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Forecasting oil tanker shipping market in crisis periods: Exponential smoothing model application

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ABSTRACT

This paper fills the gap in the literature of applying an exponential smoothing model in the oil shipping market forecasting. The author refines the adaptive combined model with B-criterion based on Brown's model with modification by Trigg and Leach. Forecasting the values of the average time-charter equivalent of a tanker along 6 different routes of oil transportation in the world ocean during the crisis period 2015–2019. The accuracy of the proposed method is superior to naive, autoregression methods and machine learning models in all used error metrics. The obtained accuracy in 71% of cases is available for commercial use by operators and charterers of the tanker fleet.

1. Introduction

The primary method of oil and petroleum products transportation is transporting by sea tankers, which accounts for about 80% of the total volume of transportation (UNCTAD, 2017). According to the Clarksons report (Clarksons research, 2016), the volume of this market achieved $717 billion as of 2015. However, the market price of oil fluctuates remarkably, that's why tanker freight rates are subject to constant fluctuations (Drobetz, Richter, & Wambach, 2012; Kavussanos, 1996a; Tsouknidis, 2016). This value is the complex one and depends on a variety of parameters, but the greatest influence on it is exerted by the international demand for a cargo of oil and petroleum products traded on the international commodity exchange (Stopford, 2009). Considering the fact, the tanker freight rate is subject to the same effects of volatility as stock market quotes.

Surveys subject to this effect applying methods of the GARCH family were reflected in Adland and Cullinane (2006), Alizadeh and Nomikos (2011), Chen and Wang (2004), Drobetz, Richter, and Wambach (2012). These works reflect the importance of modeling and forecasting prices for transportation of oil and petroleum products as the world's main source of energy nowadays. Kavussanos early surveys (Kavussanos, 1996a, 1996b) reveal the following outcomes: (a) freight rates and ship prices change over time; (b) the volatility of large vessel rental prices is higher for small vessels; (c) using the oil price as the main forecasting variable significantly improves the accuracy of freight rate forecasting. The same researcher also reveals the effect of asymmetry in his paper (Chen & Wang, 2004) when freight rates are getting lower, there is a greater effect of volatility than when they raise. Alizadeh and Nomikos (2011) point out the dependence of rates on the market structure, where the effect of asymmetry is also observed—the volatility of rates is higher when the freight market is located in backwardation and lower under contango conditions. Drobetz et al. (2012b) apply GARCH-X and EGARCH methods to study the dynamics of the tanker transport market in comparison with the dry bulk cargo market. The authors demonstrate that there are no asymmetry effects in the dry cargo market and that they are traced in the tanker transport market. This is probably why some researchers used ARIMA family methods to model the dry cargo market (Kim, 2018) and did not use them for oil transportation processes.

In the works of Shi, Yang, and Li (2013) the relationship of sharp jumps during unpredictable spurs in oil prices of various origins to tanker freight rates is investigated. Killian was the first to discover this dependence (Kilian, 2009) and revealed its origin from uncontrolled geopolitical and natural factors (Kilian & Park, 2009). Using the Baltic dirty tankers index (BDTI) as an example, the authors show that the impact of surges in crude oil supply is much higher than the impact of surges in oil demand, and the impact of changes

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in tanker freight rates is minimal. In the studies of Chen, Miao, Tian, Ding, and Li (2017) and Zhou (2012) the correlation of the BDTI index with the West Texas crude oil index (WTI) is estimated using a multi-fractal cross-correlation analysis without trend (MF-DCCA). The authors reveal that the degree of short-term cross-correlation is higher than during the long term and that the strength of multifractality after a financial crisis is greater than before than the aforesaid crisis. However, when using an aggregate tanker freight rate index, such as BDTI, effects arising from different types of contracts (spot or time charters) and different types of tankers (VLCC, Panamax, Suezmax, Aframax, "clean" MR) are not considered. One of the last fundamental outcomes in the study of the impact of sharp jumps in oil prices and on the cost of transportation was made by Gavriilidis, Kambouroudis, Tsakou, and Tsouknidis (2018), who demonstrated that the inclusion of oil prices as an exogenous variable in the GARCH-X family models significantly increases the accuracy of the volatility forecast.

Despite the outcomes achieved in this area, the ongoing research demonstrates that there is still an issue of insufficient forecasting accuracy for commercial purposes. Some researchers have sought a way out of this problem by applying some non-standard methods. Batchelor, Alizadeh, and Visvikis (2007) disclosed the predominance of vector equilibrium correction (VECM) over autoregression models. Chen et al. (2019) applied wavelet analysis to predict the long-term trend of freight rate changes. Duru, Bulut, and Yoshid (2010) researched the field of indistinct logic application for heuristic algorithms for long-term forecasting of dry bulk cargo transportation rates. Reglia and Nomikos (2019) proposed an unusual way to improve the accuracy of forecasting by correlating with the location of the "free" tanker fleet in the ocean from information from the global satellite ship tracker (AIS).

