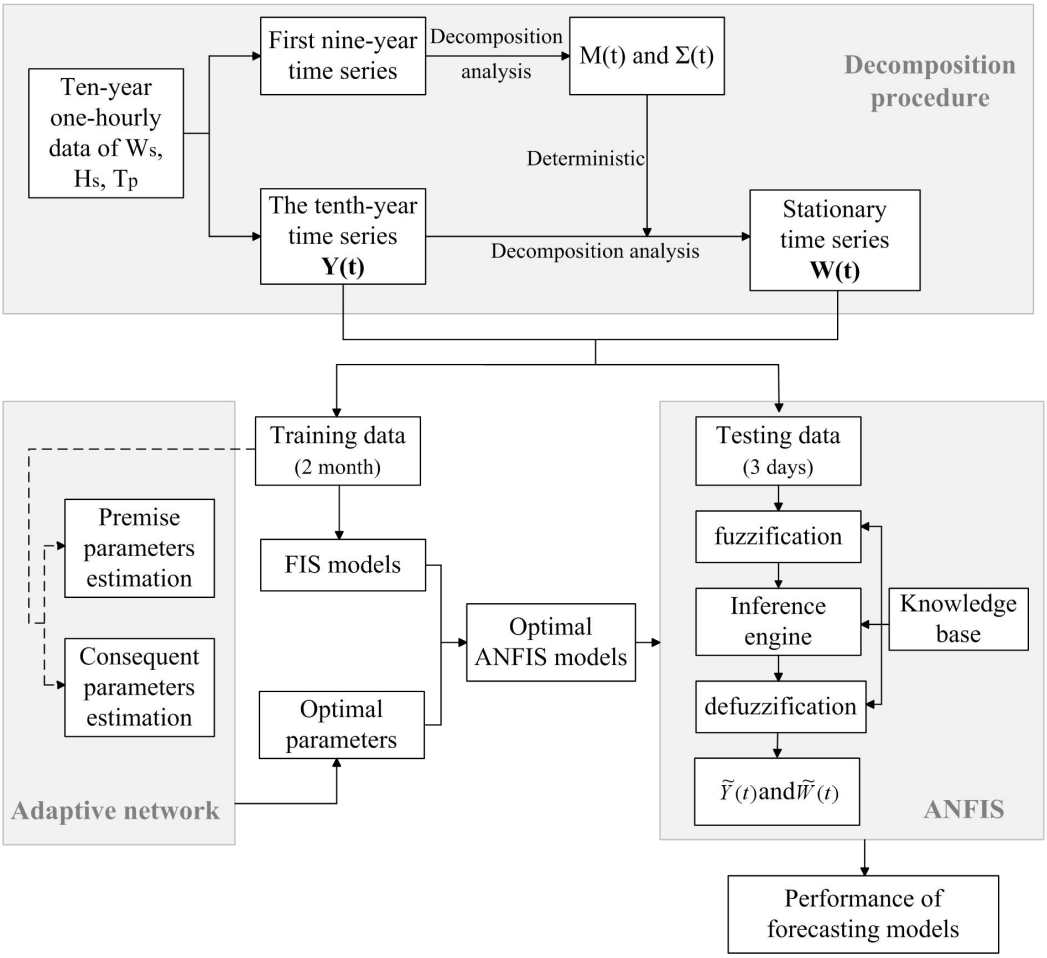


Figure 3. Flowchart of short-term weather conditions prediction

3 NUMERICAL RESULTS AND DISCUSSION

3.1 *Validation of the decomposition-ANFIS model*

The procedure used in the prediction of short-term weather conditions in this study are illustrated in Figure 3.

As can be seen from the Figure 3, the first step is decomposition procedure. In this step, the total time series of U_w, H_s and T_p is divided into two parts. The first nine-year (2001-2009) time series is referred to as the historical data, and is decomposed by means of the non-stationary modelling which is described in Section 2.2.1 to estimate the seasonal patterns. Meanwhile, the tenth-year (2010) is referred to as the study period. This initial non-stationary time series is Y(t) and it can be decomposed by using the seasonal patterns calculated from the previous nine years to obtain the stationary time series W(t). Then, the same period of data (in this case, two-month data in summer season) are selected from Y(t) and W(t) as training data respectively, and according to the duration required for transportation and installation of offshore wind turbines, the corresponding series of the following three days are selected as testing data. The next step is to determine proper ANFIS models to do prediction. Firstly, the initial FIS models are developed using the training data whose structures are summarized in Table 1. The U_w-FIS model or H_s-FIS model consists of two membership functions for each input. Gaussian type MFs is chosen for inputs and constant type MFs for output. However, since the T_p-FIS model has a comparatively complex prediction system, it needs more and of different type membership functions. Specifically, the number of membership functions for each input in T_p-FIS model is 2, 3 and 4. Two membership functions for U_w corresponding to the fuzzy sets “Low” and “High”; three membership functions for H_s corresponding to the fuzzy sets “Low”, “Medium” and “High”; four membership functions for T_p corresponding to the fuzzy sets “Low”, “Medium”, “High” and “Very high”. So, there are 24 fuzzy rules for the prediction of $T_p(t+1)$. Meanwhile, the adaptive neutral network is applied to train the parameters of initial FIS models and the optimal values are obtained using the procedure described in Section 2.2.2. By replacing these parameters into the initial FIS models, the developed ANFIS models are established. After that, the last step is to apply the developed ANFIS models for predicting the wave and wind parameters. It should be noted that in this step, the applied ANFIS models are determined based on training, while the prediction is performed using testing data. Then, the performance of forecasting models is assessed by means of error measures.

