Simulation of sea state parameters process to study the profitability of a maritime line

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ABSTRACT

This paper deals with a method of studying the profitability of a maritime line under the service of a specific ship when the data describing the sea state along it are available only for a short period of time or are missing. As a specific example, the line Piraeus - Heraklion at Aegean Sea is considered, where wave data are available for a very short period (3 years). The method developed is based on the use of another larger wind database (11 years) providing realistic artificial sea-state conditions for a wider time period. This is accomplished in two steps: First, by developing a stochastic simulator of wind conditions in a point corresponding to the most severe conditions of the line (this is performed using a non-homogeneous Markov model) and second, by establishing a simple non-parametric method associating the simulated wind conditions at this point to sea-state conditions along the line. Finally, the profitability of the line is examined by combining the simulated sea-state conditions along the line with the seakeeping behavior of the ship presented in the form of a suite of polar diagrams which provide the operable regime of speed and heading of the ship for each sea-state condition.

KEYWORDS

Time series, Maritime line, Sea state simulation, Wind speed and direction, Switching autoregressive model, Non homogeneous Markov model.

INTRODUCTION

In order to assess the profitability of a maritime line, the knowledge of the sea-state climatology along the line is necessary as well as the limiting operation criteria defining the acceptable parameters (speed, direction) of the ship. For a precise calculation, a very large number of sea-states histories which could be encountered by the ship must be used. Unfortunately, these histories are limited in number by the period of simulation of the numerical models (hind- now- or fore-cast), which generally covers several years (1 up to 40 years). To overcome this constraint the development of a simulator of sea-state histories, statistically realistic, would be of great interest.

The wave data used in the present work, have been produced by the NCMR (National Center for Marine Research, Athens). They describe sea-state conditions along the line Piraeus-Heraklion during the period from October 1999 to September 2002. On the other hand, the behavior of ship in waves and the operability limiting criteria are combined in speed polar diagrams corresponding to each particular sea state and defining acceptable and unacceptable regions of ship service. These diagrams have been produced by HRS (Hellenic Register of Shipping). These polar diagrams, in conjunction with the sea state data, will permit us to assess, if the ship service, a given day, is possible and, in the case of positive answer, the duration of the trip. These results will be used in a last step to estimate the profitability of the maritime line.

To evaluate accurately the profitability of the line, results for a longer time period than the three years, where data are available from the NCMR database, are required. So, a stochastic model which describes the sea-state history conditions along the line has been developed. This task was accomplished in two steps: At first, a non homogeneous Markov model (NHMM) has been fitted to the time series of a larger database (11 years, now-cast) of wind speed and wind direction at a point near the line where the most severe conditions were observed. This model has been used to simulate artificial wind conditions at this point. In a second step, a quick and simple algorithm has been developed in order to estimate the sea-state conditions corresponding to the simulated wind data. Finally, these synthetic sea-state conditions have been used in order to assess the operability of the ship and thus, the profitability of the maritime line.

WIND AND WAVE FORECASTING FOR THE AEGEAN SEA

A main part of the POSEIDON system, Soukissian et al. (1999), is the POSEIDON forecasting system, which consists of the weather and the wave forecasting system. The weather forecasting system is based on the SKIRON model, developed at the University of Athens (Kallos (1997), Nickovic (1998)). For a detailed description of the system see Soukissian et al. (2002). The wave-forecasting model running operationally in NCMR is the WAM-cycle 4 wave model, providing forecasts for the Aegean Sea since October 1999. The complete theory, on which WAM is based, is described in detail in WAMDI (1988), while the description of the physics and the numerical schemes used by WAM-cycle 4 can be found in Komen et al. (1994). The WAM implementation for the
Aegean Sea is based on a nested version, where the outer nest covers the Mediterranean Sea and the inner nest the Aegean Sea. Thus, the boundary conditions for the Aegean Sea are obtained through the WAM-Mediterranean model. In table 1 the operational characteristics of the WAM model are summarized.

The WAM model runs operationally once a day giving forecasts for 3 hour intervals up to 72 hours ahead. The forecasts presented here correspond to the first 24 hours of the model output for the period from October 1999 to September 2002.

