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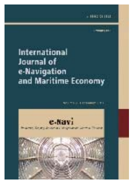

Original article

# Hedging against bunker price fluctuations by using derivative products

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## Abstract

Recent approaches and opinions support that shipping companies must take precautionary measures against financial risks and design steadier steps for financial management. The key to developing, implementing, and managing a successful hedging strategy is to use effective forecasting systems and appropriate financial derivative products.

The key objective of this study is to control risks from bunker cost fluctuations using financial derivative products. To do so, a time-series analysis is conducted using a dataset derived from a bunker index system. The artificial neural network method is used for time-series analysis with a mean absolute percentage error of 0.9182105. Next, progress predictions of bunker costs and hedging strategies are determined to use financial derivative products against their risks. Finally, this study concludes that forward agreements can serve as the perfect protection mechanism against bunker risks in tramp shipping.

*Keywords: Shipping finance, financial derivative products, hedging, maritime transportation*

## 1. Introduction

Maritime transportation is considerably sensitive toward macroeconomic indicators; in particular, global crises, and recession primarily affect the sector (Angelidis and Skiadopoulos 2008; Jing et al. 2008). Therefore, maritime transportation, being highly vulnerable to external influences, is subject to financial and cash flow risks, making the industry unbalanced and irregular (Kavussanos and Nomikos 2000; Haralambides et al. 2001; Chen and Wang 2004; Jing et al. 2008).

These imbalances and irregularities can be considered indicators of financial risks. The possible sources of such uncertainties regarding financing in marine transportation are fluctuations in freight rates, which depend on whether the transportation mode is a liner or tramp service, and input costs. In tramp transportation, the freight rate is determined on the basis of supply and demand (Borger and Nonneman 1981; Goulielmos and Psifia 2006). Thus, freight rates are determined as per market conditions, not enterprises. (Clarkson, 2004). Because of these situations, an increase in input costs may be inadequate to cover increases in freight rates (Kavussanos and Visvikis 2006a). In this case, why should ship owners adopt cost-oriented management in terms of financial sustainability? Cost-oriented management is a major strategy in globally competitive environments that developed after economic, social, and technological changes throughout the world and is adopted by maritime firms as well (Karcıoğlu, 2000; Maria et al. 2009; Karcıoğlu and Temelli, 2016).

Firms that adopt cost leadership, first adopt the costs they must bear and determine their cost items in which they have manageability. Maritime transportation costs are divided into running, capital, and voyage costs (Stopford, 2009). Running costs are the total expenditures for maintaining a ship's enabled state. Capital costs include all expenses incurred to cover funds and running costs are those borne during transportation operations. The main expenditures under voyage costs are bunker costs, which comprise a ship's total bunker expenses in port and during navigation. Bunker costs vary by bunker price, fuel type, and consumption. First, bunker consumption is directly proportionate to machine power and type and is affected by ship type, size, and speed; loading and working hours; and oceanographic factors such as geographical features, distance, water depth, and weather conditions (Hellström 2004; Wong et al. 2007). Second, bunker types used in ships vary by the construction of the main and auxiliary engines. Modern ship bunker types include marine diesel oil, marine gas oil, heavy fuel oil (HFO), and international fuel oil (IFO). There are two basic grades of IFO, IFO 180 and the more widely used IFO 380 (Visweswaran 2000). The total consumption amount for HFO and IFO is approximately 80 percent amongst other bunker types (Notteboom and Vernimmen 2009). In addition, of the global volume of bunkers, 60 percent are IFO 380 (Alizadeh et al. 2004). Each bunker type has its own price, depending on where the bunker fuel is purchased. There are various factors affecting the bunker price, including economic trends, product availability, oil supplier reputation, charter routes, port delivery (ex-wharf price), and delivery to the ship (free-on-board price) (Shipping Finance Annual Report [SFAR] 2012). These factors lead to constant fluctuations in the bunker price Thus, bunker price fluctuations and the fluctuations are known as bunker risks (Kavussanos and Visvikis 2006b).

