International Journal of Maritime, Trade & Economic Issues *pp. 109-130*
Volume I, Issue (1), 2013

Forecasting Financial Indices: The Baltic Dry Indices

Eleftherios I. Thalassinos[1], Mike P. Hanias[2],
Panayiotis G. Curtis[3], John E. Thalassinos[4]

Abstract:
The main aim of this paper is to use chaos methodology in an attempt to predict the Baltic Dry Indices (BDI, BCI, BPI) using the invariant parameters of the reconstructed strange attractor that governs the system's evolution. This is the result of the new emerging field in econo-physics which mainly consists of autonomous physic-mathematical models that have been already applied to financial analysis. The proposed methodology is estimating the optimal delay time and the minimum embedding dimension with the method of False Nearest Neighbors (FNN). Monitoring the trajectories of the corresponding strange attractor we achieved a 30, 60, 90 and 120 time steps out of sample prediction.

Key Words:
Chaos methodology, False Nearest Neighbors, Baltic Dry Indices

JEL Classification: *C02, C14, C22*

[1] **Corresponding Author:** *Professor, University of Piraeus. Department of Maritime Studies, e-mail: thalassi@unipi.gr, thalassinos@ersj.eu.*

[2] *TEI Chalkidas, Athens,Greece, e-mail: mhanias@teihal.gr*
[3] *TEI Chalkidas, Athens, Greece, e-mail: pcurtis@teihal.gr*
[4] *PhD University of Piraeus, Piraeus, Greece*

1. Introduction

Predicting Baltic Dry Indices is possible applying algorithms used in physical sciences. This article combines finance and non linear methods from chaos theory to examine the predictability of the Baltic Dry Indices. The proposed methodology applies non linear time series analysis for the BCI, BDI and BPI indices covering the period from 04-01-2000 until 04-01-2008. In particular the method of the False Nearest Neighbor (FNN) is used in the first step to evaluate the invariant parameter of the system as the minimum embedding dimension. In a second stage using the reconstructed state space the article achieves an out of sample multi step time series prediction. The methodology is very dynamic compared to traditional ones (Thalassinos *et al.*, 2009). The most important property of the proposed methodology is the fact that there is no need to know from trial to error some constants to fit and extrapolate the time series. The methodology calculates the invariant parameters of the system itself. The fact that shipping indices are sensitive in irregular shocks and crises which are innate elements in chaotic systems, their predictability is much easier using chaotic methodology than any other forecasting method. Other benefits as they are pointed out in Thalassinos *et al.*, (2009) are:

- The possibility to extract information about a complex dynamic system, which generates several observed time series by using only one of them.
- To analyze the image-system with the same topology that preserves the main characteristics of the genuine system.

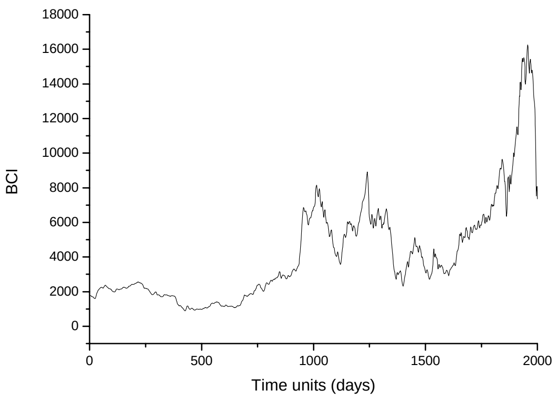
The article combines maritime time series daily data for the period of 04-01-2000 to 04-01-2008 (total number of observations 2000) with chaos methodology to examine the predictability of the three Baltic Dry Indices as the most characteristic indices in the maritime industry namely the BCI, BDI and BPI.

2. BCI Time Series

According to the theory of observed chaotic data (Abarbanel, 1996; Sprott, 2003; Hanias *et al.*, 2007a, 2007b; Thalassinos *et al.*, 2009) any non-linear time series can be presented as a set of signals $x=x(t)$ as it shown at Figure 1. The sampling rate is $\Delta t=1$ day and the number of data $N=2000$. As it is presented in Figure 1 the corresponding index had a significant number of structural shifts in the period under study with a max of 16,000 and a min of 1,000 points.

From the time series plots of the BCI in Figure 1, 1700 data points has been selected as the “training data set”, in other words the data that are used for the state space reconstruction and the other 300 data points as the “test data set” for out of sample period prediction.

Figure 1: Time Series plots of the BCI



3. State space reconstruction

3.1 Time delay τ

From the given data a vector $\vec{X}_i$, i=1, 2, … N, where N=1700, in the m order dimensional phase space given by the following relation (Kantz *et al.,* 1997; Takens, 1981; Hanias *et al.,* 2007a, 2007b; Thalassinos *et al.,* 2009) is constructed as shown in equation (1):

$$\vec{X}_i = \{x_i, x_{i-\tau}, x_{i-2\tau}, \ldots, x_{i+(m-1)\tau}\} \quad (1)$$

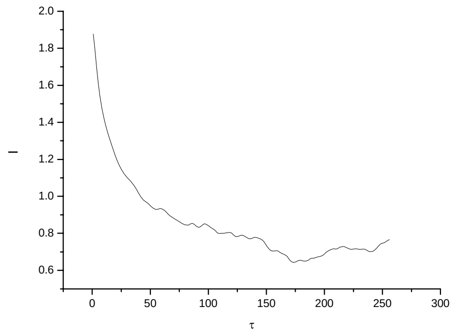
where $\vec{X}_i$ represents a point in the m dimensional phase space in which the attractor is embedded each time, where τ is the time delay τ = iΔt. The element xi represents a value of the examined scalar time series in time, corresponding to the i-th component of the time series. By using this method the phase space reconstruction to the problem of proper determining suitable values of values of m and τ is constructed. The next step is to find the time delay (τ) and the embedding dimension (m) without using any other information apart from the historical values of the indices.

Equation (2) is used to calculate the time delay by using the time-delayed mutual information proposed by Fraser *et al*., 1986 and Abarbanel, 1996.

$$I(\tau) = \sum_{x_i, x_{i+\tau}} p(x_i, x_{i+\tau}) \log_2 \left(\frac{p(x_i, x_{i+\tau})}{p(x_i) p(x_{i+\tau})} \right) \quad (2)$$

In equation (2), p(xi) is the probability of value xi and p(xi, xi+τ) denotes joint probability. I(τ) shows the information (in bits) being extracted from the value in time xi about the value in time xi+ττ. The function I can be thought of as a nonlinear generalization of the autocorrelation function. For a random process x(t) the I(t), is a measure of the information about x(t+τ) contained in x(t). The first nadir of I(τ) gives the delay, tau0, such that x(t+tau0) adds maximal information to that already known from x(t). This tau0 is returned as an estimate of the proper time lag for a delay embedding of the given time series. The time delay is calculated as the first minimum of the mutual information (Kantz *et al*., 1997; Fraser *et al*., 1986; Casdagli *et al*., 1991). Mutual information against the time delays (with a minimum at 54 time steps) for our time series is presented in Figure 2.

