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Measuring Tanker Market Future Risk with the use of FORESIM

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Abstract

Future market risk has always been a critical question in decision support processes. FORESIM is a simulation technique that models shipping markets (developed recently). In this paper we present the application of this technique in order to obtain useful information regarding future values of the tanker market risk. This is the first attempt to express future tanker market risk in relation to current market fundamentals. We follow a system's analysis seeking for internal and external parameters affecting risk. Therefore we apply dynamic features in risk measurement taking into account all Tanker market characteristics and potential excitations from non-systemic parameters as well as their contribution to freight level formulation and fluctuation. In this way we are able to measure the behavior of future market risk as long as twelve months ahead with very encouraging results. The output information is therefore useful in all aspects of risk analysis and decision making in shipping markets.

Keywords: Tanker Market, Freight Rates, Forecasting, Modeling, Simulation, Artificial Neural Networks (ANN)
JEL Classification: C6, C450, G17

1. Introduction

A popular definition of "forecast" is that it is a reference to future trends usually in the form of probability that is realized by processing and analyzing available data. Then a set of questions slip into mind: In a volatile market such as the one of shipping freight rates, is it possible to acquire information regarding its future evolvement? How can we predict the events that will influence the future state of the market? Future shipping market risk has always been an attractive thematic issue for many maritime economists. Especially in the era of risk management attempts in shipping, measuring market risk is a key point to the success of the whole process. Selecting between Spot and Period Charter or where to place a vessel, is a tricky question, which, nevertheless, can be successfully approached by using the appropriate risk management tools. There are two major characteristics of the shipping market that turned risk management to a necessity: variability and uncertainty. Risk management can do very little to reduce market variability, but can be very effective in reducing uncertainty for those involved in risk-taking decisions. Alternately FFA's are the latest tools in hedging shipping risk aiming to be a gowning parallel market next to the physical one. So either we speak about physical market chartering strategies or “paper” market trading strategies, future market risk knowledge is essential for efficient decision-making.

There are two main approaches regarding the estimation of future market risk. The first one is based on univariate stochastic models. This approach applies models like the GARCH, ARIMA, Geometric Brownian Motion (GBM), Ornstein-Uhlenbeck (O-U) process, Jump-Diffusion (O-U with Jumps) etc based on the admission that all the necessary information to estimate future values is located in the precedent historical data of the time series. This admission is quite defective by a simple consideration of the tanker and bulk shipping market mechanism. For that reason researchers developed static econometric models (Zannetos, 1966, Norman, 1979 & 1981, Evans 1994) or dynamic (Eriksen & Norman 1976, Strandenes 1986, Beenstock & Vergotis 1989, Lyridis 2004a&b).

Although this paper presents an application in Tanker vessels and more specifically in Very Large Crude Oil Carriers (VLCC), the methodology can also be applied in the bulk market. Both markets operate in a system with numerous interactions. Shipping market mechanism is full of causality terms balancing the output in the time field – the freight rates. The formulation mechanism for the tanker market is not clearly known but the fact is that it is dependent on the global socioeconomic status. The interaction of the market and the variables is either direct or indirect according to the way and the time lag that they interact. For example VLCC rates have a direct and positive correlation with the orderbook in real-time. As the observed phenomenon of the Shipping cycle describes, following a high freight rate period new vessels enter the market resulting into an increase in the total transport capacity and subsequently into a drop in the rates. Therefore, the two variables have a negative correlation when examined under a specific time lag. All variables, apart from demand for sea transport, are in some way correlated to market trends and vice versa. However, demand for sea transport is determined by other factors and not by the state of the shipping market. For example, while the level of oil production by OPEC has a strong influence in the market, there is no feedback from the shipping market to the level of oil production. But which are the variables that influence demand in the shipping market? In the case of VLCC carriers the demand is related to the following:

- The growth of world economy
- Oil shocks
- War – hostile acts near oil production facilities
- Oil reserves
- Oil price
- Climate conditions
- Political decisions – OPEC policy
- New reserves

Many shipping parameters have a dominant role in freight rates future possible realizations. This leads to the statement that the initial state of the shipping system as described by the fundamental variables has a leading affect to how this system may react to excitations such as a demand increase or decrease, a pipeline closure, an oil shock etc. To be more specific, a congested shipping market with increased volumes of laid up vessels is expected to show less sensitivity to demand changes comparing to a balanced market. As known high volumes of laid up vessels is a characteristic of markets with low freight rates. The laid up vessels will absorb any demand increase by entering to operational state. To the contrary scenario if the market experiences a demand decrease for transport services then the already low freight rates levels cannot fall down from a minimum point relatively to the operating expenses. Another crucial parameter is the volume of tonnage under construction (order book). This parameter seems to give an important indication for the future levels of tonnage supply. Hence it is obvious that a systemic modeling of shipping market would lead to more bounded possible future states subject to the constrains of the fundamental explanatory shipping parameters. Forecasting the need for sea transport is very difficult since it is related to quantitative and qualitative variables with unforeseen trends. What can be done is to “feed” the forecasting model with different scenarios and generate a stochastic ‘description’ of the future. This is why FORESIM was conceived as a complete simulating procedure. The entire shipping market parameters such as active fleet or scheduled deliveries play a predetermined role in future freight rate levels. Additionally crucial parameters that affect freight rate levels (the OPEC oil production in our case) and have unpredictable random behaviors are stochastically generated in the corresponding simulation time period.