Meanwhile, the available literature has not proposed any modern works on applying exponential smoothing methods for predicting tanker freight rates. Exponential smoothing methods are very popular in supply chain management and business analytics due to their simplicity, transparency, and accuracy (Dekker, van Donselaar, & Ouwehand, 2004; Fliedner, 1999; Gardner, 1985, 2006). They are grounded on the assumption that the observed time series can be additively or multiplicatively decomposed into levels, trends, and seasonal patterns. These models are widely applied in various empirical applications to filter random variations from observed series and to determine principal trends and seasonal fluctuations. Besides long-standing traditions, they are currently one of the most recommended means for predicting time series. Despite their great age, they performed surprisingly well in forecasting in comparison with more complex approaches (Makridakis & Hibon, 2000; Makridakis et al., 1982). After being fully systematized in a single "single source of errors" (SSOE) structure (Hyndman, Koehler, Ord, & Snyder, 2008) in 2008, the literature on exponential smoothing has grown rapidly over the past few years (Liu, Taylor, & Choo, 2020; Rendon-Sanchez & de Menezes, 2019; Smyl, 2020). Exponential smoothing methods were used to forecast dry bulk cargo rates only (Duru & Yoshida, 2009) in the sphere of maritime transportation. In this paper, the hypothesis is put forward and tested that the method of exponential smoothing can give more accurate results of forecasting the oil transportation market in comparison with modern methods. This fills a gap in the existing literature on the use of exponential smoothing methods in tanker shipping and on the forecasting performance of the oil shipping market that is not satisfying to commercial consumers today.

2. Problem

As practice demonstrates, in large corporations operating the tanker fleet, the largest revenue is generated by tankers used on a time-charter basis. In contrast to the spot type of lease, the integral indicator of the tanker's efficiency is the profit it makes per unit of time ($ per day). This value is nominated as a tanker Time Charter Equivalent (TCE). This value remarkably depends on the status-quo on the oil market, technical characteristics of the tanker, external conditions of the route, etc. TCE is subject to strong shocks from changes in supply and demand for oil transportation in a particular region of the world, as well as unpredictable natural and geopolitical factors.

While a manager chooses a new contract for the transportation of crude oil or petroleum products, the most useful knowledge is the forecast of TCE value for this very tanker for the entire duration of the transportation route (on average, from 2 to 6 weeks). However, the complexity of forecasting the TCE is higher than that of other indicators due to its instability, non-stationary nature, unpredictable extremal shocks and bad ACF and PACF values.

This sets the task of forecasting a time series $\{x_t\}$ consisting of the average tanker revenue per day (TCE) for the considered typical route for transporting oil or petroleum products (for example, one of the Baltic International Trade Routes). Statistics for the last few years are available and applied as input data. It is necessary to create a forecast of TCE values $\left\{x_{t+i}\right\}$, $i = 1 \ldots \tau$, where τ – the forecast horizon is on average 30 days.

3. Methodology

To solve this problem author propose to use the modified method of exponential smoothing. Three main variants of exponential smoothing have generally been applied within our survey: simple Brown's exponential smoothing (Brown, 1959); exponential smoothing with Holt trend correction (Holt, 2004); and the Holt-Winters method (Winters, 1960). To solve the posed issue, we will apply the first method developed and generalized by Brown in (Brown, 1963). Subsequently, various upgrades and improvements to this method were carried out by Brown and Meyer (1961), Trigg (1964), Trigg and Leach (1967) and other researchers. Nowadays, 24 variations of the exponential smoothing methodology are known (Hyndman, Koehler, Snyder, & Grose, 2002).

The hybrid adaptive combined model with the B-criterion (ACM-B) based on the Brown model (Trigg, 1964) was chosen to forecast the TCE values. It is shown below how the author has modified the classic ACM-B model according to the ideas of Trigg and Leach, which was applied to another group of models (Trigg & Leach, 1967).

The initial data set in the form of TCE values for a specific route per day is a time series, consisting of the trend ξ_t, which is a characteristic of the market at the time, and noise, reflecting market fluctuations around the trend:

$$x_t = \xi_t + \varepsilon_t$$

Our task is to highlight the trend, remove noise and continue the trend into the future to make a forecast. For this, as suggested by Brown and Meyer (1961), 3 polynomials of zero, first and second degree are distinguished, respectively:

$$\xi_t = a_1 \tag{1}$$

$$\xi_t = a_1 + a_2 t \tag{2}$$

$$\xi_t = a_1 + a_2 t + \frac{1}{2} a_3 t^2 \tag{3}$$

As shown in Fig. 1 the zero-degree polynomial is the most "calm", smooths out sharp emissions and stably holds the average value, however, it reacts rather slowly to market changes that are taking place.