Figure 2: Mutual information I vs. time delay τ



3.2 Embedding dimension m

After obtaining the satisfactory value of τ, the embedding dimension m is to be determined in order to finish the phase space reconstruction. For this purpose the method of False Nearest Neighbors (Kantz *et al*., 1997 Kennel *et al*., 1992) is used. More specifically, the method is based on a fact that when embedding dimension is too low, the trajectory in the phase space will cross itself. If we are able to detect these crossings, we may decide whether the used m is large enough for correct reconstruction of the original phase space, when no intersections occur or not. When intersections are present for a given m, the embedding dimension is too low and we have to increase it at least by one. Then, we test the eventual presence of self-crossings again (Kennel *et al*., 1992; Abarbanel 1996). The practical realization of the described method is based on testing of the neighboring points in the m-dimensional phase space. Typically, we take a certain amount of points in the phase space and find the nearest neighbor to each of them. Then we compute distances for all these pairs and also their distances in the (m+1) dimensional phase space. The rate of these distances is given by equation (3) as follows:

$$P = \frac{\left\| \mathbf{y}_i(m+1) - \mathbf{y}_{n(i)}(m+1) \right\|}{\left\| \mathbf{y}_i(m) - \mathbf{y}_{n(i)}(m) \right\|} \qquad (3)$$

where yi(m) represents the reconstructed vector, belonging to the i-th point in the m-dimensional phase space and index the n(i) denotes the nearest neighbour to the i-th point. If P is greater than some value Pmax, we call this pair of points False Nearest Neighbors (i.e. neighbors, which arise from trajectory self-intersection and not from the closeness in the original phase space). In the ideal case, when the number of false neighbors falls to zero, then the value of m is found. For this purpose we compute the rate of false nearest neighbours in the reconstructed phase space using the formula in equation (4):

$$\left| x_{i+m\tau} - x_{n(i)+m\tau} \right| \geq R_A \tag{4}$$

where RA is the radius of the attractor,

$$R_A = \frac{1}{N} \sum_{i=1}^{N} \left| x_i - \overline{x} \right| \tag{5}$$

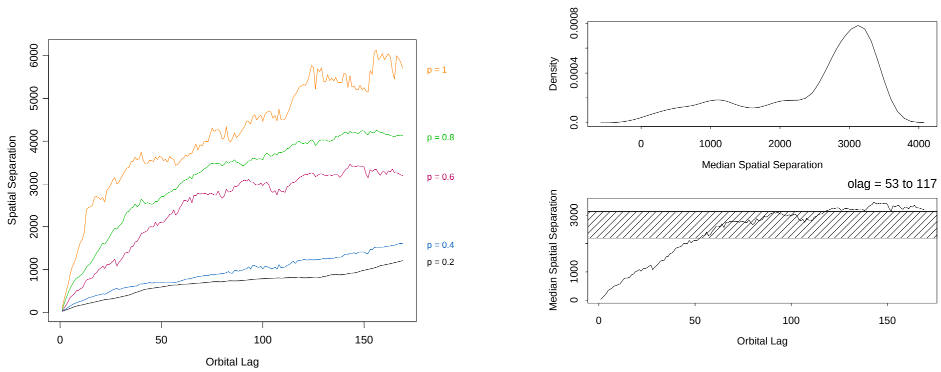
and

$$\overline{x} = \frac{1}{N} \sum_{i=1}^{N} x_i \tag{6}$$

is the average value of time series.

When the following criterion $P \geq P_{\max}$, (7) is satisfied then it can be used to distinguish between true and false neighbours (Kennel *et al.*, 1992). The dimension m is found when the percent of false nearest neighbors decreases below some limit, (Kugiumtzis *et al.*, 1994), so we choose Pmax=10 as used typically. Before we apply the above procedure, we must determine the Theiler window for out time series and exclude all pairs of points in the original series which are temporally correlated and are closer than this value of Theiler window. For this purpose we produce space time separation plots (Kantz *et al.*, 1997) as shown in Figure 3(a).

Figure 3: Space time separation plot



(a) (b)

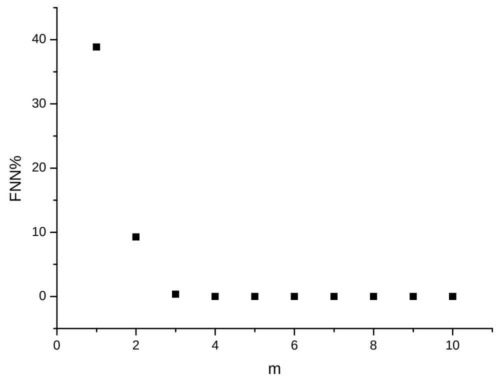
(a) Density function estimate of the median contour (upper graph) in addition to a suggested range of suitable orbital lags. (b) The most populous values of the median contour are highlighted by a cross-hatched area that covers a plot of the median curve (lower).

The space time separation plots where produced with a desired embedding dimension 5, τ=54, and the probability associated with the first contour equal to 0.2

In Figure 3 we had plot a summary of the space-time contours including a density function estimate of the median contour in addition to a suggested range of suitable orbital lags. In the latter case, the most populous values of the median contour are highlighted by a cross-hatched area that covers a plot of the median curve. The suggested range for a suitable orbital lag is based on the range of values that first escape this cross-hatched region, so we can choose a Theiler window from 53 to 117. In our case we choose the Theiler window to be 65. Then we used matlab code to calculate the quantity P.

The rate of false neighbors that is under the above limit Pmax=10 is achieved for m = 4, thus this value should be suitable for the purpose of phase space reconstruction. This is shown in Figure 4 for our time series.