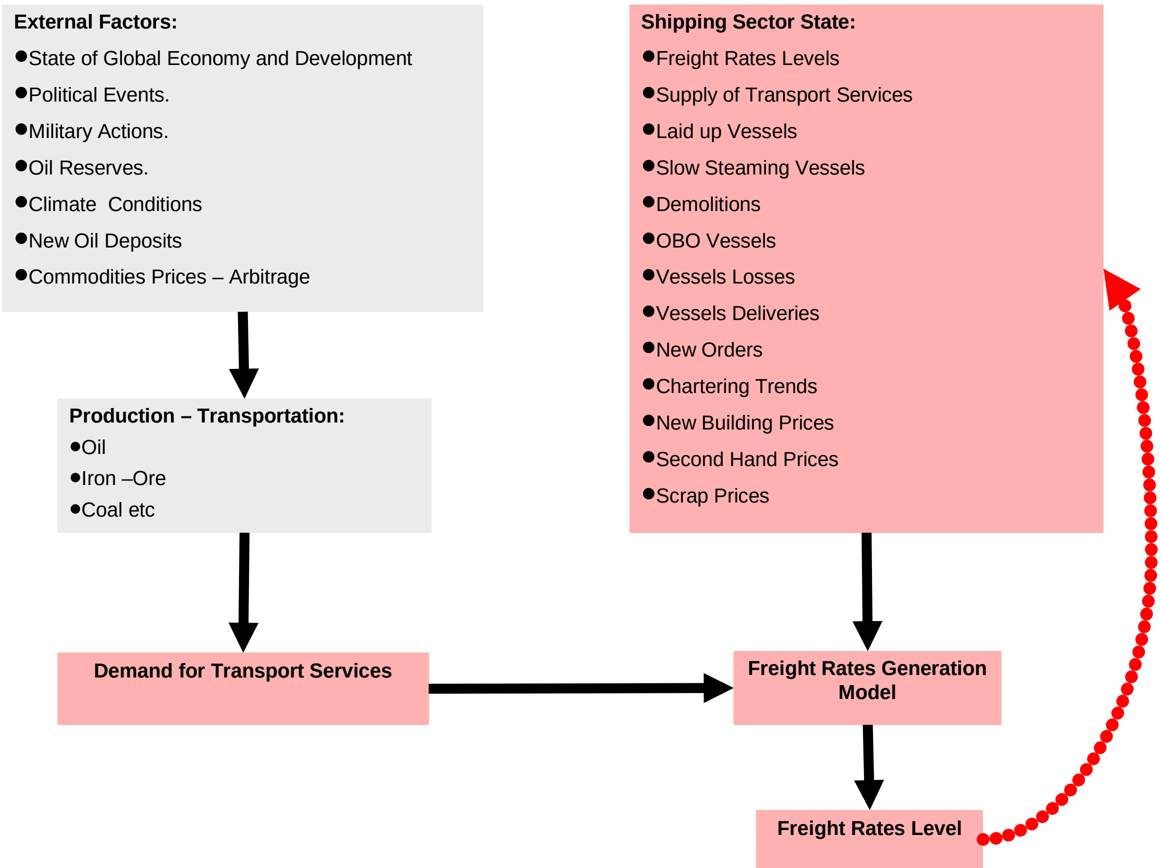
This paper is structured as follows: methodology is described in the next section. FORESIM technique is applied in order to simulate tanker VLCC market. The third section presents the results regarding future market risk estimation. The paper finishes with interesting conclusions about FORESIM application and market characteristics.

2. Methodology

FORESIM is a simulation technique developed especially for the shipping system. It is used in order to obtain a solid future view of the maritime trends. The first step is the definition of the system and the variables to be simulated. This is what is called a systemic analysis in order to obtain absolute knowledge of the examinant system. Next step is to construct a model capable of simulating the physical market. FORESIM uses the power of Artificial Neural Models in what is called function approximation seeking for relations between input vector and desired output. Artificial neural networks are mathematical models imitating human brain functionality and are used as an advanced pattern recognition technique with application in time series forecasting. According to the literature, ANNs are suitable for analysis of non-stationary nonlinear time series. Focusing in tanker freight forecasting, in comparison to other methods such as linearly based autoregressive models, artificial neural networks are proven to be at least as accurate while, in many cases, yielding impressive results (Lyridis 2004a&b). The possible outer system excitations are entered into the model with the usage of GARCH-family models. Then to model processes like oil production, where covariance is not constant in the time domain, GARCH family models has been fairly successful (Bollerlev, and Engle 1994).

