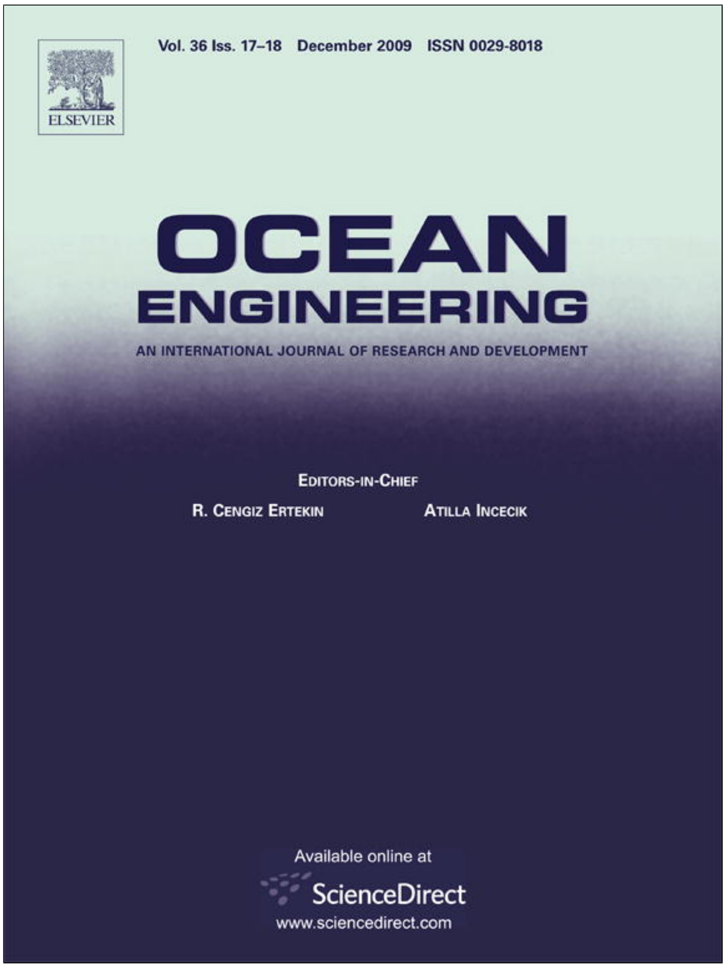
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A fuzzy inference system for wind-wave modeling

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ABSTRACT

Forecasting of sea-state characteristics, with warning time of a few hours, appears a necessity in Operational Oceanography, linking sophisticated marine monitoring systems with forecasting modeling tools. In this paper, instead of using conventional numerical models, a Takagi–Sugeno-rule-based Fuzzy Inference System (FIS) was developed aiming at forecasting wave parameters based on the wind speed and direction, and the lagged-wave characteristics. Initial and final antecedent fuzzy membership functions were identified using the subtractive clustering method. The model was applied on the wind and wave dataset recorded in years 2000–2006 by an oceanographic buoy deployed in the Aegean Sea. The model showed perfect fit for the training period (2000–2005; 12,274 data points), and expanded its hindcasting ability during 2006 (1044 data points), as the verification part of the series. Model results, for a lead time of 3 h, showed good agreement between the predicted and the observed significant wave height (RMSE=0.216) and zero-up-crossing period (RMSE=0.315). According to other model performance criteria, the fuzzy model slightly underpredicted both wave characteristics (the linear regression slope was 0.911 for wave height and 0.788 for wave period), and reduced its forecasting ability at higher prediction intervals (+6 to +12 h). Overall, model results illustrated that the developed FIS could serve as a valuable tool for the operational prediction of wave characteristics in Northern Aegean Sea, through the utilization of the POSEIDON network.

1. Introduction and background

Increased reliability in real-time wave prediction over the time span of a few hours appears to be of crucial importance in coastal, harbour and ocean engineering, allowing the safe and efficient coastal and open-sea activities, as offshore drilling, naval operations, merchant vessel routing and nearshore construction (Mandal and Prabaharan, 2006). As wave buoys deployment became popular, providing real-time wave datasets and saving long-term historic events, station-specific forecasts involved the classical time-series approach, employing stochastic ARMA or ARIMA models (Agrawal and Deo, 2002) or the development of artificial neural networks (ANNs) (Deo and Kiran Kumar, 2000; Deo et al., 2001; Makarynskyy, 2004; Rao and Mandal, 2005; Jain and Deo, 2007). Current experience with ANNs showed that an appropriately trained model could provide satisfactory results in the deep open ocean (Deo and Jagdale, 2003), but less accurate wave predictions in coastal or harbour areas, due to the increased uncertainty introduced in the system (Tsai et al., 2002; Makarynskyy, 2004). Similarly, wave parameter prediction following a Takagi–Sugeno (TS) rule-based Fuzzy Inference System (FIS) produced fairly accurate solutions of wave characteristics (Kazeminezhad et al., 2005; Özger and Sen, 2007). The use of the fuzzy logic theory allows the user to include the unavoidable imprecision and uncertainty in the data. Moreover, the representation of the whole dataset by one model poses a disadvantage for classical approaches and shows limited validity. In the case of fuzzy models, fuzzy representations combine a set of linear independent models, obtained through fuzzy rules, covering the whole range of input signals through multiple partitions corresponding to these weighted multiple linear models.