Table 1. Structure of ANFIS model

Prediction parameter	IF-THEN rules type	MFs type		No.of MFs
		Input	Output	
U_w	$U_w(t+1)=f_1(U_w(t))$	Gaussmf	Const.	2
H_s	$H_s(t+1)=$ $f_2(U_w(t), H_s(t))$	Gaussmf	Const.	2 2
T_p	$T_p(t+1)=$ $f_3(U_w(t),H_s(t),T_p(t))$	Gauss2mf	Const.	2 3 4

The predictions based on the two kinds of time series are performed and the error statistics for each model are calculated and shown in Table 2. As it can be seen, the ANFIS models are suitable in the estimation of both wave and wind parameters. The R^2 are larger than 0.94 and the SI are less than or equal to 7% for all of the models. It is also interesting that the accuracies of the models using initial- and stationary-time series are nearly the same. Therefore, it can be concluded that when large amount of historical data are available to construct the ANFIS model, there is a good agreement between actual data and predictions regardless of the initial or stationary time series applied.

Practically, measurements are often used in weather forecasting for decision-making during the execution of marine operations. However, since the measured wave and wind data are scarce and the measurement are difficult, costly and time-consuming, continuous time series for a long duration is not available at every site. In order to verify the performance of ANFIS which is closer to reality, the length of training data is reduced to 12 days, and the testing period remains 3 days. Following the aforementioned procedure, ANFIS models with initial- and stationary-time series are developed to forecast the three parameters, respectively. The comparison of actual and forecast values is shown in Figures 4-6. In each figure, the (a) depicts the results based on the 'initial-method', while the (b) depicts the results based on the 'stationary-method'. The corresponding error statistics are summarized in Table 3.