The experience obtained so far by using WAM model is that it can sufficiently describe the trends of the wave climate, but its key shortcoming is the underestimation of the severe sea states.

Table 1. Operational characteristics of the WAM model

<table>
<thead>
<tr>
<th>Domain of application</th>
<th>Mediterranean Sea (34°N – 41°N)</th>
<th>Aegean Sea (20°E – 29°E)</th>
</tr>
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<tbody>
<tr>
<td>Grid</td>
<td>1.250 (Mediterranean Sea)</td>
<td>0.050 (Aegean Sea)</td>
</tr>
<tr>
<td>Time step</td>
<td>180 sec</td>
<td></td>
</tr>
<tr>
<td>Spectral discretization</td>
<td>16 discrete directions</td>
<td></td>
</tr>
<tr>
<td></td>
<td>30 discrete frequencies (logarithmically)</td>
<td>0.05054 - 0.66264 Hz</td>
</tr>
<tr>
<td>Wind input</td>
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<td></td>
</tr>
</tbody>
</table>

STOCHASTIC SIMULATION OF SEA-STATE CONDITIONS

We will assume that the WAM model provides an acceptable description of the sea-state conditions along the examined line during the last 3 years. With these data, we could estimate the joint distribution of $H_s$, $T_p$ and $\Theta_m$, where $H_s$, $T_p$ and $\Theta_m$ represent respectively the significant wave height, the peak period and the mean direction, on the maritime line. With this distribution we could calculate the probability that severe conditions (according to some criteria giving by the polar diagram) occurs on the line, and thus, for example, the percentage of cancelled or delayed crossings.

However, this method would fail if we are interested in estimating more complicated quantities, like the mean time of crossing, where the knowledge of the space-time structure of the sea-state along the line is necessary. On the contrary, if we find an efficient way of simulating artificial sea-state conditions on the line on a long period of time, we will be able to simulate a great number of scenario of exploitation of the line, and so, will be able to provide reliable assessment of the profitability.

Simulation of sea-state conditions

At first, let $(x_1, ..., x_N)$, with $N$ equal 17, be points on the grid of the WAM model lying also along the maritime line Piraeus-Heraklion (Fig. 1). The distance between adjacent points is about 12 nautical miles.

We now use another data base, produced by ECMWF, giving only the wind conditions but having the advantage to contain data for a longer period of time (11 years). In particular, this data base describes wind conditions in the period January 1992-December 2002, with a time step of 6 hours at the point (36N 27.75E), denoted by $x_0$, which is closed to the line and in the area where the most severe conditions were observed (figure 1).

We first used ECMWF data in order to simulate artificial wind conditions at the point $x_0$. To perform these simulations, a stochastic model (described below) of the time evolution of the bivariate process $(X(t), \theta(t))$, has been developed $(X$ the wind speed, $\theta$ the wind direction).

In a second step, a simple algorithm has been used in order to associate realistic sea-state conditions at the points $(x_1, ..., x_N)$, corresponding to these artificial wind conditions.

### Table 1. Operational characteristics of the WAM model

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### Stochastic model for the wind

**Model for $X$.** Several authors have worked on the problem of modelling and simulating the process $X$ (Brown, 1984). As this process is usually nonstationary (seasonal and diurnal components) and non-Gaussian, a transformation is usually first applied to the data in order to get a stationary and Gaussian time series. Then, an ARMA model can be fitted to the transformed time series.

![Fig. 2. Evolution of the wind speed (11 years of data, ECMWF)](image)

Elimination of the nonstationary components. In our data base, no significant daily nonstationarity has been observed but there are important seasonal variations (figure 2) with, for example, more severe storms in winter than in summer. Several models have been proposed in order to describe this non-stationarity (Cunha (1997)). In present work, these models have not been applied, but instead of this, we made the assumption that the data are strictly stationary within each month, that is all months of January are statistically similar, as are months of February, March, ... (in other words, we assume that there is no long-term trend in the data). Thus, a different model has been adjusted for each month and each of them has been fitted by using 11 (11 years) time series, assumed independent, of length 122 (one average month, each 4 hours). This method seems to work satisfactorily when the available data cover a relatively long period of time.