In this paper, the application of various dynamic TS fuzzy inference systems to predict the impact of wind speed on the deep-sea wave characteristics propagating along the North Aegean Sea is established. The Takagi–Sugeno fuzzy systems have been widely applied in environmental studies due to their simplicity in the inference procedure and the possibility to incorporate a general condition on the physical structure of the system into the fuzzy system (Sylaios et al., 2008). The TS fuzzy inference system produces a flexible, user friendly, fuzzy-rule-based model, in which the user imports raw data of a series of predictor variables and the developed system defines the fuzzy sets according to a collection of "IF–THEN" rules; it then produces an output highly comparable to the actual values observed in the real world. Özger and Sen (2007) presented a dynamic FIS to model the wave characteristics recorded from a NDBC buoy

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moored off California coast. They noted that the one-step ahead significant wave height ($H_S(t+1)$) and zero-up-crossing wave period ($T_{02}(t+1)$) predicted values, showed strong dependence on the current wind speed ($U(t)$), but also on the previous state of these parameters ($H_S(t-1)$, $T_{02}(t-1)$). This is the dynamic part of the model, as a high serial correlation between successive H_S and T_{02} values exists in long-term wave records. Such approach implies that low wave heights are more likely to be followed by low ones, and high wave heights by high ones (Özger and Sen, 2007). In this paper, this approach was followed and was further expanded to determine the appropriate input variables and the time-delay coordinates to reconstruct the phase space of the observed dynamic system. Such approach led to the inclusion of the wind direction as an input variable to the developed FIS (Zamani et al., 2008).

2. Methods and dataset

2.1. The fuzzy inference system

A Fuzzy Model is a tool utilizing the information observed from a complex phenomenon to derive a quantitative model. A fuzzy system is a nonlinear mapping between inputs and outputs. The mapping of inputs to outputs is in part characterized by a set of "IF–THEN" rules. A typical rule for the multiple-input–single-output Takagi–Sugeno fuzzy system is of the form

$$R_r : \text{IF } (x_1 \text{ is } A_r^{(1)}, x_2 \text{ is } A_r^{(2)}, \ldots, x_p \text{ is } A_r^{(p)} \text{ THEN } y_r = f_r(x_1, x_2, \ldots, x_p) \quad (1)$$

where $A_r^{(i)}$ is the fuzzy set corresponding to a partitioned domain of input variable x_j in the rth IF–THEN rule, p the total number of antecedents consisting the fuzzy model input variables, $f_r(.)$ denotes the linear function of the p input variables, and y_r the consequent of the rth inference rule. It is assumed that there are R_r ($r=1,2,\ldots,n$) rules in the above-mentioned form. The linear functions f_r are model consequents defined as linear functions of the inputs by the following expression:

$$y_r = f_r(x_1, x_2, \ldots, x_p) = b_r(0) + b_r(1)x_1 + b_r(2)x_2 + \cdots + b_r(p)x_p \quad (2)$$

where $[b_r(0), b_r(1), b_r(2), \ldots, b_r(\text{p})]$ is the parameter vector.

The crisp output of the fuzzy system may be determined by

$$y = \frac{\sum_{i=1}^{R} w_i y_i}{\sum_{i=1}^{R} w_i} \quad (3)$$

where w_i denotes the degree of fulfillment of the ith fuzzy rule, defined using the minimum or the product conjunction operators.

The present fuzzy-rules-based systems for the hindcasting of buoy wave characteristics were developed on the standard Adaptive Neural Fuzzy Inference System (ANFIS), implemented in Matlab 7.0 (Jang, 1993). The ANFIS approach defines a TS FIS through a multi-layer feed-forward Neural Network approach, by defining the following steps: the fuzzification of input values through the defined membership functions leading to membership values, the aggregation of membership values by the application of a t-norm in the premise parts, the evaluation of basis functions by normalizing the aggregated membership values, the weighting of basis functions with linear consequent functions and the final evaluation of output value by applying Eq. (3). ANFIS supports two different methods for antecedent membership function identification: grid partition (GP) (Jang, 1993) and subtractive clustering (SC) (Chiu, 1994). The grid partition method divides the data into rectangular subspaces based on the pre-defined number of the membership functions and their types, producing rule base explosion. On the contrary, the subtractive clustering method determines datapoint clusters by measuring their potential in the feature space. This method has the advantage of avoiding the explosion of the developed rule base, a problem known as the "curse of dimensionality".

In the present work, initially the grid partition method was used to initialize the membership functions. The parameters of the membership functions were optimized on the identification dataset by a neural network back-propagation learning algorithm, while the consequent parameters were calculated by the linear least squares method. Best model results were obtained when initial partition was achieved through three Gaussian-type membership functions for each antecedent variable. Additional model runs were conducted using triangular, trapezoidal and bell-shaped membership functions and membership functions number varying between 2 and 5, but with poorer results. In another approach, the initial model parameters were formed using the subtractive clustering method. The same procedure as for the grid partition model was performed to optimize the parameters of the membership functions and to compute the consequent parameters. In order to produce the optimal model, the parameters of the subtracting clustering algorithm were varied between 0.5 and 2 for the quash factor, and 0.1 and 1.0 for the cluster radius and accept and reject ratios, respectively.

2.2. Dataset description

The wind and wave dataset imported into FIS was obtained by an oceanographic buoy located near Athos Peninsula (39.96°N, 24.72°E, water depth 220 m) (Fig. 1) in years 2000–2006. Meteorological and wave data were recorded as part of POSEIDON sea observatory network operated by the Institute of Oceanography of the Hellenic Centre for Marine Research (HCMR) (Soukissian et al., 1999, 2002). The recording interval of measurements was 3 h and the sampling period of free surface elevation was 17 min. The meteorological dataset involves the time-series of gust wind speed (m/s), wind speed (m/s) and wind direction (deg), recorded at 3 m height above sea level. The most important recorded wave parameters are the spectral significant wave height H_{m0}, the mean zero-up-crossing T_{02}, and the mean wave direction θ_W (Soukissian et al., 2002).