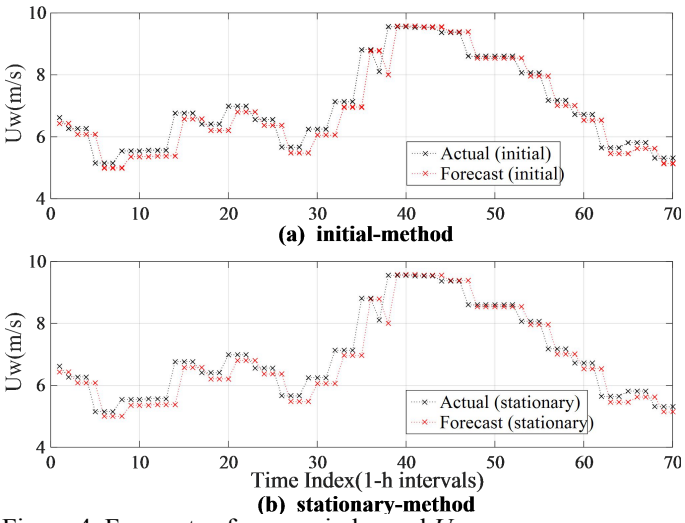


Figure 4. Forecasts of mean wind speed U_w

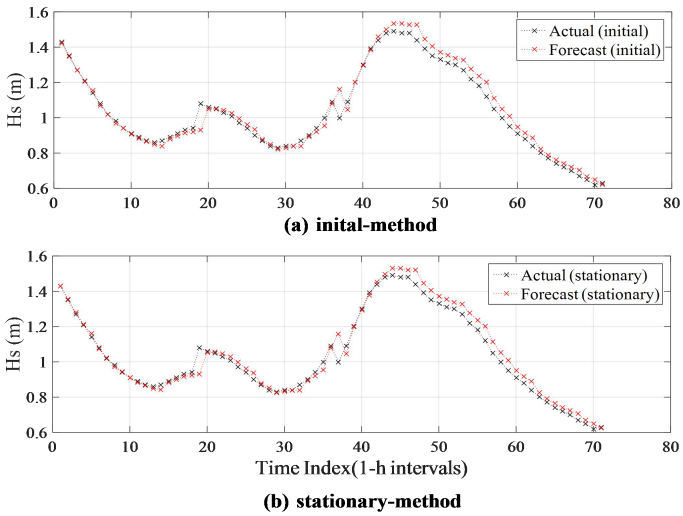


Figure 5. Forecasts of significant wave height H_s

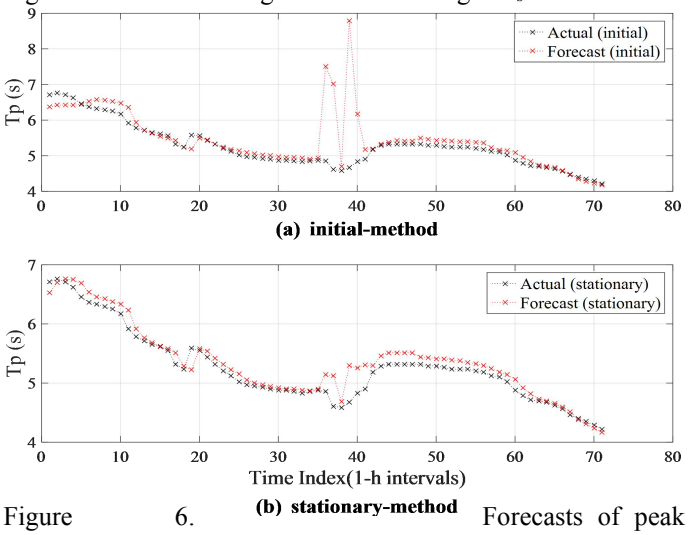


Figure 6. Forecasts of peak spectral wave period T_p

In Table 3 one can see that for the cases of H_s and U_w, the accuracy of the both methods (initial- and stationary-method) is satisfactory enough. It is apparently seen in Figures 4-5 that all rising and falling trends of the actual H_s and U_w are properly followed by the predictions. However, for a relative complex prediction system, the T_p predictions of initial-method are less reliable. It is noted that, there is an improvement in the prediction performance of T_p by means of the stationary-method, which is reflected in the reduction of the errors. Specifically, the error reduction is generally between 48% and 79% and with minimum and maximum values at 48.6% (Bias) and 78.5% (SI), respectively. Furthermore, the peaks and troughs are relative accurately estimated by the proposed stationary-method (see Fig. 6). This shows a great enhancement of the short-term prediction by introducing the decomposition procedure before the ANFIS model is established. Generally speaking, the non-stationarity is an important factor affecting the short-term prediction accuracy of ANFIS model. When only limited data is available, the ANFIS models using the stationary time series typically give better results than that of the initial time series.

Table 2. Error measures (training period is 2 month)

Parameter	Bias	SI	R^2	RMSE
U_w (initial)	-0.036	0.064	0.946	0.451
U_w (stationary)	-0.041	0.065	0.946	0.452
H_s (initial)	0.017	0.039	0.986	0.041
H_s (stationary)	0.013	0.038	0.987	0.040
T_p (initial)	0.067	0.023	0.981	0.120
T_p (stationary)	0.071	0.021	0.984	0.109

Table 3. Error measures (training period is 12 days)

Parameter	Bias	SI	R^2	RMSE
U_w (initial)	-0.080	0.066	0.943	0.481
U_w (stationary)	-0.078	0.066	0.943	0.480
H_s (initial)	0.015	0.040	0.986	0.041
H_s (stationary)	0.015	0.039	0.987	0.040
T_p (initial)	0.208	0.130	0.564	0.684
T_p (stationary)	0.107	0.028	0.961	0.173

3.2 *Sensitivity analysis*

In addition, further investigations are also required to study the influence of the length of both the training and the forecasting period in short-term prediction. Since there is a significant difference of performance between the two methods for predicting peak spectral wave period, the accuracy of T_p prediction is used for the following sensitivity analysis. On one hand, to determine the impact of training period on model's predicting ability, the forecasting horizon is fixed for 3 days and the historical time series varies from 3 days (72 points) to 3 month (2160 points).

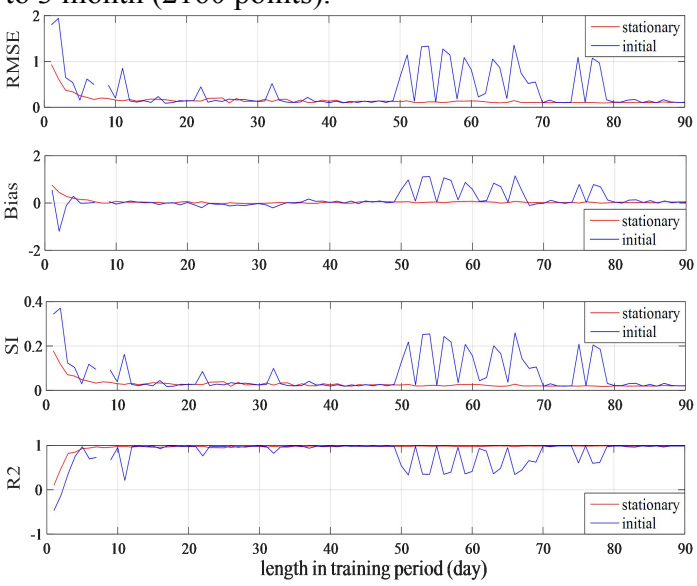


Figure 7. Error measures vs length in training period (site 15)