The second-degree polynomial can be called "panic"—it reacts most quickly to market changes in the form of the initial series,

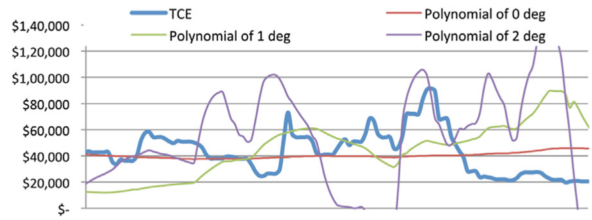

Fig. 1. Polynomial of 0, 1 and 2-degree appearance.

seeks to reduce the discrepancy as quickly as possible it is very unstable and fluctuates strongly around the initial series. The polynomial of the first degree is a "compromise" among them.

All three polynomials lead a separate forecast model and do not exchange data with each other. To determine which of the polynomials at the current moment is the closest to the true value of the forecast, the following control signal (Trigg, 1964) is applied, which is calculated for all three polynomials in the same way:

$$K_t = \frac{\hat{e}_t}{\sim e_t} = \frac{(1-\gamma)\hat{e}_{t-1} + \gamma e_t}{(1-\gamma)\sim e_{t-1} + \gamma |e_t|}.$$

The tracking signal is the ratio of the exponentially smoothed prediction error $\hat{e}_t$ to its absolute value $\sim e_t$, is calculated separately for each of the polynomials and varies in the interval $[-1; 1]$. Here γ is the smoothing parameter, e_t is the polynomial prediction error at time t. The values of the tracking pilot signal are used when calculating the parameter of smoothing time series as a function of (Trigg & Leach, 1967):

$$\alpha_t = f(K_t).$$

For a polynomial of degree zero, single smoothing is performed, for the first degree, double smoothing, for the second degree, triple (Brown, 1963). The smoothed average value of S_t is the sum of the previous value of S_{t-1} and the new value of the series x_t, multiplied by the smoothing coefficients α_t and $\beta_t = 1 - \alpha_t$. Depending on their size, the smoothing is sharper or smoother:

Polynomial of 0-degree:

$$S_t = \alpha_t x_t + \beta_t S_{t-1}$$

$$\alpha_t = 0,01\sqrt{K_t}$$

Polynomial of 1-degree:

$$S_t = \alpha_t x_t + \beta_t S_{t-1}$$

$$S_t^{[2]} = \alpha_t S_t + \beta_t S_{t-1}^{[2]}$$

$$\alpha_t = 0,05\sqrt{K_t}$$

Polynomial of 2-degree:

$$S_t = \alpha_t x_t + \beta_t S_{t-1}$$

$$S_t^{[2]} = \alpha_t S_t + \beta_t S_{t-1}^{[2]}$$

$$S_t^{[3]} = \alpha_t S_t^{[2]} + \beta_t S_{t-1}^{[3]}$$

$$\alpha_t = 0,1\sqrt{K_t}$$

The form of function $\alpha_t = f(K_t)$ in this case, is selected empirically as the most appropriate for the conditions of the problem. According to (Brown, 1963), estimates of the coefficients of polynomials (1)–(3) are calculated as follows:

Polynomial of 0-degree:

$$\hat{a}_{1t} = S_t \tag{4}$$

Polynomial of 1-degree:

$$\hat{a}_{1t} = 2S_t - S_t^{[2]} \tag{5}$$

$$\hat{a}_{2t} = \frac{\alpha_t}{\beta_t}\left(S_t - S_t^{[2]}\right)$$

Polynomial of 2-degree:

$$\hat{a}_{1t} = 3S_t - 3S_t^{[2]} + S_t^{[3]} \tag{6}$$

$$\hat{a}_{2t} = \frac{\alpha_t}{2\beta_t}\left((6-5\alpha_t)S_t - 2(5-4\alpha_t)S_t^{[2]} + (4-3\alpha_t)S_t^{[3]}\right)$$

$$\hat{a}_{3t} = \frac{\alpha_t^2}{\beta_t^2}\left(S_t - 2S_t^{[2]} + S_t^{[3]}\right)$$

Forecasting functions take the form of polynomials (1)–(3) with estimates of the coefficients (4)–(6) (Brown, 1963):