A complex wind regime is depicted with more frequent (approximately 40%) NNE and NE winds (directions 30–60°),

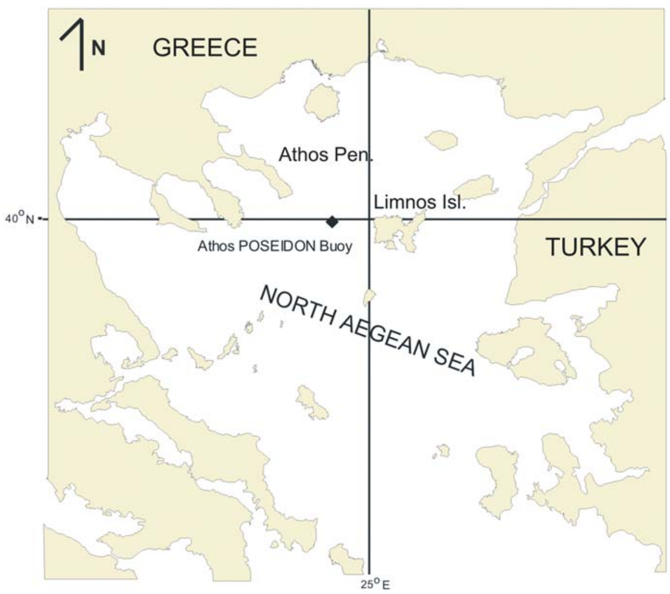

Fig. 1. North Aegean Sea and position of POSEIDON buoy for the monitoring of meteorological and wave parameters during the years 2000–2006.

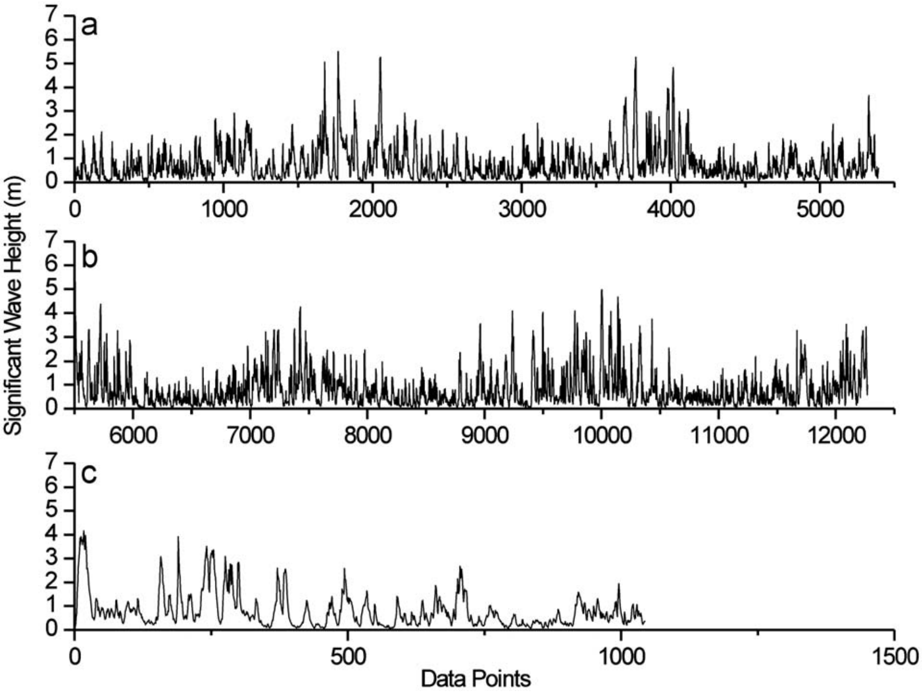

Fig. 2. Temporal variability of significant wave height (m), during (a) 2000–2003, (b) 2004–2005 (training dataset) and (c) 2006 (validation dataset).

followed by the SSE and SE winds (23%) with increased occurrence during the period of September to December. Mean wind speed 4.7 m/s was observed, ranging between zero speed values and the maximum value of 22.0 m/s. Wind speed median was computed to 4.0 m/s. The more frequent waves produced (about 50%) propagate from NNE to ENE directions with a maximum H_S=5.50 m and T_{02}=7.2 s, while SSE waves (about 12% frequency of occurrence) produced maximum H_S=5.1 m and T_{02}=7.2 s. The relation between the significant wave height H_S and the mean zero-up-crossing period T_{02} for the wave dataset showed a satisfactory linear correlation (R^2_{HT}=0.83). The temporal variability of significant wave height and wave zero-up-crossing period obtained from POSEIDON buoy are shown in Figs. 2 and 3.