The results shown in the present work were obtained by considering data for the month of January.

**Autoregressive model for $X$.** The process $X$ is non-Gaussian (figure 3). Its distribution is defined on the positive real axis and is generally positively skewed. In order to fit an autoregressive model to $X$, a transformation is usually first applied to the data in order to get a process with a Gaussian distribution (Brown, 1984). In this work, the non-Gaussian character of the data has been directly modelled using a Gamma autore-
gressive model of order $k$ (Gamma AR(k)). More precisely, we will assume that (Toll (1997))

$$X(t) - \gamma(\alpha(t), \beta(t))$$

with density

$$\gamma(x; \alpha, \beta) = \frac{\alpha^\beta}{\Gamma(\beta)} x^{\alpha-1} e^{-x/\beta}$$

where

$$\alpha(t) = \frac{\mu_t(t)}{\sigma^2(t)} \text{ and } \beta(t) = \frac{\mu_t(t)^2}{\sigma^2(t)}$$

and $\mu(t)$ and $\sigma(t)$ represent respectively the conditional mean and standard deviation of $X(t)$ and are given by the following equations:

$$\mu(t) = \alpha_t \mu(t-1) + \ldots + \alpha_k \mu(t-k) + \beta$$

$$\sigma(t) = \sigma$$

The parameters have been estimated using numerical maximum likelihood conditionally to the first $k$ observations for each of the 11 sequences.

Validation of the model. In order to check the ability of this model to describe the non-Gaussian character of the process, we have simulated with this model 500 sequences of length 122 (it corresponds to 500 months of January) and we have compared the distribution of these synthetic data with the one of the original data. The maximum likelihood estimates of the parameters have been calculated by numerical optimization in the M algorithm, with a numerical optimization in the Maximization step. As the likelihood function can be multi-modal, the E.M algorithm may converge to a local maximum. In order to avoid these local maxima, we run the algorithm several time with different, randomly chosen, initial values.

Model selection. In order to select the best model, which means selecting $M$ the number of regime and $k$ the order of the autoregressive models, we have found that the Bayes Information Criterion (BIC) is useful in the sense that it identifies relatively parsimonious models which fit the data well. This criterion is defined as

$$BIC = -2LL + N \log(T)$$

with $LL$ the log-likelihood of the model, $N$ the number of parameters and $T$ the number of observations.

Table 2. Comparison of the different models

<table>
<thead>
<tr>
<th>$k$</th>
<th>$M=1$</th>
<th>$M=2$</th>
<th>$M=3$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$N=3$</td>
<td>$N=9$</td>
<td>$N=17$</td>
</tr>
<tr>
<td></td>
<td>LL=-2641.1</td>
<td>LL=-2506.6</td>
<td>LL=-2543.8</td>
</tr>
<tr>
<td></td>
<td>BIC=5305.8</td>
<td>BIC=5186.0</td>
<td>BIC=5210.1</td>
</tr>
<tr>
<td></td>
<td>$N=4$</td>
<td>$N=11$</td>
<td>$N=20$</td>
</tr>
<tr>
<td></td>
<td>LL=-2640.1</td>
<td>LL=-2559.1</td>
<td>LL=-2540.0</td>
</tr>
<tr>
<td></td>
<td>BIC=5309.0</td>
<td>BIC=5197.5</td>
<td>BIC=5222.4</td>
</tr>
<tr>
<td></td>
<td>$N=5$</td>
<td>$N=13$</td>
<td>$N=23$</td>
</tr>
<tr>
<td></td>
<td>LL=-2619.9</td>
<td>LL=-2556.4</td>
<td>LL=-2535.1</td>
</tr>
<tr>
<td></td>
<td>BIC=5295.9</td>
<td>BIC=5206.4</td>
<td>BIC=5235.8</td>
</tr>
</tbody>
</table>

This criterion selects the model with $M=2$ (2 weather types) and $k=3$.