Figure 4: Percent of False Nearest Neighbors number vs. m



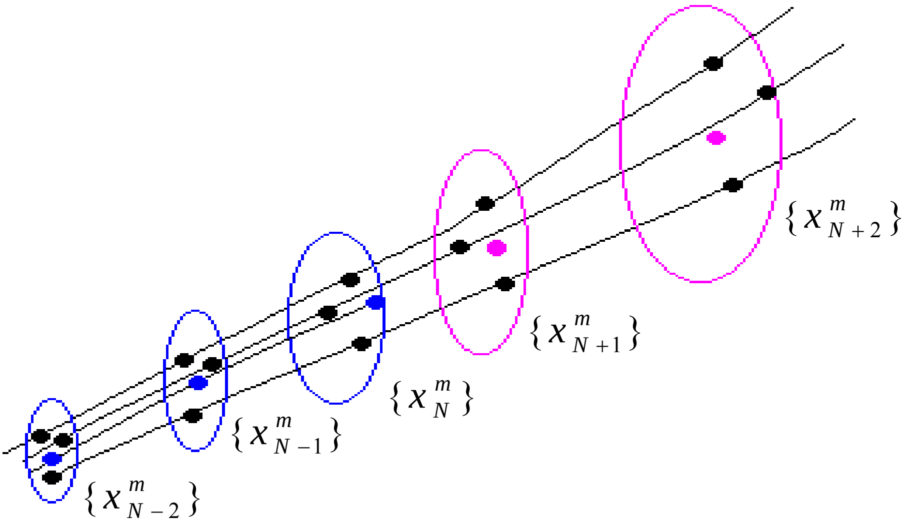
4. Time Series Prediction of BCI

The next step is to predict the evolution of BCI by computing weighted average of evolution of close neighbors of the predicted state in the reconstructed phase space (Miksovsky *et al.*, 2007; Stam *et al.*, 1998). The reconstructed m-dimensional signal projected into the state space can exhibit a range of trajectories, some of which have structures or patterns that can be used for system prediction and modeling. Essentially, in order to predict k steps into the future from the last m-dimensional vector point $\{x_N^m\}$, we have to find all the nearest neighbors $\{x_{NN}^m\}$ in the ε-neighborhood of this point. To be more specific, let's set $B_\varepsilon(x_N^m)$ to be the set of points within ε of $\{x_N^m\}$ (i.e. the ε-ball). Thus any point in $B_\varepsilon(x_N^m)$ is closer to the $\{x_N^m\}$ than ε. All these points $\{x_{NN}^m\}$ come from the previous trajectories of the system and hence we can follow their evolution k-steps into the future $\{x_{NN+k}^m\}$. The final prediction for the point $\{x_N^m\}$ is obtained by averaging over all neighbors' projections k-steps into the future. The algorithm can be written as in equation (8) as follows:

$$\{x_{N+k}^m\} = \frac{1}{|B_\in(x_{NN}^m)|} \sum_{X_{NN}^m \in B_\in(x_{NN}^m)} x_{NN+k}^m \qquad (8)$$

where $|B_\in(x_{NN}^m)|$ denotes the number of nearest neighbors in the neighborhood of the point $\{x_N^m\}$(Kantz *et al.*, 1997). As an example we suppose that we want to predict k=2 steps ahead. The basic principle of the prediction model is visualized in Figure 5. The blue dot $\{x_N^m\}$ represents the last known sample, from which we want to predict one and two steps into the future. The blue circles represent ε-neighborhoods in which three nearest neighbors were found.

Figure 5: Basic prediction principle of the simple deterministic model



The next step in the algorithm is to check that the projections, one and two steps into the past, of the points in $\{x_{NN}^m\}$ are also nearest neighbors of the two previous readings $\{x_{N-1}^m\}$ and $\{x_{N-2}^m\}$ respectively. This criterion excludes unrelated trajectories that enter and leave the ε-neighborhood of $\{x_N^m\}$ but do not 'track back' to ε- neighborhoods of $\{x_{N-1}^m\}$ and $\{x_{N-2}^m\}$, thus making them unsuitable for prediction. Assuming that any nearest neighbors have been found and checked using the criterion detailed previously, we project their trajectories into the future and average them to get results for $\{x_{N+1}^m\}$ and $\{x_{N+2}^m\}$. We used the values of τ and m from our previous analysis so the appropriate time delay τ was chosen to be τ=54. We use as embedding dimension the 2*m = 8 (Sprott J. C) and for the optimum number of nearest neighbors we used the value of embedding dimension m= 4. These values of embedding dimension and number of nearest neighbors gave the better results for k=30 time steps ahead. We apply the procedure for in sample forecasting until data point 1700 as shown at Figure 6 then we applied the procedure for out of sample prediction from data point 1700 to data point 1730 as shown in Figure 7.

Figure 6: Actual and in sample predicted time series for k=30 days ahead

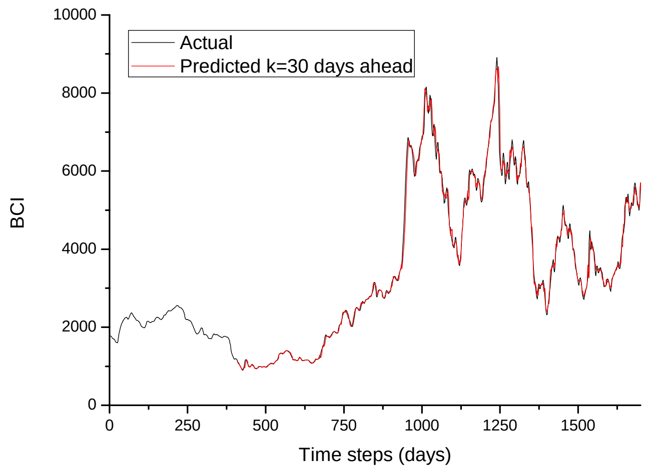
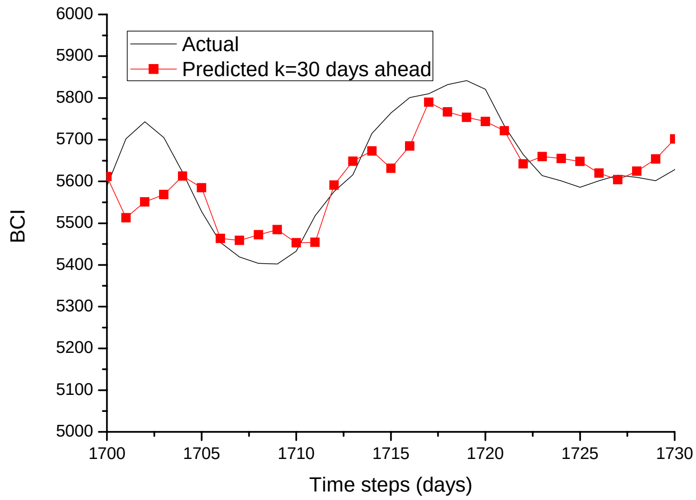


Figure7: Actual and out of sample predicted time series for k=30 days ahead



Actual and predicted time series for k=60, 90, 120 time steps ahead are presented in Figures 8, 9, 10 respectively for out of sample period.