In addition, trading volume of the worldwide bunker market is $150 billion, and the largest fleets spend several billion dollars a year on bunker purchases, with bunker prices accounting for up to 60 percent of total transportation costs (Spring, 2000; Alizadeh and Nomikos, 2004; Stopford, 2009; Bunker Bulletin 2012). Even a small improvement in bunker prices can save millions, and thus, focusing on voyage bunker prices appears to be appropriate

In the financial derivatives market, companies use financial derivative products to take a position against present risks and minimize them at lower costs (Kavussanos et al. 2004). To control risks arising from bunker prices, futures, forwards, and options can be used (Froot and et al. 1993; Ross et al. 2008; Gilleshammer and Hansen 2010). It is crucial to note that derivative products should not be used as a potential source of revenue (Masry et al. 2010). The aim of a derivative product is not to cancel out the risks but to deal with unexpected loss of cash flow (Goulielmos and Psifia 2006).

In this respect, the present study aims to analyse future price movements in light of an effective prediction system against bunker risks in maritime transportation and to eliminate uncertainties by using derivative products. In doing so, it focuses on ways to reduce maritime transport costs, or at least, fixed future cash outflows with stable prices in present-day conditions.

The remainder of this paper is organized as follows. Section 2 provides a brief background. The dataset used in the study is defined in section 3. Section 4 discusses the findings and estimation results related to the forecasting model. Section 5 concludes with an implementation summary.

## 2. Background

The literature includes a large number of similar applications on transportation costs and factors affecting these costs (Thorburn 1960; Kendall 1972; Robinson 1978; Jansson and Shneerson 1982, Wong et al. 2007; Talley 1990; Stopford 2009; Chen 2010). However, a few studies focus on precautions against the probable risks arisen from prices fluctuations (Chen et al. 1987, Haushalter 2000, Menachof and Dicer 2001, Alizadeh et al. 2004, Gilleshammer and Hansen 2010 and Masry et al. 2010; Erol and Dursun, 2015). These studies examine the performance of financial derivative products using traditional price estimating methods to eliminate risks from fluctuations in bunker and input prices.

Modern computing models such as artificial neural networks (ANN$_s$) are used in the literature. artificial neural networks involves database training to predict the input of the initial values of the variables, while the output layer shows the results of the network for two-dimensional problems because it is able to imitate the learning capability of human beings. Thus, the network learns directly from the examples without any prior formula regarding the nature of the problem and can independently generalise knowledge (Wang et al., 2015; Erol, et al., 2017). So, in this study, bunker prices are predicted using ANN$_s$. Besides, a large amount of financial research uses ANN$_s$ (Callen et al. 1996; Wang and Leu 1996; Wittkemper and Steiner 1996; Desai and Bharati 1998; Saad et al. 1998; Yang 1999; Qi 1999; McKee and Greenstein 2000; Atiya 2001; Chen et al. 2003; Butler and Kazakov, 2011; Duru and Butler 2016). ANN models overcome limitations in traditional forecasting methods, including misspecifications, biased outliers, linearity assumptions, and re-estimations (Grudnnitski and Osburn 1993; Lawrance 1997; Hill et al. 1996; Qi and Wu 2003; Zhang 2003; Hosoz and Ertunc 2006).

## 3. Dataset and Model

This section first describes the dataset used in the study, followed by the ANNs method. Then, it presents the structure of the model and performance criteria.

### *3.1. Dataset*

The dataset (Fig. 1) utilized to predict bunker price fluctuations are obtained from the bunker index system. The Bunker Index (BIX) is the average global bunker price for all individual port prices published on the Bunker Index website and is calculated on the basis of marine fuel prices for ports around the world. As for delivery size, individual 380-cst and 180-cst port prices (high and low sulphur) are calculated as per the average delivery size of 500 metric tonnes. The unit is US$/metric tonne.