The conditional standard deviations of this model are $\sigma^{(1)} = 1.56$ and $\sigma^{(2)} = 2.96$. Thus, the first weather type is associated to wind speed evolving slowly whereas the second is associated to periods with a more important variability (stronger conditional standard deviation). In order to visualize it, we have applied the Viterbi algorithm to the data: it permits to calculate the most likely values of the process $W$ according to the observations (figure 4).
Validation of the model. With the selected model, we have generated 500 artificial time series of length 122 (each corresponding to a month of January), and we have compared some statistical properties of these artificial sequences with the original ones of the database. We also compared these results to the ones previously obtained with the only use of the Gamma AR(3) model (best model for $M = 1$ according to the BIC criterion; see Tab. 2).

![Wind speed for the month of January 1995 and corresponding values of $W$. Dates with $W = 1$ are represented with a dashed line and $W = 2$ with a continuous line](image1)

Fig. 4.

![Comparison of the autocorrelation functions. Observations (continuous line), Gamma AR(3) model (dotted line), switching Gamma AR(1) model (dashdotted line)](image2)

Fig. 5.

![Distribution function of the storm duration (Wind speed above $13 ms^{-1}$). Observations (continuous line), Gamma AR(3) model (dotted line), switching gamma AR(1) model (dashdotted line)](image3)

Fig. 6.

The statistical properties of the simulated sequences with the two models are close to the properties of the original data; compare e.g., the probability density functions, the autocorrelation functions (figure 5) or the time of duration of the storms (figure 6). For these data, the benefits of the more elaborated model with switching parameters are not obvious (except a better fit of the autocorrelation functions). However, in other works on wind data in the Bay of Biscay, where the difference between the weather type is more significant, this model outperforms more clearly the simple autoregressive model with fixed parameters.

Model for $(X, \theta)$. There may exist a strong relation between the wind speed and the wind direction. In order to link the evolution of these two processes, we have used a non-homogeneous Markov model (NHMM) in which the wind direction modifies the transition probabilities of the hidden Markov chain which represents the weather type. A NHMM model has also been proposed by Hughes (1999) for relating broad scale atmospheric circulation to local rainfall occurrences. More precisely, we will assume that (7) still holds and that

\[
P(\theta(t)|W_{t-1}, X_t, \theta_{t-1}) = P(\theta(t)|\theta(t-1))
\]

(12)

\[
P(W(t)|W_{t-1}, X_t, \theta_t) = P(W(t)|\theta(t), W(t-1))
\]

(13)

The assumption (12) means that $\theta$ is a first order Markov chain. In order to parameterize $P(\theta(t)|\theta(t-1))$, we could use one of the autoregressive models for circular data proposed in Breeding (1989) or Fisher (1994). However, these models are not suitable when the distribution of the process is multi-modal, as it is the case in Aegean sea (figure 8). Here, one of the modes corresponds to wind blowing from the north and the other one from the west. For this application (profitability of the maritime line), a precision of $20^\circ$ on the wind direction seems sufficient. Thus the wind direction has been classified into 18 sectors $I_1, \ldots, I_{18}$ of equal widths. Let $Q$ be the $18 \times 18$ transition matrix of the Markov chain ($Q(i,j) = P(\theta(t+1) = I_j|\theta(t) = I_i)$). MacDonald (1997) proposed to use a second order Markov chain model (the Raftery model). This model outperforms the simple first order Markov chain for wind data in Koeberg (South Africa). As the results we have obtained with the first order Markov chains were satisfactory, this more elaborate model has not been tested.

![Example of time series of wind direction. Data (top) simulated with a first order Markov chain (bottom)](image4)

Fig. 7.

Assumption (13) states that given the history of the weather type up to time $t - 1$ and of the wind speed and direction up to time $t$, the weather type at time $t$ depends only on the previous weather type and the current wind direction. The wind direction at time $t$ is thus used to modify the transition probabilities of the hidden process.