2.3. Data pre-processing

The standard wind speed at 10 m reference level was obtained following the US Army (2003) approximation:

$$U_{10} = U_Z\left[\frac{10}{z}\right]^{1/7} \tag{4}$$

where U_{10} is wind velocity at 10 m height from the sea level and U_z the wind velocity at elevation z (3 m). Furthermore, U_{10} wind velocity was converted to the friction wind velocity U_* with

$$U_*^2 = C_D U_{10}^2 \tag{5}$$

where C_D is the wind drag coefficient, with values as (Wu, 1982):

$$C_D = \left\{ \begin{array}{c} 1.2875 \times 10^{-3} \text{ if } U_{10} < 7.5 \text{ m/s} \\ (0.8+0.065U_{10}) \times 10^{-3} \text{ if } U_{10} \geq 7.5 \text{ m/s} \end{array} \right\} \tag{6}$$

Finally, wind direction transformation was achieved using an encoding method, allowing the encoded wind direction to range between 0 and 1, as

$$\Theta = \left\{ \begin{array}{c} 1-(\Psi/180) \text{ if } 0^o \leq \Psi \leq 180^o \\ (\Psi-180)/180 \text{ if } 180^o \leq \Psi \leq 360^o \end{array} \right\} \tag{7}$$

where Ψ is the wind direction in degrees and Θ the transformed direction.

2.4. FIS input variables determination

The average mutual information (AMI) method was used to determine the input variables imported in the fuzzy inference system for each output, following Abebe and Price (2004) and Zamani et al. (2008). Supposing two systems, A and B, with measurements a_i and b_k, then the amount one learns in bits about a measurement of a_i from a measurement of b_k is given by the arguments of information theory (Gallager, 1968) as

$$I_{AB}(\alpha_i, b_k) = \log_2\left(\frac{P_{AB}(\alpha_i, b_k)}{P_A(\alpha_i)P_B(b_k)}\right) \tag{8}$$

where the probability of observing an out-of-the-set of all A is $P_A(a_i)$, and the probability of finding b in a measurement B is $P_B(b_k)$, and the joint probability of the measurement of a and b is $P_{AB}(a_i, b_k)$. AMI expresses a measure of the mutual information two variables share, thus a zero-AMI-value represents two statistically independent variables, while a high AMI-score represents two strongly related variables. Also, the average mutual information between observations at time n and $n+\tau$ is then

$$I_{AB}(\tau) = \sum_{a_i, b_k} P_{AB}(a_i, b_k) I_{AB}(a_i, b_k) \tag{9}$$

Fraser and Swinney (1986) have suggested, as a prescription, that it is necessary to choose that τ where $I(\tau)$ falls below a certain limit. For the Athos POSEIDON dataset the AMI scores of wind–wave, wave–wave, wind difference–wave, wind difference–wave difference and wind–wave difference were computed to determine the input variables for the wave height and wave period FIS (Fig. 4). It occurs that only the wind–wave and wave–wave relations exhibit increased AMI values, with the higher values obtained at zero lag for the wind–wave relation and at zero and one lags for the wave–wave relation, for both wave characteristics

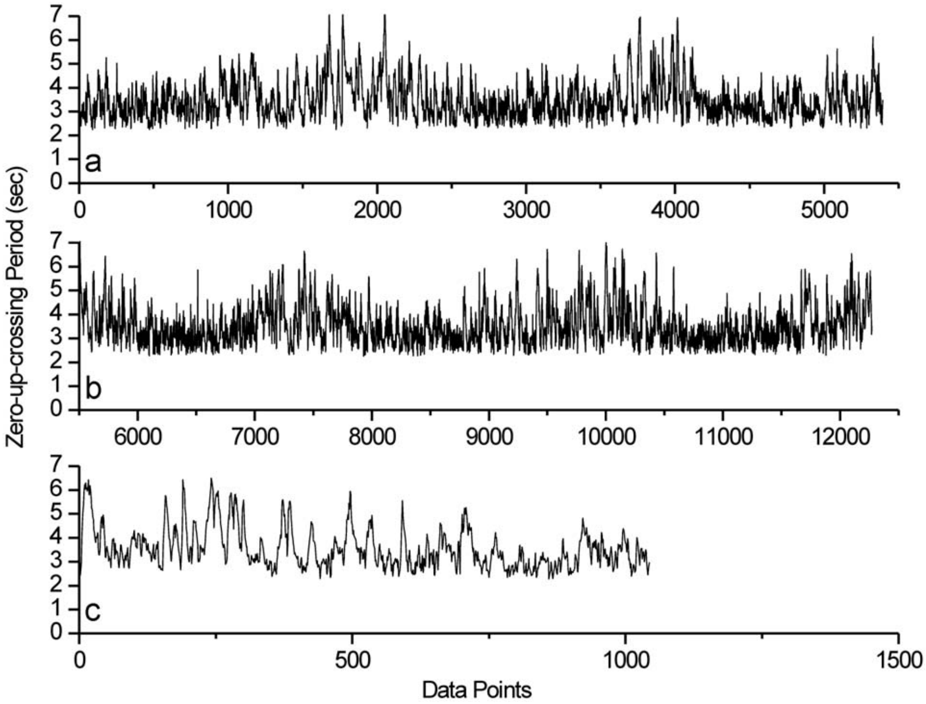

Fig. 3. Temporal variability of zero-up-crossing period (sec), during (a) 2000–2003 (b) 2004–2005 (training dataset) and (c) 2006 (validation dataset).

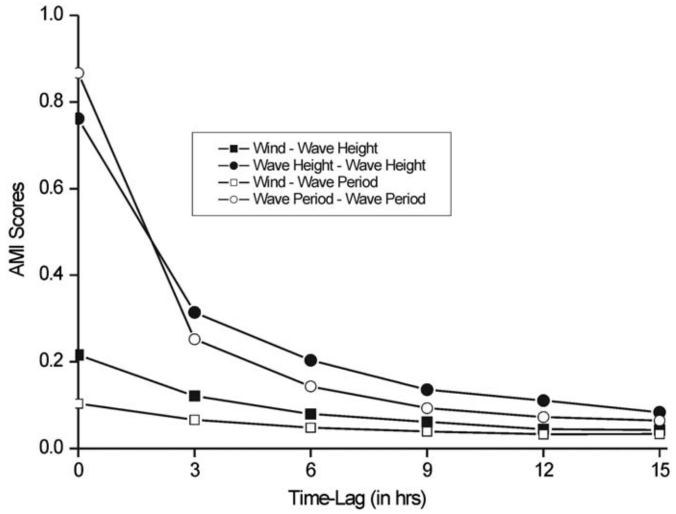

Fig. 4. AMI-scores for various time-long periods.