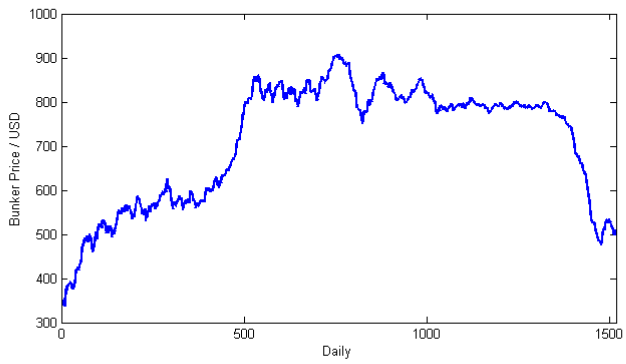


**Figure 1: Dataset (Bunker Index, March 15, 2015)**

The dataset comprising a nonlinear structure is 1.519 days of daily bunker prices from March 2, 2009, to March 3, 2015 (excluding weekends). To conduct a time-series analysis, this study predicts the future trends of bunker prices by using the data. ANN$_s$ can be used to solve nonlinear complex time-series and is used in the prediction stage.

### *3.2. Artificial Neural Network*

ANN simulates a human brain in a computerized manner. Using experimental samples, ANN (Fig. 2) can be applied to problems with no or too complex algorithmic solutions (Korkmaz et al. 2012). ANNs are a class of generalized nonlinear nonparametric models inspired by studies of the brain and nervous system (Alon et al. 2001). They consist of hierarchically bound artificial cells and work in a parallel system similar to biological cells. These cells are process elements that are hierarchically tied to each other.

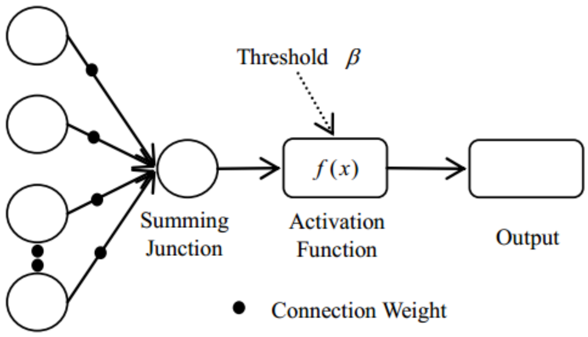


**Figure 2: Basic ANN architecture (Karia et al. 2013)**

Multilayer perceptron (MLP) is the most common ANN type used for forecasting. It is crucial to determine variables such as input, hidden layers and output neurons, and transfer functions. The quantitative form of an $ANN_s$ model is

$$Y = f[\sum(x_1 w_1 + x_2 w_2 + \cdots + x_t w_t) + \beta] \quad (1)$$

Where Y is the output from the neuron and $x_t$ is the input value. $W_t$ and β are the connection weights and bias value (threshold). f is the transfer function typically known as the sigmoidal function, $f(x) = 1/(1+e^{-x})$ (Karia et al. 2013). However, these variables tend to vary. The number of input neurons is one of the most important variables in MLP. Others include the number of hidden layers and neurons. $ANN_s$ can cover more than one hidden layer, although one of these layers is generally being used (Cybenko 1989; Hornik et al. 1989). The number of output neurons directly related to the problem also affects MLP. If the forecasting horizon involves one period, then the number of output neurons is one (Hamzacebi 2008). The output of a neuron is determined by transfer functions, which are mathematical formulae. As for the hidden layer function in an MLP with forecasting purposes, the function used is a sigmoid or a hyperbolic tangent function, whereas that used for an output layer is a linear activation function.

On the other hand, the methods adopted are subject to certain limitations. First, methods based on artificial intelligence cannot be used to predict systematic risks as in the case of wars, political crises, or natural disasters because economic and political factors play an important role in forecasting future production and an enormous amount of data is required to capture various complexities in the analysis (Managi et al. 2004).*3.3. Network Structure and Performance Criterion*

In this case, $ANN_s$ modelled for forecasting purposes consists of three layers. It is designed with five neurons in the input layer, 15 neurons in the hidden layer, and one neuron in the output layer. The total function is used as a junction function (equation (2)) and the sigmoid functions are transfer functions (equation (3)). The error in every input is evaluated using the mean square error (MSE), as shown in equation (4):

$$net\ input_j = \sum_i w_{ij} x_i, \quad (2)$$

$$f(x) = \frac{1}{1+e^{-x}} \quad (3)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2, \quad (4)$$

Where $w_{ij}$ is the weight values matrix, $x_i$ is the forecasted value, $y_i$ is the realized values for the year, e is euler number and n is number of years.