Models using the weather type to link the relation between the wind directions and the wind speed has already been used (for example in Castro, 1998). The weather type is calculated as a deterministic function of the wind direction (the directions are usually divided in 2 or 3 sectors) and a different model is fitted to the wind speed in each of these weather types. These models can be written as special cases of the NHMM by forcing $P(W(t)|\theta(t), W(t-1))$ to be degenerate.

In order to parameterize $P(W(t)|\theta(t-1), \theta(t))$, we used the fact that:
\( P(\mathbf{W}(t) = j|\mathbf{W}(t-1) = i, \theta(t)) = \frac{P(\theta(t)|\mathbf{W}(t-1) = i, \mathbf{W}(t) = j)P(\mathbf{W}(t) = j|\mathbf{W}(t-1) = i)}{\sum_j P(\theta(t)|\mathbf{W}(t-1) = i, \mathbf{W}(t) = j)P(\mathbf{W}(t) = j|\mathbf{W}(t-1) = i)} \) \hspace{1cm} (14)

Then, we used the following assumption:

\( P(\theta(t)|\mathbf{W}(t-1) = i, \mathbf{W}(t) = j) = P(\theta(t)|\mathbf{W}(t) = j) - V(\theta_j, \kappa_j) \) \hspace{1cm} (15)

with density (Von Mises distribution)

\[ V(\theta_j, \kappa_j) = \frac{1}{2\pi\kappa_j} e^{\kappa_j \cos(\theta - \theta_j)} \] \hspace{1cm} (16)

Finally we get

\[ P(\mathbf{W}(t) = j|\mathbf{W}(t-1) = i, \theta(t)) = \frac{P(\theta(t)|\mathbf{W}(t-1) = i, \mathbf{W}(t) = j)P(\mathbf{W}(t) = j|\mathbf{W}(t-1) = i)}{\sum_j P(\theta(t)|\mathbf{W}(t-1) = i, \mathbf{W}(t) = j)P(\mathbf{W}(t) = j|\mathbf{W}(t-1) = i)} \] \hspace{1cm} (17)

with the constraints \( \sum_j \gamma_j = 1 \) to ensure identifiability of the parameters.

The maximum likelihood estimates of the parameters have been calculated with the E.M algorithm (Hughes). This algorithm is computationally expensive because of the numerical optimization used in each step of the algorithm. As it was the case for the Switching Gamma AR(k) model, we used randomly chosen initial values in order to initialize the algorithm, and we used the BIC criterion in order to choose the best model. The model with \( k = 1 \) and \( M = 2 \) has been selected.

Validation of the model. In order to validate the model, we have simulated 200 realisations of length 122. At first, we have compared the bivariate distribution of the original data with the one of the simulated sequences (figure 8).

**Fig. 8.** Joint distribution of the wind speed and the wind direction. Observation (left), simulated (right)

The observed distribution is bimodal, with 2 prevailing directions (west and north). The simulated distribution is a good approximation of the observed one. Other characteristics, like the autocovariance functions of the wind speed and the time of duration of the storms and the direction in which the wind is blowing in these events, have also been compared and are in a good agreement.

Simulation of sea-state conditions from wind conditions

This part describes a simple non-parametric method linking the temporal evolution of the wind conditions at the point \( x_0 \) (input data) to the sea-state conditions all along the line (output data).

**Notations.** Let

\[ Y(x_i, k) = (H_x(x_i, k), T_p(x_i, k), \Theta_m(x_i, k)) \] \hspace{1cm} (18)

where \( H_x(x_i, k) \), \( T_p(x_i, k) \) and \( \Theta_m(x_i, k) \) represent respectively the significant wave height, the peak period and the mean direction of the sea-state at time \( k \) for the point \( x_i \) \( (i \in \{1, ..., N\}) \) as calculated by the WAM model. The time index \( k \) is supposed to be in \( \{1, ..., T\} \) with \( T \) the number of available data during the three years the forecast model was operational.

\[ Y(k) = [Y(x_1, k), ..., Y(x_N, k)]' \] will represent the sea-state conditions at the different points along the line at time \( k \).