(significant wave height and the wave period). Thus the following FIS models were built:

(a) for significant wave height:

$$H_S(t+1) = f(U(t), H(t), H(t-1), \Theta(t))$$

(b) for zero-up-crossing wave period:

$$T_{02}(t+1) = f(U(t), T_{02}(t), T_{02}(t-1), \Theta(t))$$

The above-proposed Fuzzy Inference Systems utilized the Athos POSEIDON transformed dataset for the training and validation procedures. The available data ensured the approximate statistical similarity between both data sub-sets and the occurrence of similar extreme events in both sub-sets. The time-series of significant wave height (H_S) and mean zero-up-crossing period (T_{02}) for the period 25/5/2000–31/12/2005 was considered as the training dataset (12,274 data points), while the series from 1/1/2006 to 15/6/2006 was left for validation (1044 data points) (Figs. 2 and 3).

2.5. FIS model development

The design and construction of a FIS appears to be a heuristic process, involving several designer choices based on experience; these include: choice of fuzzy predictor parameters, the type of fuzzy model, the form of membership functions and the number of rules established. In this study, two separate fuzzy inference systems were developed to model the significant wave height H_S and the zero-up-crossing period T_{02}. The ANFIS algorithm used appears advantageous for large datasets, as those imported here, since it maps locally using fuzzy rules, and thereby resulting in reduced errors for the current training pattern and minimum interference with the learning already made. Each model had a four-input–one-output structure. All input variables were partitioned into three fuzzy sets. ANFIS structure training was achieved at 100 epochs before obtaining the resulting fuzzy inference system with the modified (adjusted) parameters (i.e., premise parameters—the membership function parameters, the consequent parameters—the linear polynomial parameters and the fuzzy-inference-system rules). Fig. 5 presents the modified membership functions of the premise parameters. The structure of the "IF–THEN" rules produced through subtractive clustering for these two models is presented in Tables 1 and 2, respectively.

2.5. Model validation criteria

The validity of the output of FIS models was tested using various statistical tests:

(a) The root mean square error (RMSE) and the scatter index (SI) of the modeled and observed values of significant wave height H_S and zero-up-crossing period T_{02} were computed. RMSE was

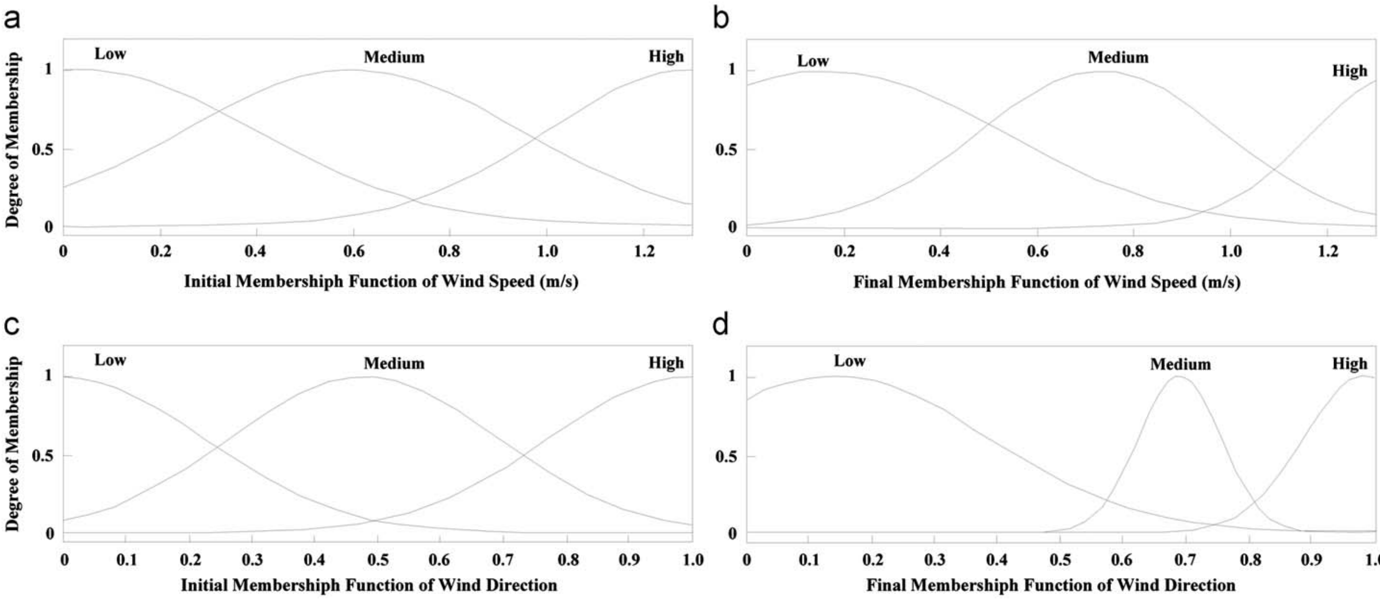

Fig. 5. Initial and final membership functions of wind speed and direction for significant wave height prediction.