In Figure 7 the error measures are shown versus the length of the training period. By inspecting this figure, one can observe that in the stationary-method the error measures are stabilized after 9 days (approximately 3 times the forecasting horizon). While in the initial-method the error measures are likely to oscillate in the entire 3-month period, and, therefore, a stable point cannot be determined. Especially, in the range of 50-80 days, poor accuracy and numerical instability is obtained when dealing with initial time series. Thus, the ANFIS models using stationary time series give better results with lower error measures and higher stability than ANFIS models using initial time series.

On the other hand, in order to evaluate the short-term predicting performance of ANFIS model with the given training period when different forecasting horizon are required, the length of training data is fixed for two month (1440 points), the forecasting horizon is let to vary from 1 day (24 points) to 1 month (720 points). In Figure 8 it is shown that with the increase of testing period, the results obtained from the stationary-method are always better which remain lower error measures and higher stability.

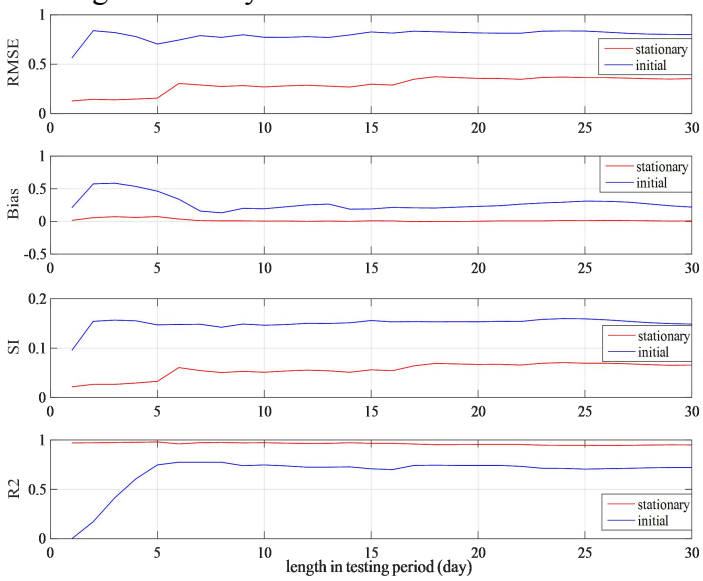


Figure 8. Error measures vs length in testing period (site 15)

3.3 *Uncertainty quantification analysis*

The examples in the previous sections focus on the performance of forecasting models for predicting short-term environmental conditions during the summer season which is relatively calm. In order to quantify the uncertainty in all seasons for the whole year, uncertainty quantification analysis is required. The purpose of this section is to quantify if the proposed models still perform well in short-term

prediction whichever seasons and weather conditions are taken into account.

Since the accuracy for the forecasts at different time instants in the future is important, in the following analysis, the forecast error factor $\varepsilon_M(t)$ is used to quantify the uncertainty of the corresponding forecast performance in a prediction model. It is defined as the ratio between forecasted and actual value in testing data:

$$\varepsilon_M(t) = \frac{f(t)}{a(t)} \tag{21}$$

where t is the lead time (in day), $f(t)$ and $a(t)$ are the forecasted and actual value at the tth day ahead around 9am, respectively.

The methodology for estimating the uncertainty in forecasting model with a given length of training and testing data is as follows:

1. The length of training and testing data in each ANFIS model are assumed to be t_1 and t_2 days, respectively.
2. The short-term predictions of wave and wind conditions are performed by applying ANFIS methods in the entire ten-year period of the data. For example, the first $t_1 \times 24$ datapoints in the first-year time series are chosen to estimate the first ANFIS model. This model is then applied to predict the next $t_2 \times 24$ datapoints. The second ANFIS model is established with the subsequent $t_1 \times 24$ datapoints and the following $t_2 \times 24$ datapoints are predicted. The procedure is repeated until the entire ten-year period is covered. A number of N cases and corresponding forecasting results are obtained.
3. Calculate the forecast error for each case from Eq.(21). It can be seen that for a given t, $\varepsilon_M(t)$ is a random variable with N datapoints.
4. Calculate the statistical parameters of random variable $\varepsilon_M(t)$ and fit a proper probability distribution to show its properties.

Assuming the length of training and testing time are fixed to 50 days and 3 days respectively, the aforementioned procedure is performed to investigate weather forecast uncertainty. Similarly, the accuracy of T_p prediction is used for the following uncertainty quantification analysis. A comparison between the initial- and stationary-methods is shown in Figure 9 in the form of density distributions with respect to the forecast error factor ε.