Let \( X(k) = (u(k), v(k)) \) where \( u(k) \) and \( v(k) \) denote respectively the meridional and the zonal component of the wind at time \( k \) for the point \( x_0 \) as given by ECMWF data base.

**Algorithm.** We need to develop a quick and efficient algorithm which associates artificial sea-state conditions \( Y_{sim}(t) \) along the maritime line to the input sequence \( X_{sim}(t) \), \( t \in \{0, ..., T_{sim}\} \), representing simulated wind conditions at the point \( x_0 \). The observed conditions \( X \) and \( Y \) will be used to train the algorithm.

**Initialisation:** let

\[ t_0 = \arg \min_t \| X(t) - X_{sim}(0) \| \ \text{if} \ \{t \in \{1, ..., T\}\} \] \hspace{1cm} (19)

be the date in the training sequence when the wind conditions are the more similar to the current wind conditions and let

\[ Y_{sim}(0) = Y(t_0) \] \hspace{1cm} (20)

**Recursion:** suppose we have already calculated \( Y_{sim}(k) \). Let

\[ t_{k+1} = \arg \min_t \left[ \| X(t + 1) - X_{sim}(k + 1) \|, Y(t) \right] \ \text{if} \ \{t \in \{1, ..., T\}\} \] \hspace{1cm} (21)

be the date in the training sequence when the conditions (wind and wave) are the more similar to the current conditions according to the distance \( d \) and let \( Y_{sim}(k + 1) = Y(t_{k+1}) \).

The distance \( d \) has been chosen as

\[ d_{\sim}(X_{sim}(k + 1), Y_{sim}(k)) = w_1 \|X_{sim}(k + 1) - X(t + 1)\| \] \hspace{1cm} (22)

\[ + w_2 \|Z_{sim}(x_{i_0}, k + 1) - Z(x_{i_0}, t + 1)\| + w_3 \|Y_{sim}(x_{i_0}, k) - Y(x_{i_0}, t)\| \]

where \( x_{i_0} \) is the point of the line closest to \( x_0 \), \( (w_1, w_2, w_3) \) are fixed weights, and

\[ Z(x_i, t) = (H_x(x_i, t) \cos(\Theta_m(x_i, t)), H_x(x_i, t) \sin(\Theta_m(x_i, t))) \] \hspace{1cm} (23)

and similarly for \( Z_{sim} \).

Validation of the model. In order to check the ability of this algorithm to simulate realistic sea-state sequences, we used the data of the first two years (sea-states from POSEIDON and wind from ECMWF) and we predicted sea-state conditions of the third year using the wind conditions at the point \( x_0 \).

![Fig. 9. Comparison of X and Y_sim for the month of January 2002 at the point x_0. WAM data (dotted line), and calculated from EC-](image-url)
The comparison at the other points of the line gives also good results. The comparison of these simulated sea-state conditions with the original data by the POSEIDON system shows that this very simple algorithm is able to predict efficiently the sea-state conditions at the different points \((x_1, \ldots, x_k)\) from the wind conditions at \(x_0\) (figure 9). For example, if \(x(t) = H_{\text{sim}}(x_{\theta}, t) - H_{\text{obs}}(x_{\theta}, t)\) is the error of prediction on significant wave height for the point \(x_{\theta}\), we get \(\epsilon = 0.02\) and \(\text{var}(\epsilon) = 0.092\). The comparison at the other points of the line gives also good results.

**PROFITABILITY OF THE MARITIME LINE**

**Polar Diagrams**

Ship responses in a seaway, as a result of the wave induced motions, should not exceed specific limiting values in order to allow safe sailing, not only from the structural point of view but also from the crew effectiveness and passenger comfort aspects. These operability limiting criteria (named also seakeeping criteria) define the level of ship responses at which appropriate actions by the shipmaster are to be taken in order to reduce their magnitude and consequently their effects. The most important seakeeping criteria concern vertical and lateral motions and acceleration, rolling, and also phenomena like bow slamming, propeller raising and deck wetness. Proposed limiting values may be found in the literature (e.g. Karpen, 1987). In the present work, in order to study the profitability of the maritime line, two criteria were used: the vertical acceleration at forward perpendicular below 0.18g and the roll angle below 4deg.