Next, we use the Levenberg–Marquardt's learning algorithm. In our network model, there is one hidden layer with 15 processing elements. The structure of the developed ANN models for the bunker prices is shown in Fig. 3.

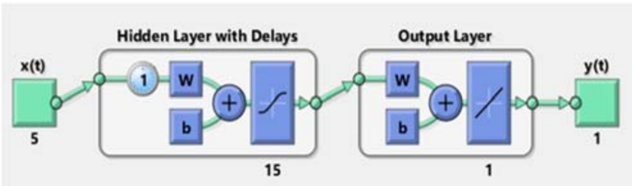


**Figure 3: Structure of developed ANN models**

Performance criteria are measured using mean absolute percentage error (MAPE) and mean absolute scaled error (MASE).

$$APE = \left|\frac{e_i}{Y_i}\right| * 100 \qquad MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{e_i}{Y_i}\right| * 100 \quad (5)$$

$$MASE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{|e_i|}{\frac{1}{n-1}\sum_{i=2}^{n}|Y_i - Y_{i-1}|}\right) \quad (6)$$

Where $e_i$ denotes the difference between forecasted and realized values, $Y_i$ is the realized values for the day, and n is number of days.

## 4. Findings and Estimation Results

From the total data obtained from BİX, 1063 day-bunker price (70%) were chosen as training data, 228 day-bunker price (15%) as validation data and 228 day-bunker price (15%) as test data. The error ratio (MSE) for $ANN_s$

was 0.001. Data for the bunker price for last the five days were entered in the ANNs model as input. Next, a forecast was made for the bunker price of the following day. We used Matlab R2013a as ANN software development material. The learning curve for the network configuration is shown in Fig. 4. On the other hand, the training process ends at the 13th iteration. The difference between the forecasted and actual outputs and this study's process is given in Fig. 5. The model demonstrates the inputs and reasonable.

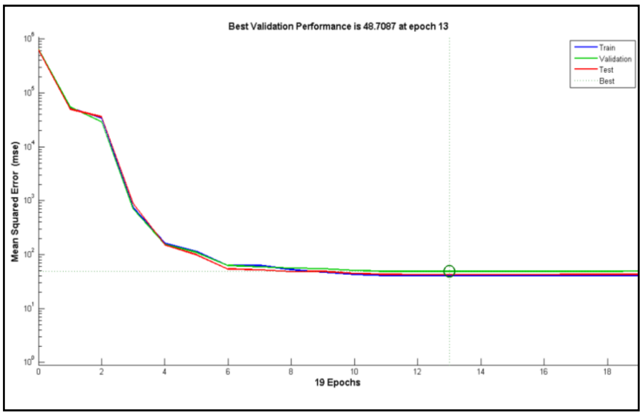


**Figure 4: Learning curve for the network configuration**

The forecasting period continues for one month subsequent to the dataset period, as estimating several time series on a monthly basis can present seasonality (Geomelos and Xideas 2014). Table 1 shows the performance of the ANNs model. In addition, it shows the output error.

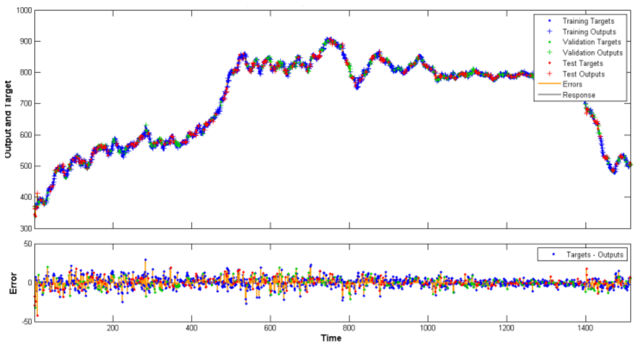


**Figure 5: Response to output element 1 for time series 1**

After that, in order to show the performance of the ANNs model, realized bunker prices are compared with ANNs outputs and ARIMA outputs. ARIMA creates model objects for stationary or unit root nonstationary linear time series model. Contraction of the model shown in equation 6 is Mdl = arima(p,D,q) creating a nonseasonal linear time series model using autoregressive degree p, differencing degree D, and moving average degree q.