The systemic analysis showed that the independent variables that can be divided in two major categories. The first has to do with variables related to demand for transport in and the second with those that are related to the supply of tonnage. The figure 1 shows a schematic approach of the shipping system regarding the freight rates generation mechanism.

Figure 1: Schematic Approach Of Freight Rates Generation Mechanism



The importance of investigating these sets of variables is very high since they determine the freight rates as the result of the equilibrium between supply and demand. A few from the variables used in modeling the market are the following:

- Freight rates
- Active fleet
- Demand for transport in the specific market
- Orderbook
- Demolitions
- Laid-up vessels etc.

By using expert judgment and statistical tools to measure correlation and to avoid co-linearity, the input vector is constructed. The table 1 shows the input vector for the three months ahead simulation of VLCC WS freight rates (Ras Tanura - Rotterdam) and the corresponding Variance Inflation Factor (VIF). The input vector consists of 8 variables:

Table 1

Input Vector for Three Months Ahead Model

Independent Variable	VIF
Oil Price	2.858
VLCC Supply	4.213
OBO Supply	6.260
VLCC Demolition Prices	1.946
VLCC WS Rate	3.727
OPEC Production	4.148
OPECDIF_3 (Percentage Difference After Three Months)	1.104
ARBITRAGE of Oil Prices	4.941

By applying the same process the corresponding input vector for the twelve months ahead is shown at the table 2.

Table 2

Input Vector for Twelve Months Ahead Model

Independent Variable	VIF
VLCC Supply	3.179
OBO Supply	8.144
VLCC Demolition Prices	1.749
VLCC Orderbook	5.001
WS	2.829
OPEC Production	4.211
OPECDIF_12 (Percentage Difference After Twelve Months)	2.029

It is remarkable that as expected the Orderbook variable is shown to have a statistical important influence on the dependent variable of freight rates after twelve months. It also expected that variables like oil price and Arbitrage can influence the freight rate generation mechanism only in a short-term basis. By constructing appropriate input vectors for up to a twelve months period ahead FORESIM is capable of simulating the VLCC market.

Oil production time series data like many time series usually exhibit a characteristic known as volatility clustering, in which large changes tend to follow large changes, and small changes tend to follow small changes. Engle's test is applied in Oil production time series data to seek for the presence of ARCH effects. Pre-estimation process includes the $Opec_i$ time series transformation using the following equation:

$$Opecret_i = \frac{Opec_{i+1}}{Opec_i} - 1$$

Under the assumption that the transformed Oil production time series data is a random sequence of Gaussian disturbances (i.e., no ARCH effects exist), this test statistic is also asymptotically Chi-Square distributed (Engle 1995). The test results reveal that the ARCH effect is present hence serial dependence of volatility exists. Following this specific preprocessing procedure by applying Ljunx-Box-Pierce Q-test (Gourieroux 1997) it is clear that no serial dependence of mean exists hence there is no need to use a conditional mean model such as ARIMA.

To feed the technique with possible future oil production volumes after a fit process an Exponential GARCH model is used. In order to fit a model in data set, log-likelihood function –LLF- criterion is calculated. In addition, Akaike and Bayesian information criteria were used to compare alternative GARCH models based on parsimony and penalize models with additional parameters. (Box, and Jenkins 1970). Table 3 shows the results:

Table 3

Input Vector for Twelve Months Ahead Model

Model	Selection Criteria		
	LLF	AIC	BIC
EGARCH11ARMA00T	819.079	-1628.158	-1608.341

The E-GARCH(1,1) (Student t distributed) include a term to capture the leverage effect, or negative correlation, between examinant variable returns and volatility (Nelson 1991). As estimated in the fit process the model will have the following coefficients as shown in table 4:

Table 4

Input Vector for Twelve Months Ahead Model

Coefficient	Value
C	0.00011918
K	-0.10279
GARCH(1)	0.98584
ARCH(1)	0.18242
Leverage(1)	-0.10488

Hence the form of the E-GARCH that will be used to generate paths of transformed Opec oil production is the following:

$$y_t = 0.00011918 + \varepsilon_t$$

$$Var_{t-1}(y_t) = E_{t-1}(\varepsilon_t^2) = \sigma_t^2$$

$$\log \sigma_t^2 = -0.10279 + 0.98584 \log \sigma_{t-1}^2 + 0.18242 \left[\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - E\left(\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} \right) \right] \quad - 0.10488 \left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right)$$

Where:

$$E\{|z_{t-1}|\} = E\left(\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} \right) = \sqrt{\frac{\nu-2}{\pi}} \cdot \frac{\Gamma\left(\frac{\nu-1}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)},$$ Due to the fact that ε_t is Student's T distributed.