Table 1
Fuzzy rules for the one-step-ahead significant wave height H_S prediction.

Rules	'IF' part of the rule				'THEN' part of the rule
	$U(t)$	$\Theta(t)$	$H_S(t)$	$H_S(t-1)$	
1	L	L	L	L	$2.6847\times U(t)+0.4314\times\Theta(t)+0.4471\times H_S(t)-0.0605\times H_S(t-1)-0.4328$
2	M	M	M	M	$0.4893\times U(t)+0.0232\times\Theta(t)+1.1108\times H_S(t)-0.2249\times H_S(t-1)+0.0032$
3	H	H	H	H	$0.9488\times U(t)-0.1725\times\Theta(t)+0.8899\times H_S(t)-0.1172\times H_S(t-1)+0.0318$

here 'L', 'M' and 'H' denote the fuzzy set 'low', 'medium' and 'high', respectively.

Table 2
Fuzzy rules for the one-step-ahead mean zero-up-crossing period T_{02} prediction.

Rules	'IF' part of the rule				'THEN' part of the rule
	U(t)	$\Theta(t)$	$T_{02}(t)$	$T_{02}(t-1)$	
1	L	L	L	L	$1.3555\times U(t)-1.4344\times\Theta(t)+0.5878\times H_S(t)+0.0724\times H_S(t-1)+2.2685$
2	M	M	M	M	$1.0418\times U(t)+0.1107\times\Theta(t)+0.8793\times H_S(t)-0.0643\times H_S(t-1)+0.4501$
3	H	H	H	H	$0.4337\times U(t)-0.1089\times\Theta(t)+0.8958\times H_S(t)+0.0139\times H_S(t-1)+0.1446$

here 'L', 'M' and 'H' denote the fuzzy set 'low', 'medium' and 'high', respectively.

defined as

$$\mathrm{RMSE}=\sqrt{\frac{\sum_{i=1}^{\mathrm{N}}(y_i-\widehat{y_i})^2}{\mathrm{N}}} \tag{10}$$

where y_i is the observed time-series of H_S and T_{02}, $\widehat{y_i}$ the corresponding fuzzy model values and N the total number of dataset. The parameter RMSE has to be as close to 0.0 as possible for good prediction. The Scatter Index is defined as the ratio of the RMSE normalised by the mean of the observed values (Akratos et al., 2009), expressed as

$$\mathrm{SI}=\frac{\mathrm{RMSE}}{\text{average observed value}}\times 100 \tag{11}$$

SI has to be as close to 0.0 as possible.

(b) The validity could also be tested through scattergrams, which are graphs of the predicted versus measured H_S and T_{02} values. Best match occurs when all points fall on a 1:1 slope line. Deviation from that line is measured by fitting through the points a straight regression line of the following equation

$$y_i=\gamma\hat{y}_i \tag{12}$$

If this slope γ is less than 1.0, the FIS model underestimates the observed data. If the slope γ is greater than 1.0, the model overestimates the observed values. Another parameter that evaluates the accuracy of the agreement is the squared correlation coefficient R^2, which shows whether data scatter are around the best-fit line. The closer R^2 is to 1.0 the less the points are scattered around the straight line. R^2 is defined as:

$$R^2=\frac{ssr}{sst} \tag{13}$$

where $ssr=\sum_{i=1}^{N}(\hat{y}_i-\overline{y})^2$ and $sst=\sum_{i=1}^{N}(y_i-\overline{y})^2$, where $\overline{y}$ is the mean observed value.

(c) Finally, model's performance under extreme wave height conditions could be tested using the detection rate (DR) and the false alarm rate (FAR) parameters. DR is defined as the ratio between the number of modeled episodes, in which H_S exceeded the threshold value of 3.5 m, and the number of the observed extreme wave episodes, while FAR as the ratio of false alarms predicted by the model to the total number of observed episodes.

3. Model results and discussion

With the procedure described above, two separate FIS were developed to model the significant wave height H_S and the zero-up-crossing period T_{02} with a 3 h prediction interval, at Athos POSEIDON buoy (North Aegean Sea). The model fits well the 2000–2005 calibration data and expands its ability to the verification part of the series, during the year 2006. An illustration of the good agreement between the predicted (3 h and 12 h lead) and the observed significant wave height values for the testing dataset is shown in the diagrams of Fig. 6. It may be noted that for the 3 h and 12 h lead prediction, the rising and falling tendencies of the observed wave heights were fairly reproduced by the fuzzy model (as clearly shown in a random subset of 200 points), leading to observations and model outputs sufficiently close to each other (Fig. 6a, b). For the whole validation dataset (1044 points), it occurs that the slope of linear regression between observed and modeled values appears less than unity, indicating that the model slightly underpredicts H_S (Fig. 6c, d).

Generally speaking, the results obtained from the developed fuzzy models agree well with the measured data and coincide with our expectation after AMI analysis. All performance criteria applied on the whole validation set depicted the ability of the model to predict H_S satisfactorily at a 3-h-ahead prediction interval (Table 3). Similar order of results was also achieved using ANFIS by Mahjoobi et al. (2008). However, model's accuracy varies at different wave-height ranges, showing that the prediction errors increase at increased wave heights. Performance criteria for waves with $H_S < 1.5$ m show satisfactory agreement (RMSE=0.149, R^2=0.833, SI=26.03%, γ=0.903) with slight under-prediction, while for waves with $H_S > 3.0$ m the FIS model depicts lower accuracy (RMSE=0.613, R^2=0.793, SI=18.84%, γ=1.040) with slight over-prediction. Moderate accuracy levels (RMSE=0.413, R^2=0.804, SI=22.31%, γ=0.892) and under-prediction were achieved at intermediate significant wave heights ($1.5 \leq H_S < 3.0$). However, overall the developed FIS showed good ability to hindcast extreme significant wave events (DR=0.77, FAR=0.08), in accordance to the findings of Zamani et al. (2008), stating that the model with shear velocity as input variable shows better behaviour in the region of extreme events. Similarly to the results of Özger and Sen (2007), present model runs when performed with higher prediction intervals (+6 h, +9 h and +12 h), produced more unreliable results (Table 3).