Figure 8: Actual and out of sample predicted time series for k=60 days ahead

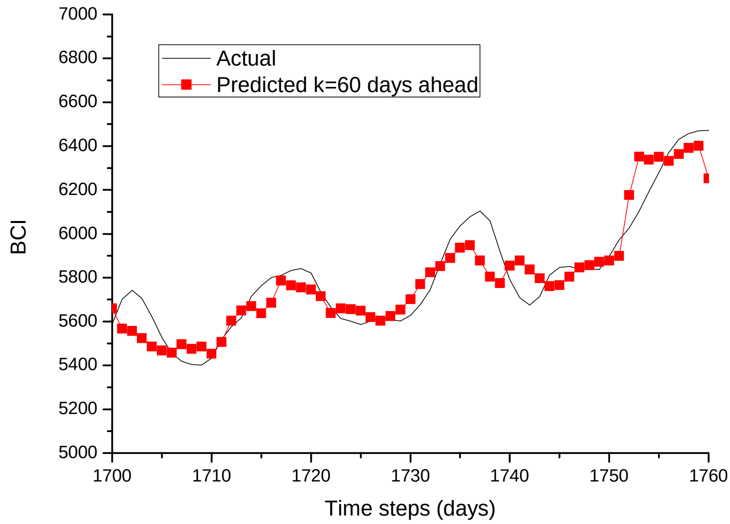


Figure 9: Actual and out of sample predicted time series for k=90 time steps ahead

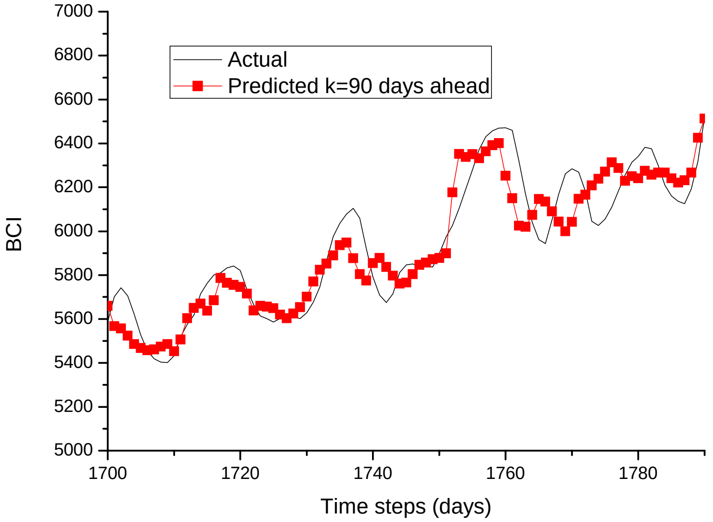
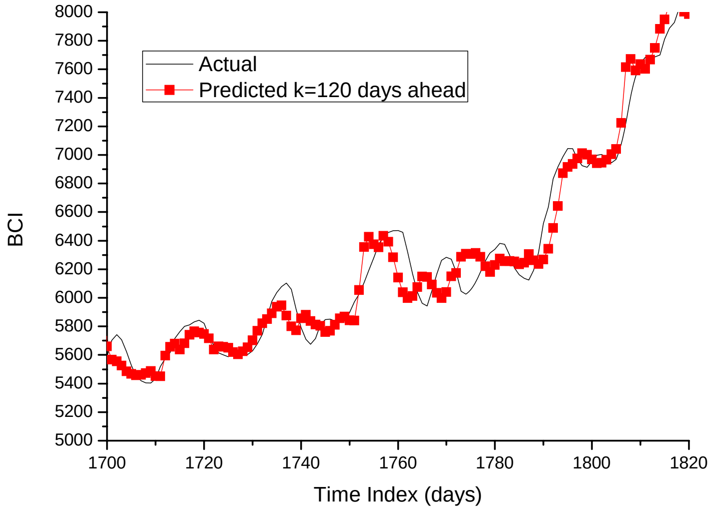


Figure 10: Actual and out of sample predicted time series for k=120 time steps ahead

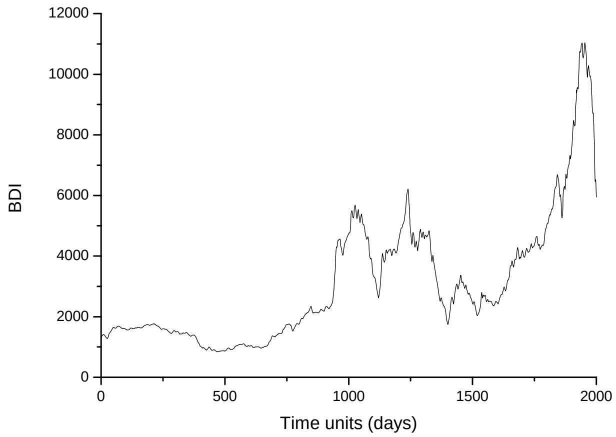


The prediction error for establishing the quality of the fit was chosen to be the classical root mean square error (RMSE) and found to be 8.99x10-2, 9.54x10-2, 2.17x10-1, 2.26x10-1 for k=30, 60, 90, 120 respectively.

5. Time Series Prediction of BDI

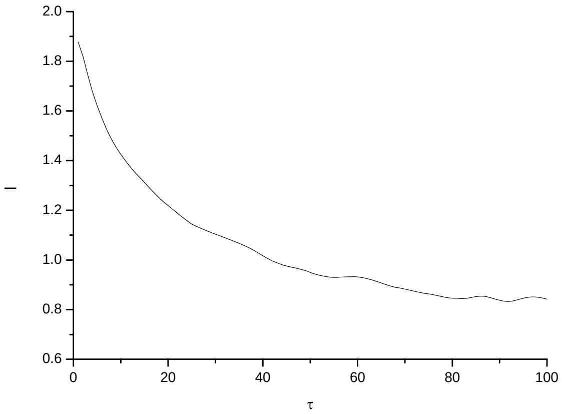
The BDI time series is presented as a signal x=x(t) as it shown in Figure 11. It covers data from 04-01-2000 to 04-01-2008. The sampling rate was Δt=1 day and the number of data are N=2000.