As illustrated in the Figure 9, when the amount of historical data is quite large compared to the forecast data, the mean values of both two statistical distributions are close to unit, which indicates that the forecast value is approximately equal to the corresponding actual value in each testing case during the whole ten-year time series despite seasonal variation. However, the shapes of the two distributions of the forecast error have large difference. The distribution of forecast error from stationary method is more concentrated around the mean value, which is closer to one. In contrast, the mean value from initial method is far from one, and the standard deviation is higher.

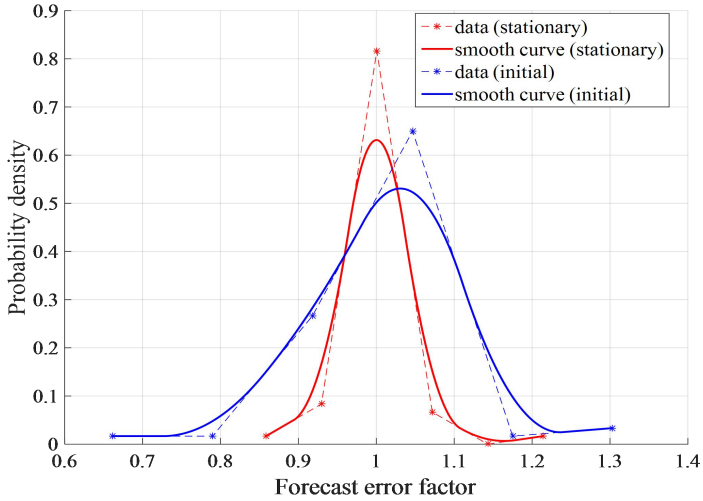


Figure 9. Forecast error factor ε distribution

It is evident that the forecast error is a function of both the actual training period and the leading time for forecast. Thus, in order to identify this feather, a period ratio R between the training period and the leading time for forecast is introduced as follows:

$$R = \frac{T_t}{T_f} \tag{22}$$

where T_t is the training period, representing the length of the available historical time series before executing a marine operation. T_f is the length of forecasting horizon.

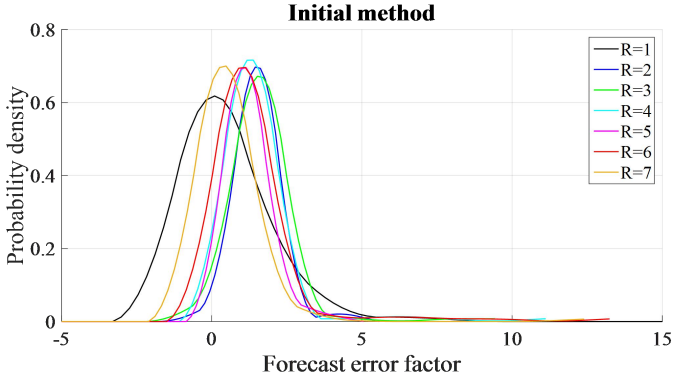
In the following case, the training period is assumed to be fixed for 21 days, 14 days and 7 days. For each training period, the period ratio R varies from 1 to 7. The forecast error distribution in each ratio is built using the corresponding number of cases of forecast error factor. By statistically analyzing the series of forecast error factor, the mean value and standard deviation are calculated and tabulated in Table 4.

The results show several features. Firstly, the ratio R would affect the short-term prediction performance and this behavior is more pronounced in results based on the initial-method. For instance, when the training period is 21 days, the forecast error distributions for 7 different ratios are illustrated in Figure 10. It is apparent that the dispersion degree of forecast error distributions using the stationary-method is generally lower than those using the initial-method. As the ratio increases from 1 to 7, the standard deviation increases significantly based on the initial-method. While in the stationary-method, standard deviations at different ratios are always less than 0.23, demonstrating the

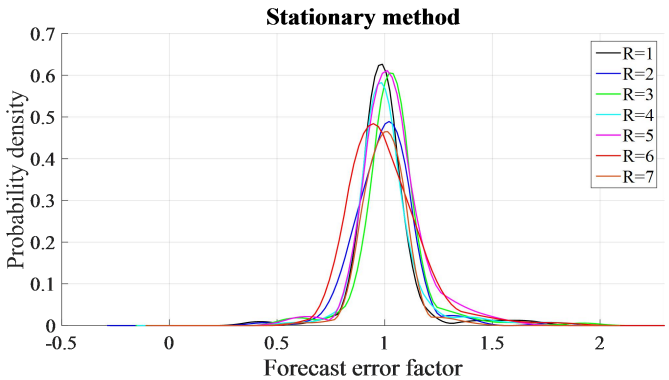
Table 4. Statistical parameter of ε (varying training period)