A convenient way to depict those combinations of ship speeds and heading angles that lead to exceedance of a certain seakeeping criterion in a specific sea state, is by means of polar diagrams (figure 10). The unshaded areas in a polar diagram show to the captain the operable regime of speeds and headings. It is clear that at certain ship-waves heading angles operability is independent of speed. On the other hand, with speed fixed there are some headings that are operable and others that are not. In practice the shipmaster can be provided on line by a suite of such diagrams. For different locations along the ship route, he uses them in order to design ship route in a manner that ship responses are acceptable (Politis et al., 2002).

![Polar diagram for \(H_s = 3m\) and \(T_p = 7s\).

The polar diagrams presented in this paper were derived by using the seakeeping software SWAN. SWAN is based on a three-dimensional Rankine Panel Method, according to which quadrilateral panels are distributed over the ship hull and part of the surrounding free surface. The free surface conditions implemented in SWAN linearize the wave potential above the double body flow. The numerical solution algorithms were derived using a rational stability analysis that leads to convergent and efficient wave flow simulation, free of numerical dissipation. The theory underlying SWAN is presented in Sclavounos (1996).

**Route simulation**

In order to simulate the voyages of the ship which leave the port at time \(d_{i+1}\), we used the following algorithm. Suppose you know \(d_k\), the time when the ship is at the point \(x_k\):

1. calculate the sea state conditions at this time and for this point by temporal linear interpolation;
2. use the polar diagrams in order to calculate the maximum speed (we assume that the direction is given) at which the ship can sail in order to reach the next point, if it is possible. If the conditions are too severe, the voyage is cancelled;
3. from this maximum speed and the distance between the points \(x_k\) and \(x_{k+1}\), calculate \(d_{k+1}\). And so on.

**Results**

We have simulated the sea-state conditions along the examined line for the equivalent of 500 months of January, and then, for each month, we have calculated the times of voyage from Piraeus to Heraklion for a daily departure at 6 o’clock (figure 11).

Then, we have compared the results obtained with these simulated sequences to the one obtained with the 3 year WAM data (table 3). We have found a higher frequency of cancelled and delayed voyages with the simulated data than given by the WAM database. This is explained by the fact that less severe storms have been observed in January in the period where the WAM model was operational (figure 2, WAM data are available during the last 3 years). The mean delay as calculated with WAM data is 22 minutes and 26 minutes with the simulated data.

![Distribution of the percentage of cancelled crossing (left), delayed crossing (middle) and distribution of the mean delay in minute (right) for the 500 simulated months of January](image)

**Table 3. Frequencies of delayed and cancelled crossings**

<table>
<thead>
<tr>
<th></th>
<th>WAM</th>
<th>simulated</th>
</tr>
</thead>
<tbody>
<tr>
<td>cancelled</td>
<td>0.00%</td>
<td>0.58%</td>
</tr>
<tr>
<td>delayed</td>
<td>11.1%</td>
<td>13.5%</td>
</tr>
</tbody>
</table>

**CONCLUSION**

In order to assess the profitability of a maritime line in Aegean sea, we used data produced by a numerical model. As these data were available on a too short period of time, we have developed a stochastic simulator of sea-state conditions along the line. At first, a new model has been proposed to describe and simulate the bivariate time series of wind speed and wind direction. This non homogeneous Markov model introduces a...
non-observable variable, the weather type, in order to relate the two processes with a non homogeneous Markov model. It has been applied to a long time series of wind conditions available at a point near the line where the most severe conditions were observed. Then, a simple method has been used in order to associate realistic sea-state conditions to these simulated wind conditions.

Finally, polar diagrams, which give the acceptable maximum speed of the ship for each sea state conditions, have been used to estimate the durations of the voyages of the ship. The results obtained with the original and the simulated data have been compared. This comparison shows that, because of the strong variability of the climatological conditions, the 3 years of data were not sufficient in order to get a reliable estimation of the profitability of the line and demonstrates the interest of the simulation strategy.

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REFERENCES