Figure 11: BDI Time Series



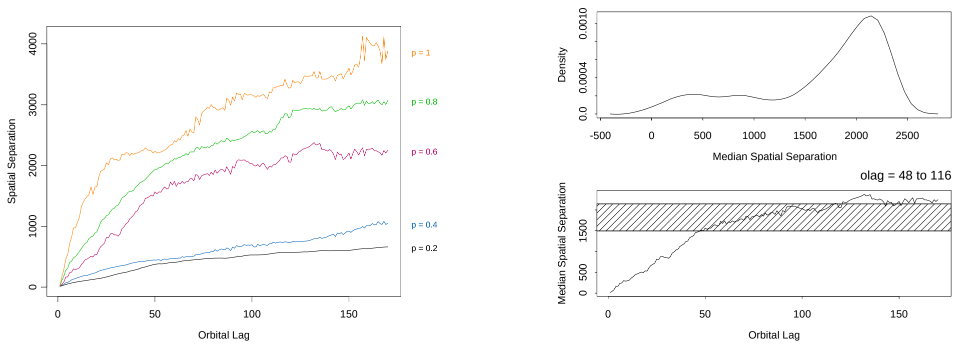
From this time series we have choose 1700 data as the "training data set", in other words the data that we used for the state space reconstruction and the other 300 data as the "test data set" for our out of sample prediction. We used the same procedure as before and we had estimated the delay time, Theiler window and embedding dimension. Mutual information against the time delays (with a minimum at 55 time steps) for BDI time series is presented in Figure 12.

Figure 12: Mutual information I vs. time delay τ



The space time separation plot and the density function estimation plots are shown in Figure 13. From this plot we estimate the Theiler window to be 100.

Figure 13: Space time separation plot

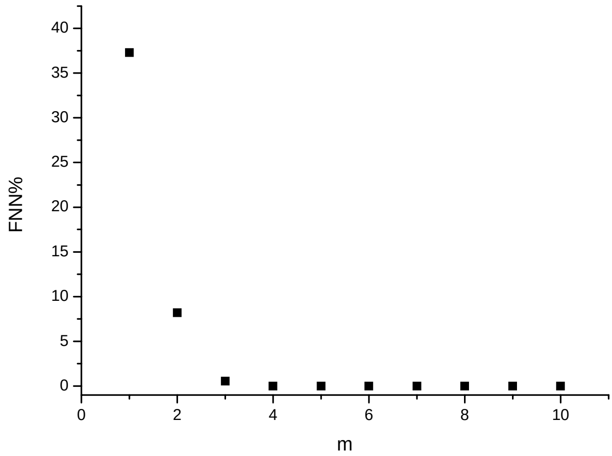


(a) (b)

(a) Density function estimate of the median contour (upper graph) in addition to a suggested range of suitable orbital lags.
(b) The most populous values of the median contour are highlighted by a cross-hatched area that covers a plot of the median curve (lower).

The percent of false nearest neighbors number FNN vs. m is shown in Figure 14. From this it is clear that the embedding dimension is 4.

Figure 14: Percent of false nearest neighbors number FNN vs. m



The next step is to predict 30, 60, 90 and 120 time steps ahead. Figures 15, 16, 17, 18 and 19 are shown the in sample and out of sample period predictions.