Mdl = ARIMA (0, 1, 1) Model Integrated with Seasonal MA (512): (7)

Distribution: Name = 'Gaussian'

| | |
|---|---|
| P | : 513 |
| D | : 1 |
| Q | : 513 |
| Constant | : 0 |
| AR | : {} |
| SAR | : {} |
| MA | : {NaN} at Lags [1] |
| SMA | : {NaN} at Lags [512] |
| Seasonality | : 512 |
| Variance | : NaN |

**Table 1: ANNs output performance**

| Days | ANN | ARIMA | Actual | ANN APE (%) | ARIMA APE (%) |
|---|---|---|---|---|---|
| 1 | 513,95 | 655,62 | 525,84 | 2,26 | 24,68 |
| 2 | 524,33 | 656,91 | 529,18 | 0,92 | 24,14 |
| 3 | 526,02 | 659,47 | 532,81 | 1,27 | 23,77 |
| 4 | 530,68 | 659,68 | 531,19 | 0,10 | 24,19 |
| 5 | 535,63 | 660,44 | 530,82 | 0,91 | 24,42 |
| 6 | 533,09 | 664,53 | 532,43 | 0,12 | 24,81 |
| 7 | 533,19 | 666,08 | 528,08 | 0,97 | 26,13 |
| 8 | 534,64 | 673,10 | 526,61 | 1,53 | 27,82 |
| 9 | 527,98 | 673,85 | 529,44 | 0,28 | 27,28 |
| 10 | 527,94 | 669,76 | 532,97 | 0,94 | 25,66 |
| 11 | 531,54 | 667,73 | 534,46 | 0,55 | 24,93 |
| 12 | 534,25 | 670,49 | 532,10 | 0,40 | 26,01 |
| 13 | 535,83 | 672,91 | 530,56 | 0,99 | 26,83 |
| 14 | 533,69 | 672,99 | 527,28 | 1,22 | 27,64 |
| 15 | 532,47 | 671,94 | 525,93 | 1,24 | 27,76 |
| 16 | 527,77 | 670,08 | 522,36 | 1,04 | 28,28 |
| 17 | 526,50 | 666,66 | 519,04 | 1,44 | 28,44 |
| 18 | 522,02 | 666,56 | 513,74 | 1,61 | 29,75 |
| 19 | 518,68 | 664,90 | 514,40 | 0,83 | 29,26 |
| 20 | 512,46 | 666,19 | 513,99 | 0,30 | 29,61 |
| 21 | 515,19 | 665,60 | 507,12 | 1,59 | 31,25 |
| 22 | 514,15 | 663,05 | 503,85 | 2,04 | 31,60 |
| 23 | 505,52 | 662,82 | 500,15 | 1,07 | 32,52 |
| 24 | 504,74 | 665,21 | 502,36 | 0,47 | 32,42 |
| 25 | 499,17 | 665,64 | 499,26 | 0,02 | 33,33 |
| 26 | 503,09 | 661,26 | 500,42 | 0,53 | 32,14 |
| 27 | 498,85 | 661,33 | 504,07 | 1,03 | 31,20 |
| 28 | 502,75 | 662,27 | 503,12 | 0,07 | 31,63 |
| 29 | 506,73 | 660,87 | 511,10 | 0,85 | 29,30 |
| 30 | 504,34 | 657,96 | 509,13 | 0,94 | 29,23 |
| | | | **MAPE** | **0,92** | **28,20** |
| | | | **MASE** | **1,72** | **52,36** |

It is shown in Table 1 that the outputs obtained using the ANNs model is closer to the real ones. But, values of MASE greater than one indicate that the forecasts are worse, on average, than in-sample one-step forecasts from the naïve method (Hyndman and Koehler, 2006). However, considering the performance criteria, the ANNs method is also seen to give better results than the ARIMA method. On the other hand, another important factor for hedging is the future trends. So, the outputs regarding the trend of future prices are shown in Fig. 6.