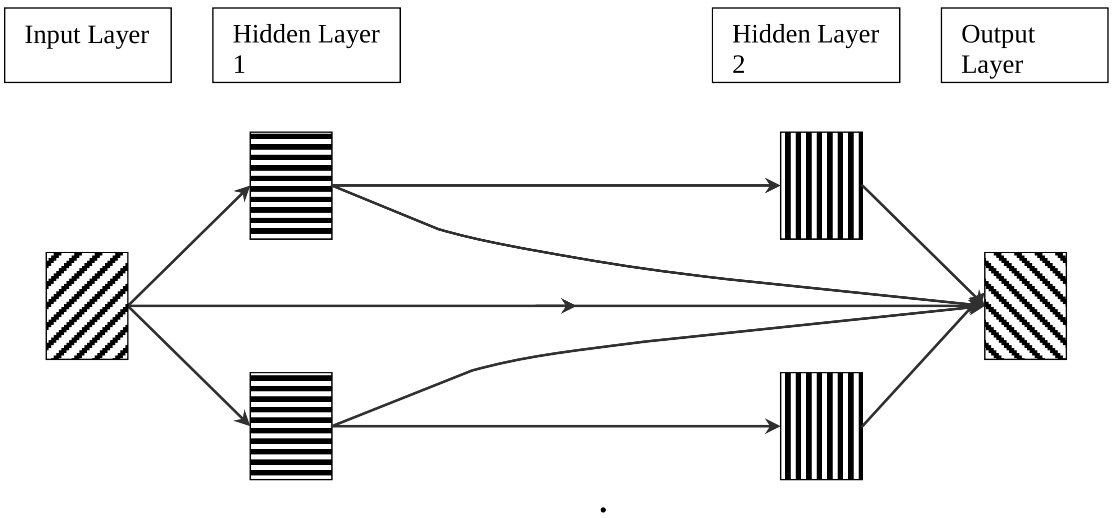
The estimated ν freedom degrees equal to3.2314 for the specific distribution hence by calculating the Gamma function values, the term $E\left(\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} \right)$ takes the value of 0.6609.

By substituting the $E\left(\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}}\right)$ term to the $\log\sigma^2$ equation:

$$\log\sigma_t^2 = -0.172109 + 0.98945\log\sigma_{t-1}^2 + 0.19252\left(\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}}\right) - 0.092892\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right)$$

A common question is which network to use in each case, as the researcher is faced with a large number of options. In this paper model the relation between the dependent and independent variables we use a special class of MultiLayer Perception networks (hereafter MLP), the modular feed-forward networks-figure 2.

Figure 2: Structure of the General Modular Artificial Neural Network



These networks are trained by a supervised learning momentum algorithm (Moreira 1995). The weight update process is the following:

$$w_{ij}(n+1) = w_{ij}(n) + \eta\cdot\delta_i(n)x_j(n) + a\left(w_{ij}(n) - w_{ij}(n-1)\right)$$

Where:

η: *learning rate*

$\delta_i(n)$: *current error*

$x_j(n)$: *current input vector*

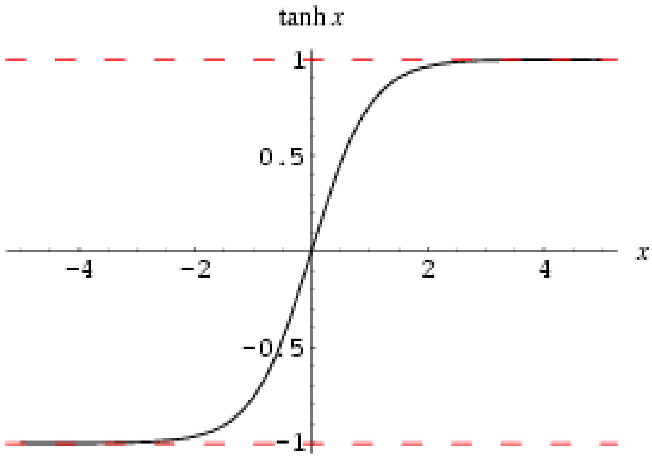
α: *momentum rate*

Modular ANN don't have full interconnectivity between neurons and the layers are divided to modules. Each module cooperates with others in order to solve part of the whole problem. Due to the partial interconnectivity a decreased number of weights is necessary and therefore the demand for training cases is decreased. The specific topology has two hidden layers with two modules per layer. The number of neuron per module is variable, subject to optimization. The transfer function is shown in figure 3:

$\tanh(x) = (e^x - e^{-x}) / (e^x + e^{-x})$

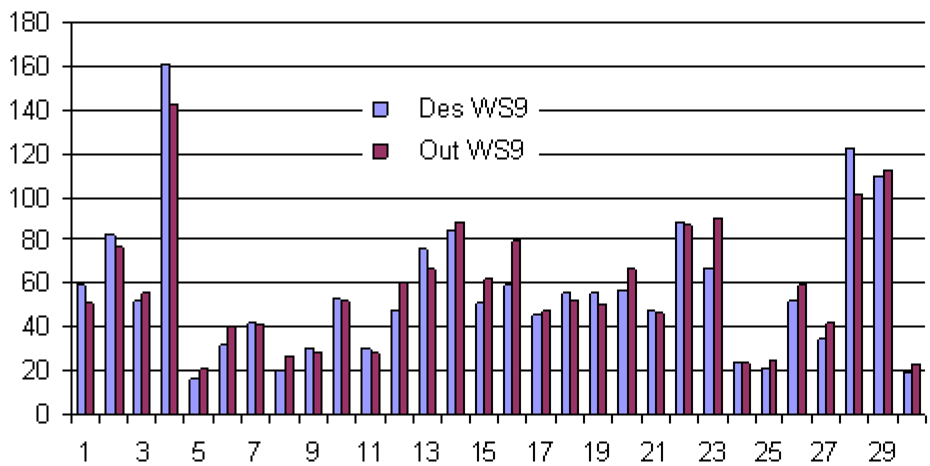
And the output of the transfer is given by the following equation: $output = \tanh(w_1 x_1 + w_2 x_2 + ... + w_n x_n)$

Figure 3: Tranfer Function of the General Modular Artificial Neural Network



It has to be mentioned that a modeler should consider basically two issues in order to obtain the ability of generalization (Jhee, M.J. Shaw). First, the explanatory model should transfer all necessary information to ANN. It is a matter of experience, deep knowledge and assiduous research effort to invoke all significant informational variables. The second crucial issue is to train the ANN using as a training data set a representative sample of data on which ANN will be used to simulate a forecast. ANN are trained using a cross validation dataset in order to avoid overtraining issues and luck of generalization ability. The cross validation data set, consist of randomly selected cases which are kept out of the training process. By this way the ANN are trained and validated under a wider range of shipping market situations. Figures 4 shows example of ANN's fit on the corresponding test dataset (30 cases) for the nine months ahead:

Figure 4: Goodness Tranfer Function of the General Modular Artificial Neural Network



The results shows that fit on test data is excellent. This means that the information provided to the networks – current market fundamental variables and future demand indicator - is sufficient in order to estimate future market values. Table 3 show the results of goodness of fit process using Mean Square Error, Normalized MSE and percentage of error criteria:

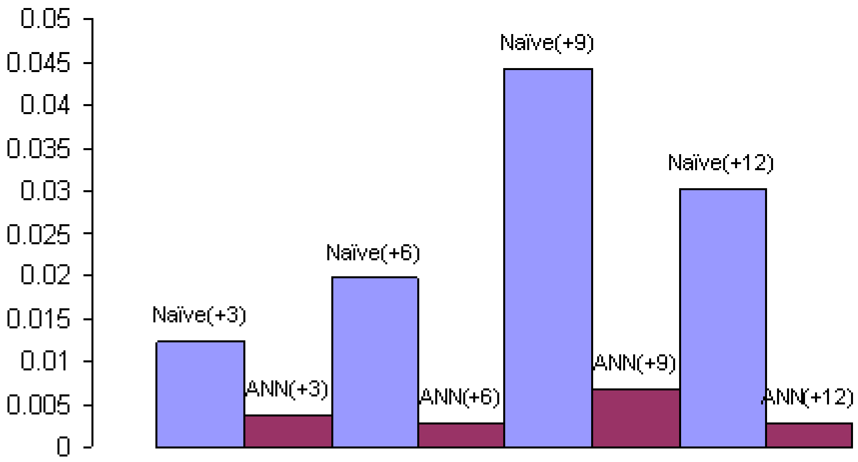
Table 5

Goodness of Fit Results for ANN

Goodness of fit Criterion	ANN(+3)	ANN(+6)	ANN(+9)	ANN(+12)
MSE	0.003703	0.002843	0.006776	0.002872
NMSE	0.082971	0.081254	0.087043	0.075537
%Error	13.665811	11.780595	13.676121	14.865287