Figure 15: Actual and in sample predicted time series for k=30 days ahead

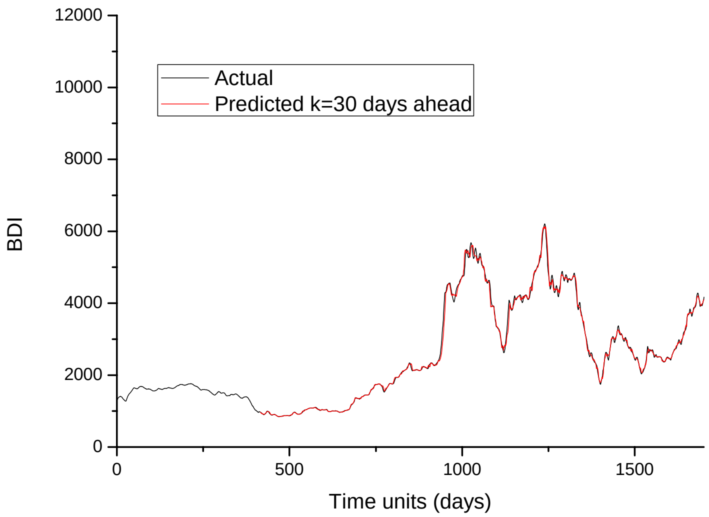


Figure 16: Actual and out of sample predicted time series for k=30 days ahead

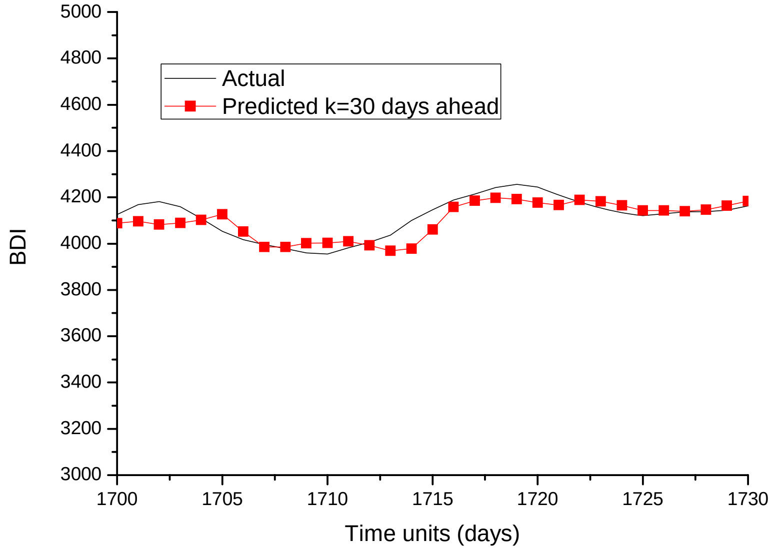


Figure 17: Actual and out of sample predicted time series for k=60 days ahead

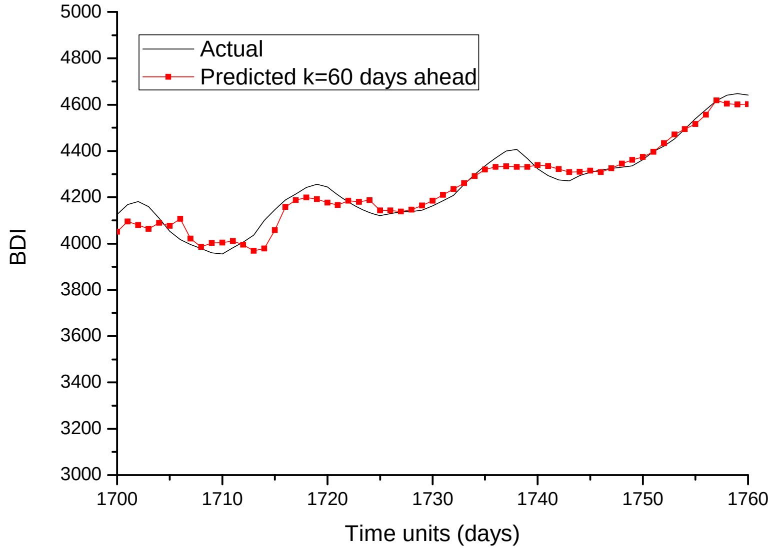


Figure 18: Actual and out of sample predicted time series for k=90 time steps ahead

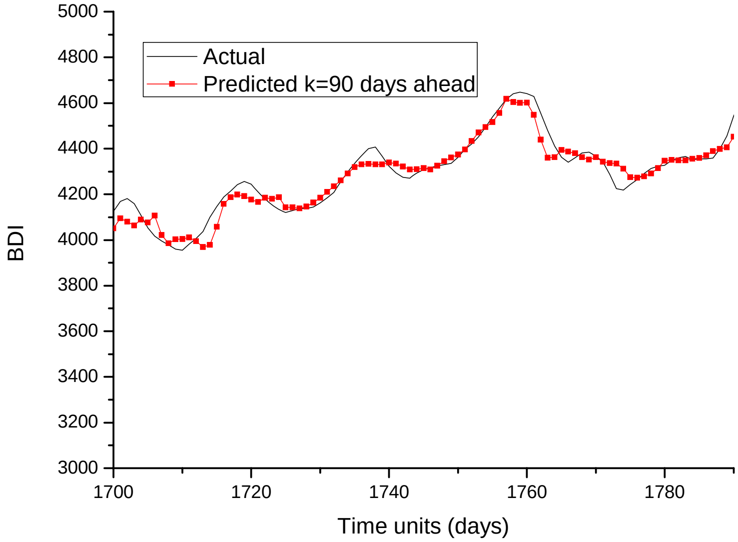
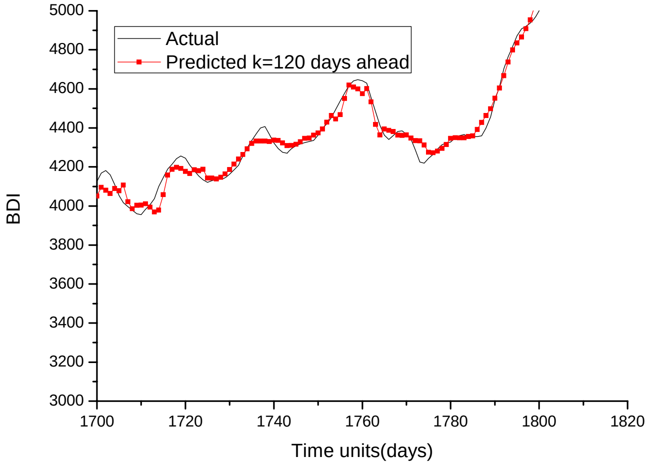


Figure 19: Actual and out of sample predicted time series for k=120 time steps ahead

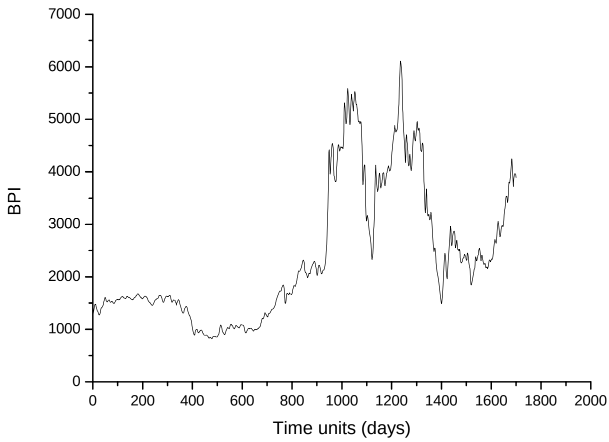


The prediction error for establishing the quality of the fit was chosen to be the classical root mean square error (RMSE) and found to be 5.68x10-2, 5.99x10-2, 6.53x10-2, 6.80x10-2 for k=30, 60, 90 and 120 respectively.

5. Time Series Prediction of BPI

The BPI time series is presented as a signal x=x(t) as it shown in Figure 20. It covers data from 04-01-2000 to 04-01-2008. The sampling rate was Δt=1 day and the number of data are N=2000.

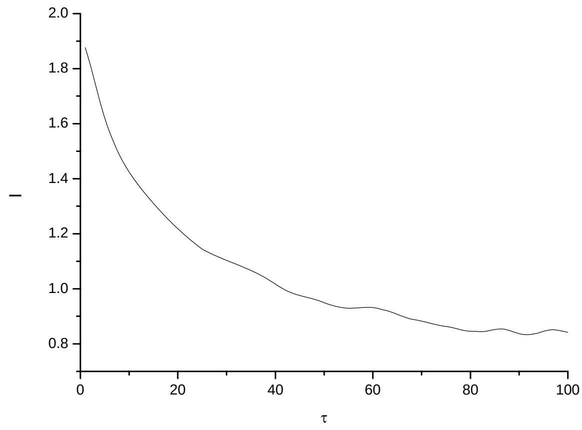
Figure 20: BPI time series



From this time series we have choose 1700 data as the "training data set", in other words the data that we used for the state space reconstruction and the other 300 data as the "test data set" for our out of sample prediction.