Training period (days)	Method	Coefficient	Period ratio R						
			1	2	3	4	5	6	7
21	Initial	m	1.4381	1.1145	1.2389	1.2737	1.1414	1.3674	1.1106
		std	2.4727	0.5952	1.0491	1.2929	0.4767	1.5122	0.9281
		No. of cases	80	110	130	130	140	140	150
	Stationary	m	1.0032	0.9914	1.0231	1.0224	1.0543	1.0335	0.9988
		std	0.1378	0.1324	0.1503	0.1386	0.2286	0.2025	0.0805
		No. of cases	80	110	130	130	140	140	150
14	Initial	m	1.6599	1.5333	1.4957	1.7399	1.5095	1.6026	1.5536
		std	3.5603	3.0716	3.0728	4.3226	3.1317	2.7403	4.0345
		No. of cases	130	170	190	200	210	220	220
	Stationary	m	1.0603	1.0309	1.0623	1.0572	1.0494	1.0656	1.0248
		std	0.4243	0.1721	0.2673	0.2956	0.2186	0.3465	0.2019
		No. of cases	130	170	190	200	210	220	220
7	Initial	m	8.6356	7.4797	4.7265	3.8716	5.3750	4.4432	5.5718
		std	41.7178	42.3232	23.6164	18.8342	23.1004	24.0071	29.4128
		No. of cases	260	340	390	410	430	440	450
	Stationary	m	1.0384	1.0587	1.0501	1.0598	1.0511	1.0523	1.0255
		std	0.2318	0.2949	0.2499	0.2916	0.2535	0.2849	0.2376
		No. of cases	260	340	390	410	430	440	450

degradation of forecasting performance not seen remarkably from the stationary-method.



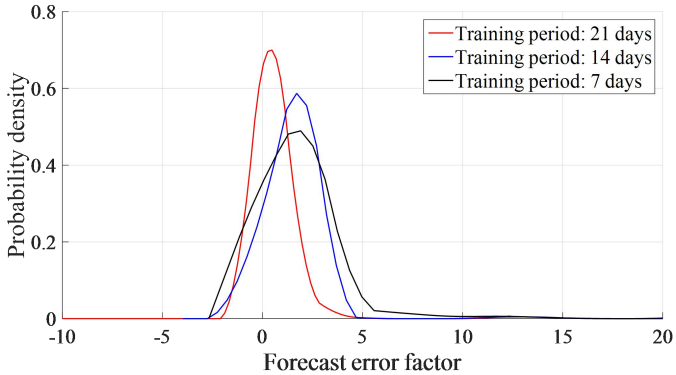
(a) Initial method



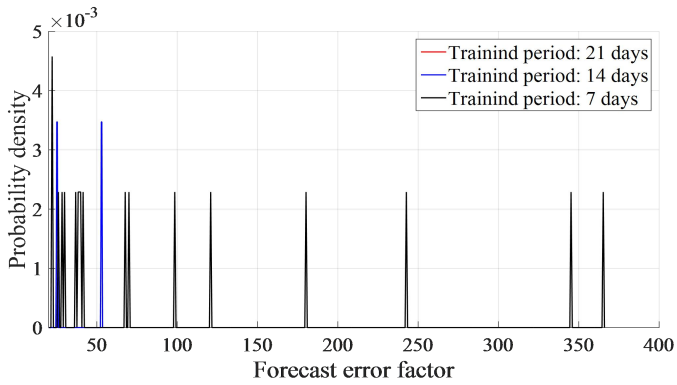
(b) Stationary method

Figure 10. Forecast error factor ε distribution vs period ratio R

Furthermore, the uncertainty of forecasts is not only affected by the ratio R, but also changes in terms of the training period, which usually increases along with the decrease of the length of available historical time series. For a given ratio R, the forecast error factors using the initial-method show an obviously divergent trend with the decrease of training period, which can be observed from the Table 4. However, in the stationary-method, the forecast error factors are always stable at different training periods. To see the difference over time more clearly, the ratio of 7 is chosen and the forecast error distribution corresponding to training period of 7, 14 and 21 days are displayed for comparison, as shown in Figure 11.

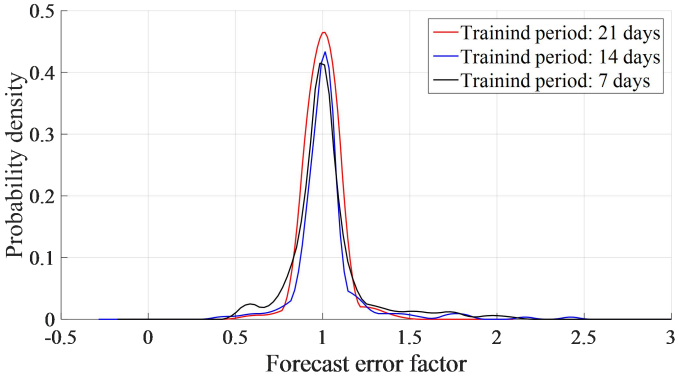


(a) Initial method



(b) Initial method (the tail part)