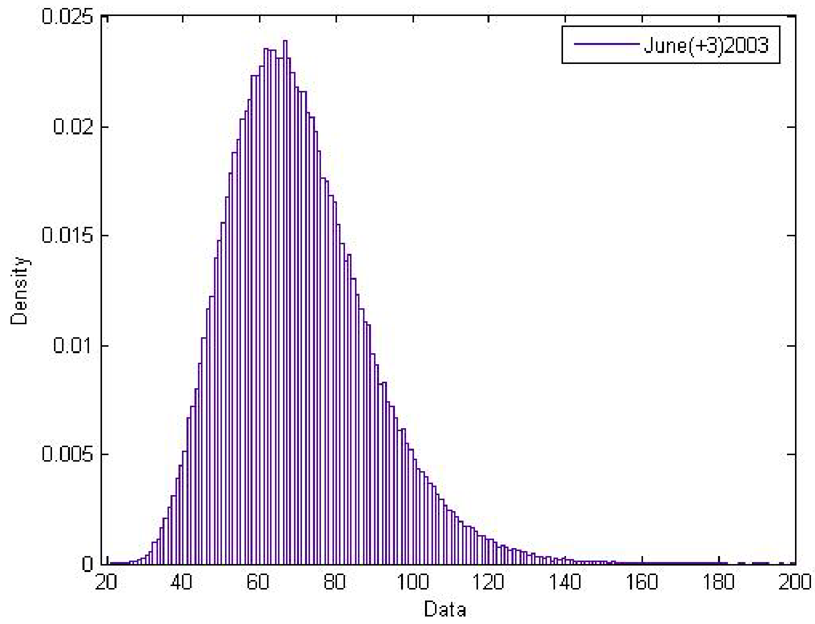
Comparing the results with the naïve model (future value is equal to the present one) it is clear that modular ANNs show a sufficient and robust error performance in the corresponding time spans of three, six, nine and twelve months. Figure 5 shows the results for the three, six, nine and twelve months ahead models:

Figure 5: Naïve Model vs Modular Artificial Neural Network Performance



The next step of FORESIM is simulation. The stochastic component (E-GARCH) feeds ANN with a pre-defined number of possible future demands indicators and the corresponding input vector containing the fundamental variables describing the current state of the market. Then the ANN produce an output vector for the corresponding time span. This vector represents the estimated future freight rate values for every possible excitation from the demand indicator. The error terms of the ANN are stochastically estimated using a number of goodness of fit tests: chi-square (Snedecor and Cochran, 1989), Kolmogorov-Smirnov (Chakravart, Laha, & Roy, 1967) and Anderson-Darling (Stephens, 1974). By using simple Monte Carlo simulation every output value of the ANN is recalculated by adding a possible error term. An example of a FORESIM simulation case (simulated case: WS rate three months ahead June 2003) can be shown in the next histogram-figure 6:

Figure 6: Histogram of Simulation Results (Case: Three Months Ahead June 2003)



3. Simulation results

In this section the results of the simulation for the time spans of three, six, nine and twelve months ahead are presented. The FORESIM technique is validated using with two different schemes. Initially an empirical rule is used to validate the ability of the technique to estimate efficiently the upper and the lower bound of the distribution. A box plot is constructed calculating defining the outlier values. An outlier is a value that is more than 1.5 times the interquartile range away from the top or the bottom of the box. The interquartile range is the distance between the 25th and 75th percentiles of the sample.

The table 6 shows the results for the twelve months ahead simulation:

Table 6

Range of Simulated Results and Actual Values for Twelve Months Ahead

	Upper Outlier	Actual Value	Lower Outlier
1	75.2599	72.5	20.2158
2	66.0354	47.	15.0780
3	86.1844	58.13	21.2355
4	66.8456	38.88	13.7901
5	33.2224	17.5	9.5265
6	131.8689	111.	4.4919
7	126.3179	33.	7.0368
8	51.4538	40.63	15.1715
9	109.5146	70.	6.8717
10	65.4181	46.75	16.5768
11	34.7190	20.38	10.3067
12	149.5547	52.5	6.4158
13	50.0841	31.5	14.7780
14	81.3655	38.	18.5744
15	102.7879	71.5	9.2897
16	41.5786	21.	12.2222
17	123.2779	51.56	10.3583
18	34.2069	17.33	9.6562

19	130.1128	76.63	11.9563
20	31.5693	19.3	9.2226
21	34.3217	18.25	9.7201
22	31.7031	18.25	9.3037
23	33.5571	24.75	9.9054
24	122.0112	59.63	9.7218
25	65.7945	44.25	15.8105
26	125.3581	39.25	9.2696
27	90.7223	63.13	22.7259
28	52.5056	30.63	15.5283
29	39.8322	24.33	11.7988

As shown in the previous table, all examinant cases have successfully include the actual values within the estimated range of the distribution. The results of distribution range validation for the four time spans are shown in table 7:

***Table* 7**

Validation for Distribution Range

	Time Span(+3)	Time Span (+6)	Time Span (+9)	Time Span (+12)
Effective Cases	28/29	29/30	30/30	30/30
%	96.55%	96.67%	100%	100%

The second validation scheme for the technique is to test the ability of estimating a range for the real future values. According to this validation scheme the range has an upper and a lower value as expressed by the following equations:

$$LV = Expected\,Value - a \times Stdev$$
$$UV = Expected\,Value + a \times Stdev \quad (5)$$

Where:

LV Lower value
UV Upper value
a Coefficient.

the validation scheme is applied to the test cases for the four time spans. The figures 7 to 10 show the percentage of success in estimating a range for the future value:

Figure 7: Percentage of Success in Estimating a Range for the Future Freight Rate (Three Months Ahead) vs Coefficient a