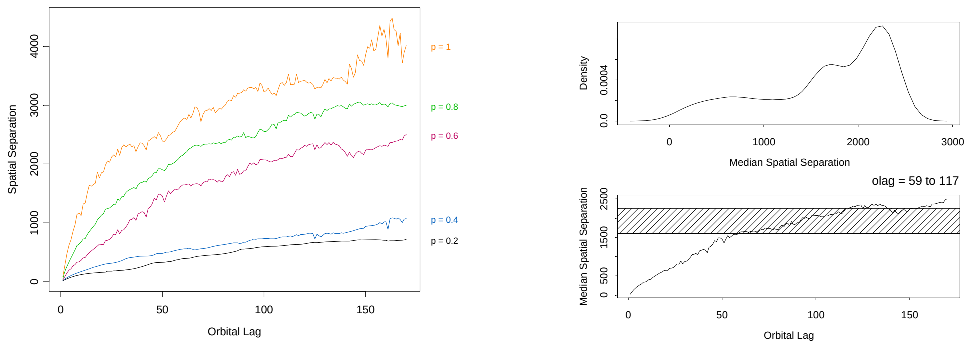
We used the same procedure as before and we have estimated the delay time, Theiler window and embedding dimension. Mutual information against the time delays (with a minimum at 55 time steps) for BDI time series is presented in Figure 21.

Figure 21: Mutual information I vs. time delay τ



The space time separation plot and density function estimation plots are shown in Figure 22. From this plot we estimate the Theiler window to be 100.

Figure 22: Space time separation plot

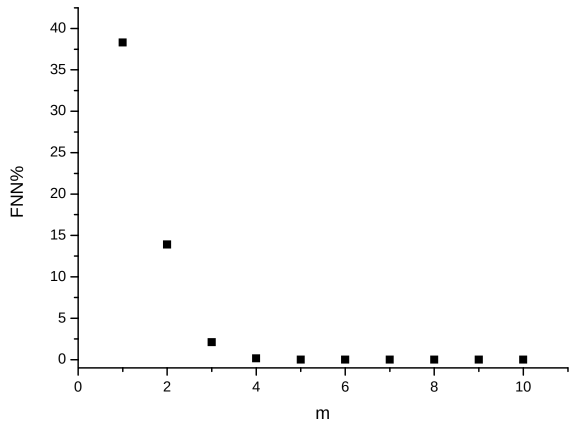


(a) (b)

(a) Density function estimate of the median contour (upper graph) in addition to a suggested range of suitable orbital lags.
(b) The most populous values of the median contour are highlighted by a cross-hatched area that covers a plot of the median curve (lower).

The percent of false nearest neighbors number FNN vs. m is shown in Figure 23. From this fig it's clear that the embedding dimension is 4.

Figure 23: Percent of false nearest neighbors number FNN vs. m



The next step is to predict 30, 60, 90 and 120 time steps ahead. Figures 24, 25, 26, 27 and 28 are shown the in sample and out of sample period predictions.