In Table 4, it can be observed that for the initial-method, when the training period decreases from 21 days to 7 days, the standard deviation of the forecast error would increase more than 30 times (from 0.9281 to 29.4128), which may be due to the seasonal effects. In this case, few training data is not



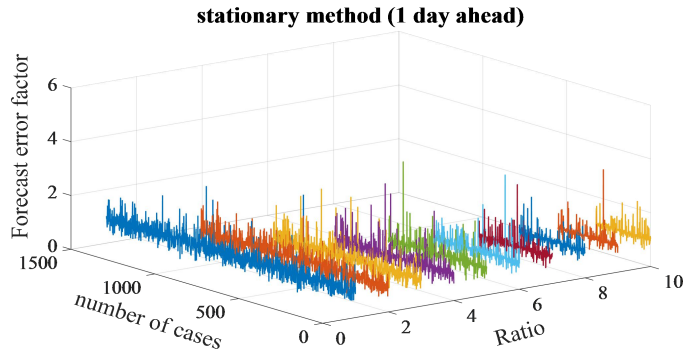
(c) Stationary method

Figure 11. Forecast error factor ε distribution vs training period (Ratio is 7)

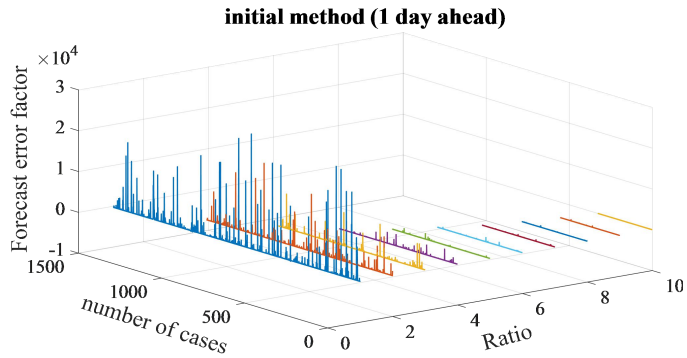
enough to predict the weather conditions in the following several days, which can be illustrated in the Figure 11 (a) and (b). As shown in these figures, as the training period decreases, not only the peak of forecast error density distribution decreases, but also there are a lot of extremely large forecast error values in the tail of the distribution. This lead to the mean value of the distribution is far from one and the standard deviation increases sharply. In contrast, forecasting performance from the stationary-method is not influenced much by seasonal effects and the standard deviations have a small tendency to fluctuate in shorter training period, which can be shown in the Figure 11 (c). Hence, it can be concluded that less uncertainty of short-term weather forecasts is reflected by the stationary-method, even in rough weather and severe sea states.

Finally, for a given period ratio and training period, the stationary-method has a much more accurate and stable performance than the initial-method for prediction of short-term weather conditions. For each case in Table 5, the stationary-method gives better results because the standard deviation of forecast errors from the stationary-method are lower than those from initial-method. In addition, it should be noted that the difference between the standard deviation from the two methods tends to increase as the training period and ratio decrease. For instance, the mean value and the standard deviation of forecast error using the initial-method are greater than 8 and 41 respectively at the training period of 7 days and period ratio of 1. This implies that the forecasts from the initial-method fluctuates too much and the results are totally unbelievable. On the contrary, the stationary-method is a better method in short-term prediction of weather conditions, with less uncertainty over the forecasts in the entire ten-year.

Moreover, in order to be more practical and to provide more guidance for marine operations, uncertainty quantification analysis of constant day-ahead weather forecasting should be investigated. In this part, the lead time is fixed to 1 day and ten different ratios from 1 to 10 are selected. The time series of forecast error factor ε for each ratio is plotted in Figure 12 and the corresponding statistical results of each time series are calculated and summarized in the Table 5.



(a) Stationary method



(b) Initial method

Figure 12. Time series of forecast error factor ε (lead time is 1 day)

It is apparently seen in Figure 12 that the proposed stationary-method has better capacity to predict the short-term weather conditions in all seasons since all time series of forecast error factors are found to be closed to 1. However, when the initial-method is applied, the uncertainties corresponding to the forecast error would significantly different from one another. As illustrated in Figure 12 (b), as the ratio decreases, the fluctuations of the forecast error factors would increase in frequency and intensity, and the maximum error value could up to 2×10^4, making it hard to get the accuracy forecasts.