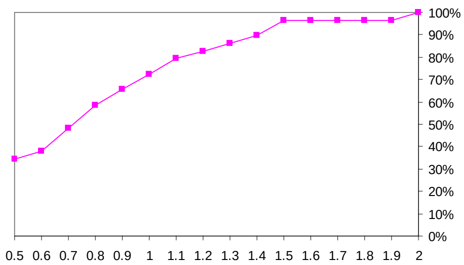


Figure 8: Percentage of Success in Estimating a Range for the Future Freight Rate (Six Months Ahead) vs Coefficient a

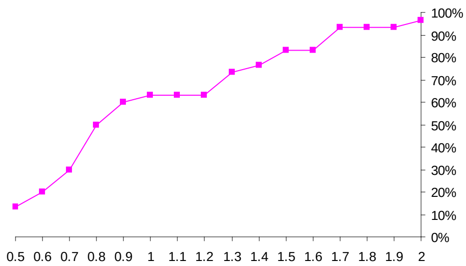


Figure 9: Percentage of Success in Estimating a Range for the Future Freight Rate (Nine Months Ahead) vs Coefficient a.

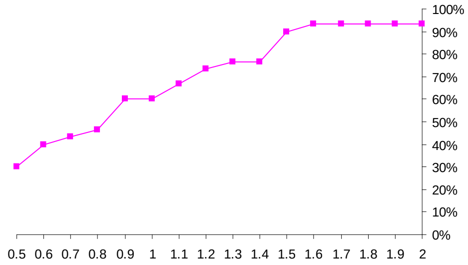
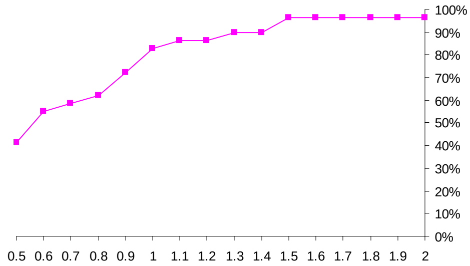


Figure 10: Percentage of Success in Estimating a Range for the Future Freight Rate (Twelve Months Ahead) vs Coefficient a



The superior advantage of FORESIM technique is the ability of simulating future market states in accordance to the fundamentals parameters and possible external excitations. According to FORESIM results a crucial parameter regarding future market risk is the level of tonnage laid up. By estimating the risk of various cases an investigation regarding the relationship between future market risk and laid up tonnage is feasible. Table 8 shows the bivariate Pearson Correlation Coefficient between laid up VLCC Tankers and the variables of estimated standard deviations of examinant cases and absolute differences of WS rates after twelve months.

Table 8

Correlation of Laid up with Market Risk and Difference (Twelve Months Ahead)

Pearson Correlation	stdev	dif
laidup	-.885	-.412

The results depict the importance of laid up tonnage in future market risk as shown from Correlation Coefficients values. Furthermore a quantitative expression of laid up vessels and future market risk is feasible by applying a model of the form:

$$Market\ Risk = a * (Laidup)^{b} \tag{6}$$

Where:

a, b Constant coefficients

Table 9 shows the estimated a, b coefficients (95% confidence bounds) and the value of the goodness of fit criterion:

Table 9

Coefficients and Goodness of fit Values

Simulation Window	+3	+6	+9	+12
Coefficient α	47.36 (29.62,65.1)	63.89 (49.13,78.66)	76.23 (61.25,91.2)	190.4 (150.3,230.5)
Coefficient b	-0.418 (-0.552,-0.284)	-0.486 (-0.556,-0.415)	-0.543 (-0.610,-0.476)	-0.736 (-0.805,-0.668)
R-square	0.7078	0.8716	0.9059	0.9647

The following figures 11 to 14 show the fit process results:

Figure 11: Market Risk (Three Months Ahead) vs Laid up

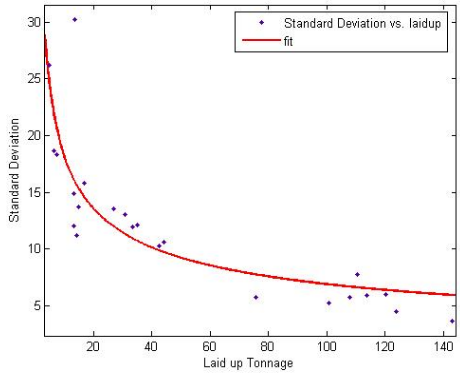


Figure 13: Market Risk (Nine Months Ahead) vs Laid up

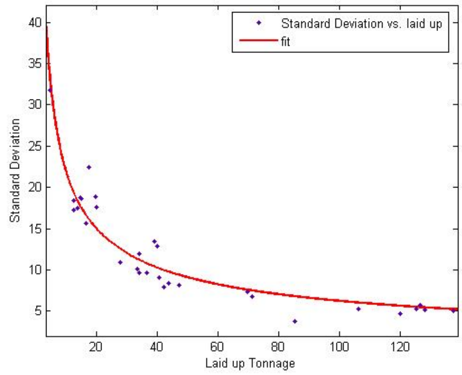


Figure 12: Market Risk (Six Months Ahead) vs Laid up

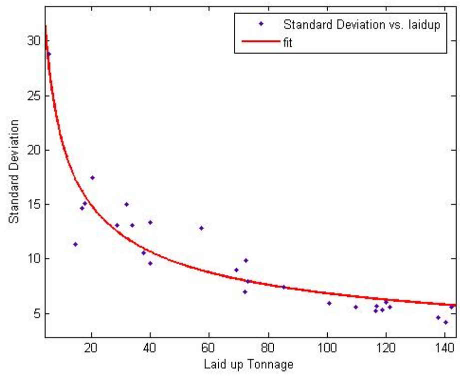
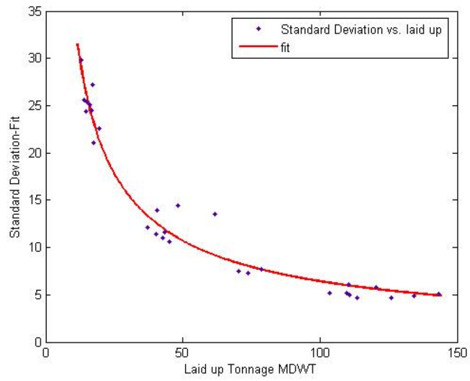


Figure 14: Market Risk (Twelve Months Ahead) vs Laid up



These figures show the importance of the laid up parameter in future system volatility. As expected market with low levels of tonnage surplus exhibit high level of risk. The shapes of the lines state the instability of the shipping market when the laid up tonnage is close to minimum values. The market reaction to low laid up values is rapidly due to the fact that the demand for transport services is inelastic. Markets modify tonnage supply by slowing down or stopping demolition rates, restoring laid up vessels or ordering new-buildings in order to satisfy demand changes. It is confirmed by FORESIM results that when tonnage surplus disposable is low these actions have rapid characteristics.

4. Conclusions

In this paper we presented the usage of an innovative simulation technique. Although FORESIM was developed based on special shipping market characteristics, it has a wide range of applications in econometric systems. Focusing on shipping needs we concluded that risk is dominant in every decision. Our research aims to measure risk and provide initially to tanker owners a decisional framework to manage risk. To achieve this, firstly a tanker market analysis since 1979 was necessary in order to reveal shipping market mechanism, establish the most important factors affecting the market and decide whether a stochastic calculus was needed. The analysis showed that the crucial non-shipping external variable affecting tanker market is the OPEC oil production level. This variable embodies political, economical, direct and indirect excitations to the shipping market. There is no better way to model and quantify excitations such as wars involving oil-producing countries affecting productivity or economical crashes or OPEC decisions leading in many cases to oil shocks. Oil Production time series includes all economic and political facts in a global level that may affect a globalize market such as Tanker shipping market.

Subsequently, and keeping the aforementioned statement in mind, we tried to simulate the behavior of this variable using an E- GARCH model. When this was satisfactorily achieved, modular Artificial Neural Networks was trained to forecast future values of freight rates. Having real historical data for the route Ras Tanura –Rotterdam we constructed the ANN so as to predict the Tanker market after, three, six, nine and twelve month periods and tested it against randomly selected out of training sample data. To be precise, in fact, separate ANNs for each point in future were constructed, trained, and tested. The results showed that all ANNs were adequately capable of simulating future freight rates.

The special characteristics of FORESIM technique are shown in the table 10:

Table 10: Simulation vs Physical System

	Systems	
	Physical Shipping Market	**Simulated System with the Use of FORESIM**
Systems Characteristics	Freight Rate Generation Mechanism	Use of Explanatory ANN to Capture Causality Relations and Interactions
	Random Excitations from External non Systemic Parameters	Use of Stochastic Models to Express Randomness
	Non Stationary System	Ability to Add/Remove Parameters and Readjust Weights (Adaptive System)
	Dynamic System- Variability of Shipping States in Time	Ability to use Technique in Real Time (Real Time Output)

The procedure was developed in order to produce future freight rates realizations depended to the current state of the market. The procedure is the first to introduce the concept of generating freight rate realizations conditional upon the current or the preceding market states and of embedding explanatory and stochastic modeling. Therefore, it creates tool for acquiring quality information regarding the trend of the market taking into consideration unforeseen parameters as well as the present status of the market.

The main applications of FORESIM are the following:

- Decision support for trading Future Freight Agreements (FFAs) and various shipping market derivatives;
- Chartering strategy – spot or time charter, duration, etc.;
- Risk management for shipping investments, in combination with cash flow and monte-carlo simulations providing distribution for financial variables;
- Estimation of financing risk such as probability of default etc.

In general it can be concluded that FORESIM represents one very promising tool in simulating freight rate time series.

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