Figure 24: Actual and in sample predicted time series for k=30 days ahead

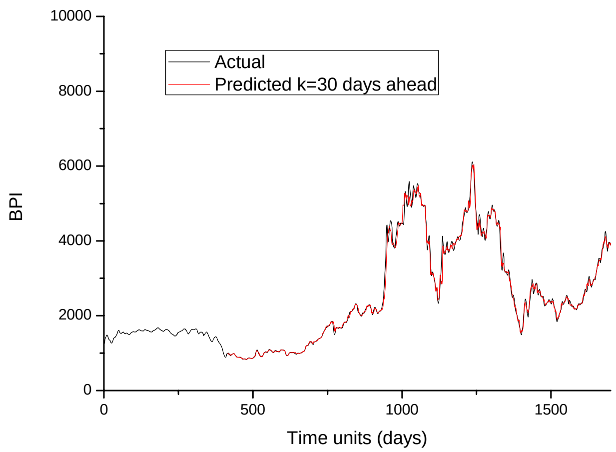


Figure 25: Actual and out of sample predicted time series for k=30 days ahead

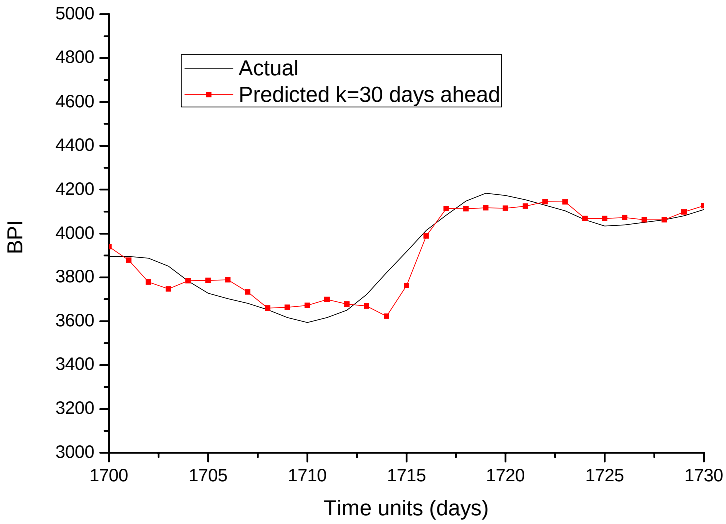


Figure 26: Actual and out of sample predicted time series for k=60 days ahead

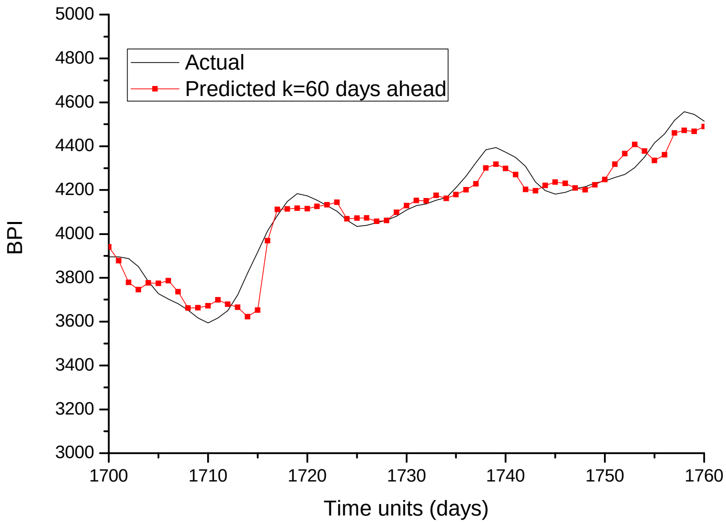


Figure 27: Actual and out of sample predicted time series for k=90 days ahead

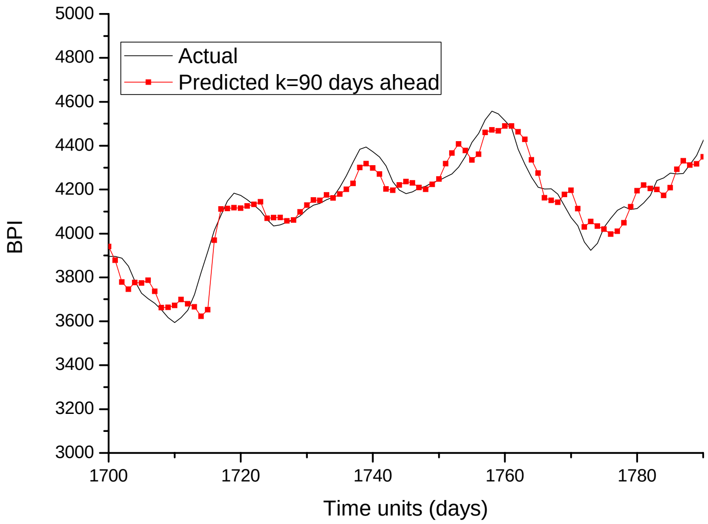
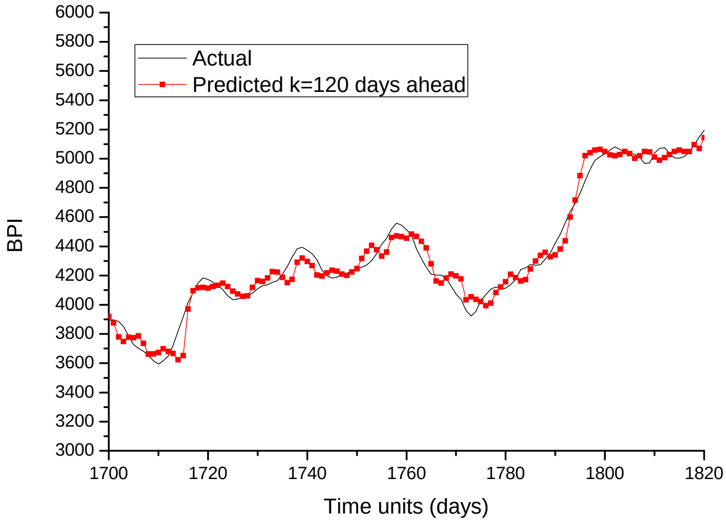


Figure 28: Actual and out of sample predicted time series for k=120 days ahead.



The prediction error for establishing the quality of the fit was chosen to be the classical root mean square error (RMSE) and found to be 7.10x10-2, 7.56x10-2, 1.24x10-1, 2.36x10-1 for k=30, 60, 90 and 120 respectively.

6. Conclusion

In this paper chaotic analysis has been used to predict Baltic Dry Indices time series. After estimating the minimum embedding dimension, the proposed methodology has pointed out that the system is characterized as a high dimension chaotic. From reconstruction of the systems' strange attractors, it has been achieved a 30, 60, 90 and 120 out of sample time steps prediction. In Table 1 the RMS values of the corresponding prediction are shown.

Table 1: RMS values

RMS				
	30 DAYS	**60 DAYS**	**90 DAYS**	**120 DAYS**
BDI	5.68×10^{-2}	5.99×10^{-2}	6.53×10^{-2}	6.80×10^{-2}
BCI	8.99×10^{-2}	9.54×10^{-2}	2.17×10^{-1}	2.26×10^{-1}
BPI	7.10×10^{-2}	7.56×10^{-2}	1.24×10^{-1}	2.36×10^{-1}

It is clear that the BDI has the minimum error and gives the best prediction compared to the other two indices. The prediction power of the suggested method is limited by the properties of the original system and the series alone. Because the series represents the only source of information for the system it is important to be as long as possible. Too short time series will not worsen the prediction only but it may also make the proper reconstruction of the phase space impossible. Another important limitation factor is the eventual contamination by noise – evidently, the more noise is included in the series, the less accurate result can be gained. However the prediction horizon of 120 days would be useful for economical analysis as it can reveal the trend in a very good manner.

References

Abarbanel, H.D.I. (1996), *Analysis of Observed Chaotic Data,* Springer, New York.

Casdagli, M., Eubank, S., Farmer, J.D. and Gibson, J. (1991), "State Space Reconstruction in the Presence of Noise", *Physica D*, 51, pp. 52- 98.

Fraser, A.M., Swinney, H.L. (1986), "Independent coordinates for strange attractors from mutual information", *Physics Review* A, pp. 33, 1134.

Hanias, M.P., Curtis, G.P. and Thalassinos, E.J. (2007), "Non-Linear Dynamics and Chaos: The Case of the Price Indicator at the Athens Stock Exchange", *International Research Journal of Finance and Economics*, Issue 11, pp. 154-163.

Hanias, M.P., Curtis, G.P. and Thalassinos, E.J. (2007), "Prediction with Neural Networks: The Athens Stock Exchange Price Indicator", *European Journal of Economics, Finance And Administrative Sciences*, Issue 9.

Hanias, M.P., Karras, A.D. (2007), "Efficient Non Linear Time Series Prediction Using Non Linear Signal Analysis and Neural Networks in Chaotic Diode Resonator Circuits", Springer Berlin/Heidelberg, *Lecture Notes in Computer Science, Advances in Data Mining. Theoretical Aspects and Applications,* Vol. 4597, pp. 329-338.

Kantz, H., Schreiber, T. (1997), *Nonlinear Time Series Analysis,* Cambridge University Press, Cambridge.

Kennel, M.B., Brown, R., Abarbanel, H.D.I. (1992). "Determining embedding dimension for phase-space reconstruction using a geometrical construction", *Physics Review* A, 45, 3403.

Kugiumtzis, D., Lillekjendlie, B., Christophersen, N. (1994) "Chaotic Time Series", *Modelling Identification and Control,* 15, 205.

Miksovsky, J., Raidl, A. (2007), "On Some Nonlinear Methods of Meteorological Time Series Analysis", *Proceedings of WDS Conference*.

Stam, C.J., Pijn, J.P.N., Pritchard, W.S. (1998), "Reliable Detection of Nonlinearity in Experimental Time Series with Strong Periodic Component", *Physica* D, Vol. 112.

Sprott, J.C. (2003), "Chaos and Time series Analysis", *Oxford University Press.*

Takens, F. (1981), "Detecting Strange Attractors in Turbulence", *Lecture notes in Mathematics*, Vol. 898, Springer, New York.

Thalassinos, I.E., Hanias M.P., Curtis, G.P., and Thalassinos, E.J. (2009), "Chaos Theory: Forecasting the Freight Rate of an Oil Tanker", *International Journal of Computational Economics and Econometrics*, Vol. X, Issue 1.