A good agreement between observations and fuzzy model results can be seen for the zero-up-crossing period, T_{02}, for both low- and medium-period waves, as well as for the peak-period conditions (Fig. 7a, c). RMSE of 0.315, R^2 0.832 and scatter index 8.83% were obtained, proving that for the one-step-ahead model (+3 h lead time), a nearly perfect fit of the model with

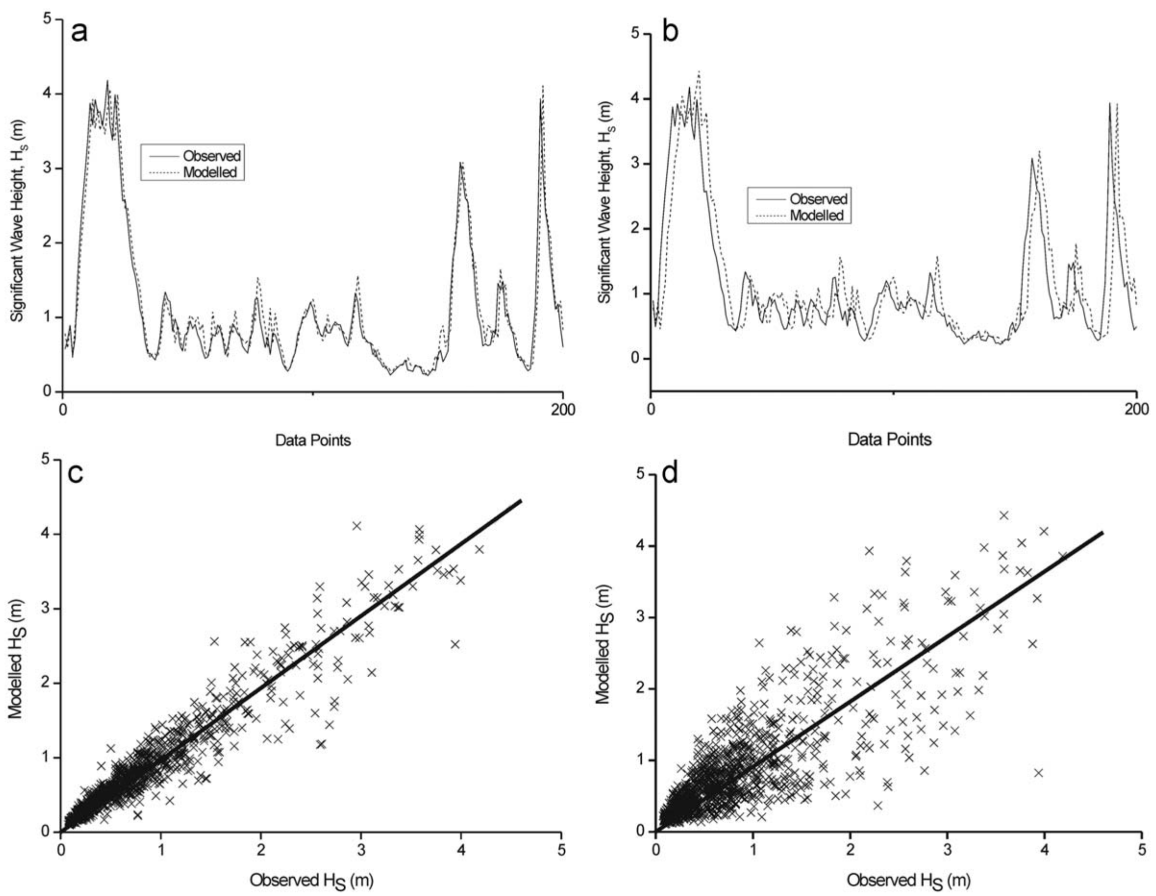

Fig. 6. Model validation for significant wave height prediction, with comparison of observed and modeled 200-points sub-sample, for (a) 3 h lead and (b) 12 h lead, and relation between observed and modeled data, for the whole testing dataset, for (c) 3 h lead and (d) 12 h lead.

observations is established. The slope γ 0.788 illustrates a slight model under-estimation of zero-up-crossing period, especially at peak-period values (>5 s). Table 3 presents the performance indices for the T_{02} model runs with various prediction intervals. This table shows that RMSE and SI increase, while R^2 decreases with increase in the prediction interval. Indeed, as several investigators proved, model's prediction for the +12 h lead period, shows lower accuracy in all statistical measures (RMSE=0.420, SI=11.77%, R^2=0.674), with under-prediction (γ=0.892) (Fig. 7b, d).

To determine the impact of meteorological input on model's predicting ability, the significant wave height and zero-up-crossing period were forecasted based solely on three wave input parameters collected at time steps t, $(t-1)$ and $(t-2)$. The H_S-prediction at lead time +3 h appeared significantly reliable (RMSE=0.230, SI=28.5%, R^2=0.901, γ=0.762). Such H_S-predictions depicted performance statistical properties similar to those obtained for the +6 h lead of the more complex wind–wave model. However, the T_{02}-wave model showed poorer predicting ability (RMSE=0.425, SI=11.92%, R^2=0.816, γ=0.775), lower than the +12 h time interval of the wind–wave model.