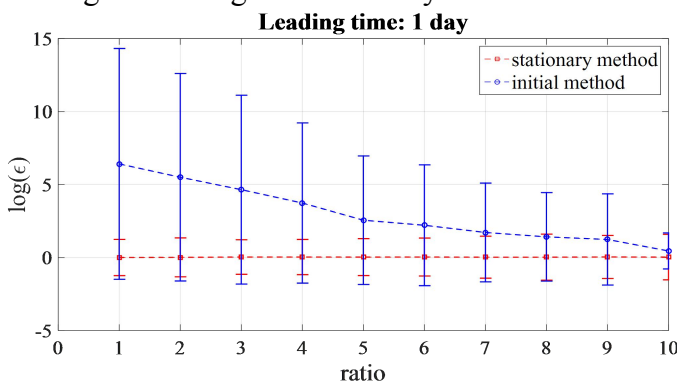


Figure 13. Error bars of logarithm transformed forecast error factor ε

Table 5. Statistical parameter of ε (lead time: 1 day)

method	coefficient	ratio									
		1	2	3	4	5	6	7	8	9	10
Initial	m	611.08	245.15	104.57	41.919	12.914	9.1350	5.5718	4.1311	3.4523	1.5732
	std	2712.8	1219.1	644.06	241.64	81.551	62.719	29.413	20.703	22.726	3.4314
	No. of cases	1820	1210	910	730	600	520	450	400	360	330
Stationary	m	1.0033	1.0145	1.0372	1.0356	1.0325	1.0382	1.0255	1.0252	1.0411	1.0315
	std	0.2892	0.2638	0.3061	0.2997	0.2827	0.2729	0.2376	0.2061	0.2293	0.2109
	No. of cases	1820	1210	910	730	600	520	450	400	360	330

In addition, error bar chart is used to indicate the difference between the uncertainty of forecasts in two methods. Since the mean value and standard deviation of each ε_M based on the initial-method are several orders of magnitude larger than those based on the stationary-method, the logarithms of these results are calculated and shown in Figure 13. The results show that based on the initial-method there is a divergent trend with the decrease of ratio. It can be seen that both the mean value and standard deviation continues to increase and a higher variability in the short-term forecasts occurs as the ratio decreases. However, the level of uncertainty in the forecasts by using stationary-method is observably low and remains stable at all ratios. In such cases, if the forecast error factor is assumed to be a Gaussian random variable, with mean value around 1 and standard deviation around 0.2, there is a probability of about 68% that the prediction lies within one standard deviation of the mean (e,g. the mean value of H_s is 1m, so the corresponding range is between 0.8-1.2m), which is satisfactory. Therefore, using the stationary-method can be seen as a credible way to predict the short-term weather conditions, especially in the case of very little historical data is available.

In summary, although a forecasting method can correctly predict the environmental conditions for a certain period, the overall forecasting performance may be quite different in the whole year. Hence, the uncertainty quantification analysis is a more comprehensive approach to assessing the short-term predicting performance of the forecasting model. The results further indicate that the proposed stationary-method is relative insensitive to the seasonal variation and has more significant advantages for short-term forecasting of waves and wind.

4 CONCLUSIONS

In this paper, an improved ANFIS model combined with a non-stationary decomposition technique is applied for prediction of short-term mean wind speed U_w, significant wave height H_s and peak spectral wave period T_p during execution of marine operations. To remove the non-stationary character of wind and wave time series, ten-year long (2001-2010) one-hourly data at the North Sea Center is used. The seasonal patterns are estimated from the first nine-year time series, and then the tenth-year initial time series is decomposed by using the obtained patterns to get a residual stationary part. Forecasting performed by applying ANFIS models with initial- and stationary-time series are called initial-method and stationary-method, respectively.

For evaluating the prediction accuracy of the two methods, several error measures such as Bias and Correlation coefficient (R^2) are utilized. The comparison of error measures indicates that, the stationary-method has a far better performance than initial-method, especially in modeling complex nonlinear systems and using limited historical data. To further validate the performance of the stationary-method, investigations on the influence of the length of both the training and the forecasting period in short-term prediction have been conducted. It is further observed that stationary-method requires less historical data to achieve a satisfactory result.

In addition, the model uncertainties in short-term weather forecasts based on both initial- and stationary-method are also investigated. For this purpose, the all ten-year long data are used to quantify the uncertainty in forecasts. Sensitivity analysis results illustrate that the forecast errors from the stationary-method suffer a relatively small uncertainty for both severe weather conditions and less historical time series. Thus, one can conclude that the stationary-method outperforms the initial-method in terms of prediction reliable.

Therefore, the proposed methodology based on the aforementioned decomposition technique and ANFIS could provide an effective way for the short-term prediction of wave and wind conditions and has a great application potential in marine operations. However, it is also worth noting that a limitation still exists in the stationary-method. In the decomposition procedure, the deterministic seasonal patterns need to be utilized to obtain the stationary wind and waves time series, which estimated based on the long-term historical data. Therefore, how to obtain the long-term historical data at any point and how to ensure the accuracy of short-term predictions in the absence of long-term data are the hotpots and difficult problems in future.

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