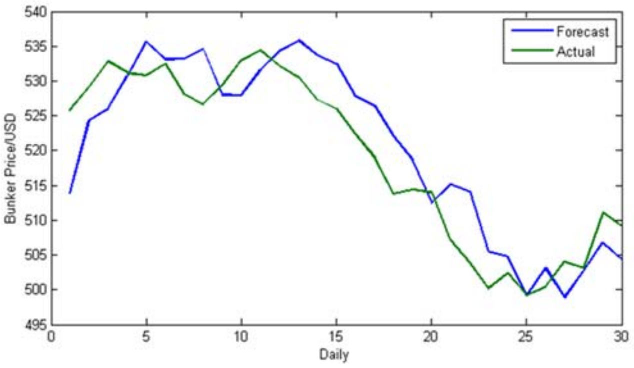


**Figure 6: Trend in forecasted bunker prices**

In general, the forecast shows a fluctuating trend. More specifically, the bunker prices are shown to reduce in specific periods and rise again from day 25. The obtained data of forecasts depict that ship owners should adopt more effective hedging strategies by taking even and well-balanced risks.

Considering the prediction that the bunker prices will rise in the forecasted period, a forward agreement can be made in the over-the-counter market. However, given the unique aspects of voyages in tramp shipping, a forward agreement may be inadequate to create a perfect protection mechanism against bunker risks (Ross et al. 2008). This is because in forward agreement, counterparties freely determine the quality, quantity, price, place of delivery, and delay of the product on the basis of their needs, whereas in future conventions, product quality, quantity, delay, and place of delivery are standardized. Thus, the bunker needs of a given company, which are shaped on the basis of tramp transportation conditions, may not be coherent with the conditions of standardized future conventions. Therefore, forward conventions are considered more suitable against bunker risk in comparison with future convention in tramp transportation (Erol and Dursun, 2015). On the other hand, in forward conventions, products have to be delivered and paid for by the expiration date. This is necessary for the counterparts to switch within the scope of the contract. However, when the ship's state (lay-up) or condition (on route or in port) are considered, or if the prices dramatically reduce, the transportation company may not prefer to buy a bunker specified in quantity, price, and type in the contract when the payment is due.

Moreover, as a safety measure and in case the prediction is inaccurate, call option agreements render bunker use as noncompulsory and thus, balance income and outcome in bunker risks. For long-term predictions, future agreements can be made to earn profit. This way, professional ship management can eliminate the risk of uncertainties in the maritime industry by stabilizing input price. On the other hand, if the bunker prices reduce, companies can buy bunkers from the spot market when they need.

In addition, it should not be ignored that the other party in agreement can also use these predictions. The effectiveness of protection mechanism relies on the future expectations of parties. Thus, the structures of bunker hedging strategies are crucial. To this effect, this study presents more accurate predictions about futures using the $ANN_s$ model.

## 5. Conclusion

This study used the $ANN_s$ method to hedge bunker risks and found that the forecasts obtained using the method showed reliable performance. In light of these forecasts, we determined hedging strategies against bunker risks. The findings of this study contribute to the literature on bunker risks in maritime transportation. In particular, it provides insight into dealing with existing risks and stabilizing prices by signalling uncertainties. Drawing on the results, this study suggests that a well-designed hedging programme is needed to provide cash flow certainty, budget certainty, and protection against potentially rising bunker fuel prices as well as lock in profit margins. We focused on savings in maritime transportation costs, or at least, guaranteeing future cash outflow along with stable prices in the present day.

The organizational structures, risk perception levels, and transportation types (tramp or liner) of maritime transportation companies can determine hedging programs. The time-series analysis revealed that the performances of the obtained data on forecasts decrease as the forecasting period moves away from the dataset period. In this case, more effective results can be obtained by developing a regression model. In addition, the dataset used in this study comprises average global bunker prices.

Thus, future studies should consider developing hedging strategies using datasets for members of regional markets. In addition, the results have implications for ship owners, charters, and bunker companies' future decisions and strategies.

In conclusion, it would be appropriate to say that it is possible for companies either to make a profit or lose money by using derivative products. Nevertheless, the use of derivative products helps eliminate risks on the basis of bunker price uncertainties. This way, cash flows in bunker prices, the most important component of transportation costs, can be guaranteed to stabilize prices set in the present time.

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