Table 3
Performance criteria for significant wave height and zero-up-crossing period prediction, using TS fuzzy models with different prediction intervals.

Hours	H_S				T_{02}			
	RMSE	SI (%)	γ	R^2	RMSE	SI (%)	γ	R^2
+ 3 h	0.216	26.76	0.911	0.913	0.315	8.83	0.788	0.834
+ 6 h	0.232	28.73	0.785	0.795	0.355	9.93	0.826	0.832
+ 9 h	0.260	32.18	0.725	0.790	0.365	9.95	0.879	0.756
+12 h	0.337	41.67	0.911	0.664	0.420	11.77	0.892	0.674

4. Conclusions

The present work dealt with the development of the TS fuzzy inference system appropriate for the processing and forecasting of wave height and period, based on previously observed wind (speed and direction) and wave records. Model application was performed on the meteorological and wave data collected by the 'Mount Athos' POSEIDON buoy, with warning times ranging between 3 and 12 h. Results indicate that the proposed methodology leads to the fast convergence of observed and predicted series. Lower warning times produced better forecasts in both wave characteristics, according to the established model performance criteria. The satisfactory accuracy of model-wave prediction obtained in all cases confirms that FIS models could effectively be used for the offshore operational-wave forecasting based on the continuous flow of wind and wave buoy observations. Model results illustrated that the developed FIS could serve as a valuable tool for the operational prediction of wave characteristics in Northern Aegean Sea, through the utilization of the POSEIDON real time data.

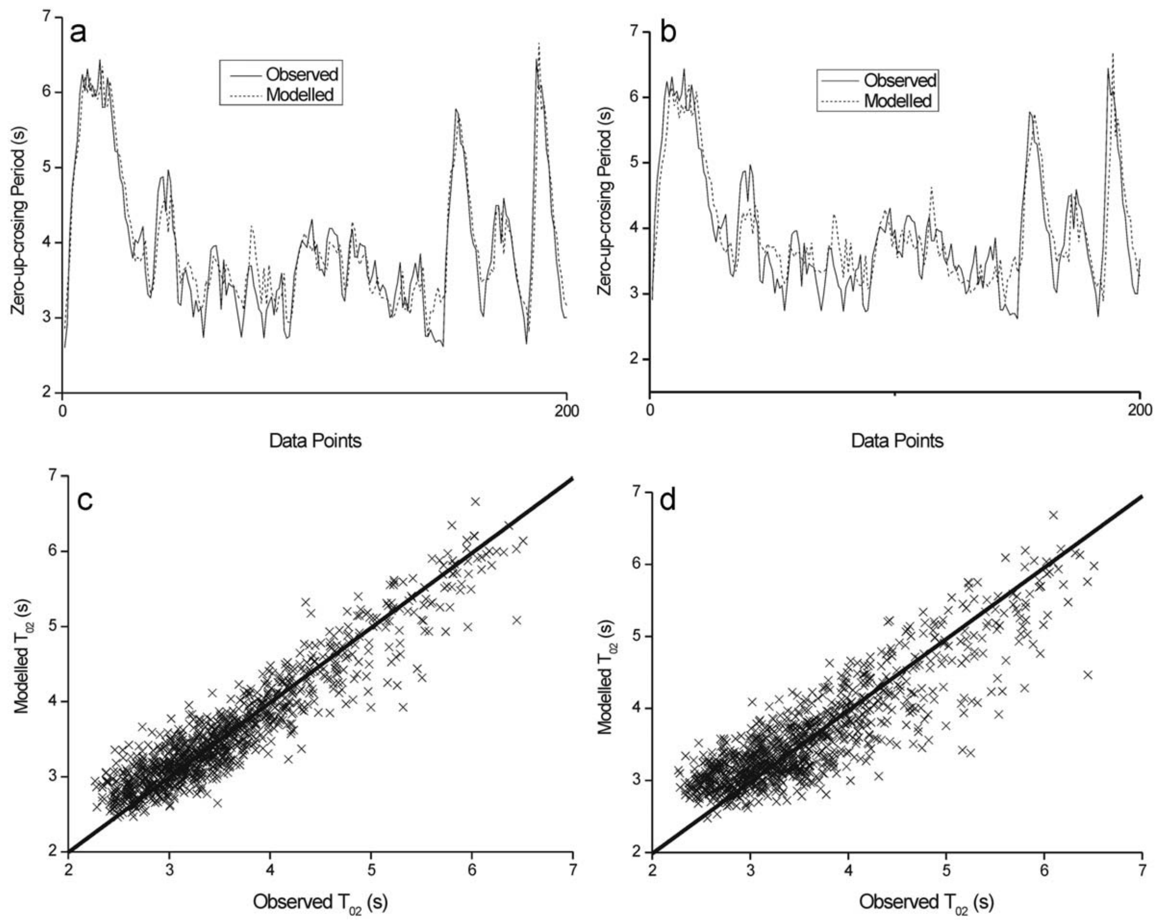

Fig. 7. Model validation for zero-up-crossing wave-period prediction, with comparison of observed and modeled 200-points sun-sample, for (a) 3 h lead and (b) 12 h lead, and relation between observed and modeled data, for the whole testing dataset, for (c) 3 h lead and (d) 12 h lead.

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