Polynomial of 0-degree:

$$\hat{x}_\tau(t) = \hat{a}_{1t} \tag{7}$$

Polynomial of 1-degree:

$$\hat{x}_\tau(t) = \hat{a}_{1t} + \tau\hat{a}_{2t} \tag{8}$$

Polynomial of 2-degree:

$$\hat{x}_\tau(t) = \hat{a}_{1t} + \tau\hat{a}_{2t} + \frac{1}{2}\tau^2\hat{a}_{3t} \tag{9}$$

Here parameter τ displays the forecast depth (forecast horizon). The forecast for these formulas is made τ days in advance. Further, from three forecast polynomials (7)–(9), one forecast function is combined that has an accuracy higher than that of each of the polynomials individually. For this, B-criterion is calculated, which reflects the deviation of each polynomial from the true value of the series by smoothing the square of the forecast error e_t^2:

Polynomial of 0-degree:

$$B_t^{(1)} = (1-\varphi)B_{t-1}^{(1)} + \varphi e_t^2$$

Polynomial of 1-degree:

$$B_t^{(2)} = (1-\varphi)B_{t-1}^{(2)} + \varphi e_t^2$$

Polynomial of 2-degree:

$$B_t^{(3)} = (1-\varphi)B_{t-1}^{(3)} + \varphi e_t^2$$

where φ is the smoothing parameter.

Since the values of B-criterion can be of different orders, the weighting coefficients ω_t are calculated for the combination of polynomials, which are the normalized values of the B-criterion:

Polynomial of 0-degree:

$$\omega_t^{(1)} = \frac{B_t^{(2)}B_t^{(3)}}{B_t^{(1)}B_t^{(2)} + B_t^{(2)}B_t^{(3)} + B_t^{(1)}B_t^{(3)}} \tag{10}$$

Polynomial of 1-degree:

$$\omega_t^{(2)} = \frac{B_t^{(1)}B_t^{(3)}}{B_t^{(1)}B_t^{(2)} + B_t^{(2)}B_t^{(3)} + B_t^{(1)}B_t^{(3)}} \tag{11}$$

Polynomial of 2-degree:

$$\omega_t^{(3)} = \frac{B_t^{(1)}B_t^{(2)}}{B_t^{(1)}B_t^{(2)} + B_t^{(2)}B_t^{(3)} + B_t^{(1)}B_t^{(3)}} \tag{12}$$

Table 1
Comparison of Naïve, ACM-B, ARIMA, GARCH, SVR, MLP on TCE datasets.

	Naïve					ACM-B				
	MAE	RMSE	MAPE	sMAPE	MASE	MAE	RMSE	MAPE	sMAPE	MASE
2015	14 965	20 521	0,4137	0,2299	14,515	9 487	16 075	0,2565	0,1570	9,064
2016	9 338	11 876	0,6540	0,2505	12,666	5 075	7 833	0,3534	0,1461	6,574
2017	5 522	7 330	1,2102	0,3517	9,803	2 973	4 323	0,8057	0,2373	5,353
2018	6 782	10 330	0,9513	0,3619	10,027	4 306	8 253	0,4885	0,2591	6,365
AVG.	**9 152**	**12 514**	0,8073	0,2985	**11,753**	**5 460**	**9 121**	0,4760	0,1999	6,839

	ARIMA					GARCH				
	MAE	RMSE	MAPE	sMAPE	MASE	MAE	RMSE	MAPE	sMAPE	MASE
2015	13 532	19 684	0,3183	0,1939	14,659	14 602	19 961	0,4414	0,1985	13,642
2016	7 938	11 625	0,6356	0,2533	10,545	8 687	12 055	0,7286	0,2628	13,292
2017	6 164	7 942	1,6747	0,4352	11,864	6 204	7 338	2,4645	0,4129	10,892
2018	8 182	12 372	1,0921	0,4192	11,247	8 110	11 643	1,2487	0,3951	14,238
AVG.	**8 953**	**12 905**	0,9301	0,3253	**12,078**	**9 400**	**12 749**	1,2207	0,3173	**13,015**

	SVR					MLP				
	MAE	RMSE	MAPE	sMAPE	MASE	MAE	RMSE	MAPE	sMAPE	MASE
2015	9 760	13 494	0,2468	0,1324	9,217	6 588	8 521	0,1942	0,0923	6,445
2016	7 024	9 183	0,6417	0,1996	9,753	5 879	7 949	0,4913	0,1707	7,807
2017	4 365	5 364	1,2885	0,2915	7,819	4 811	5 812	1,8749	0,2933	8,268
2018	6 679	9 706	1,0876	0,3296	10,495	5 800	7 630	1,2409	0,3075	8,368
AVG.	**6 956**	**9 436**	0,8161	0,2382	9,321	**5 769**	**7 477**	0,9503	0,2159	7,7219

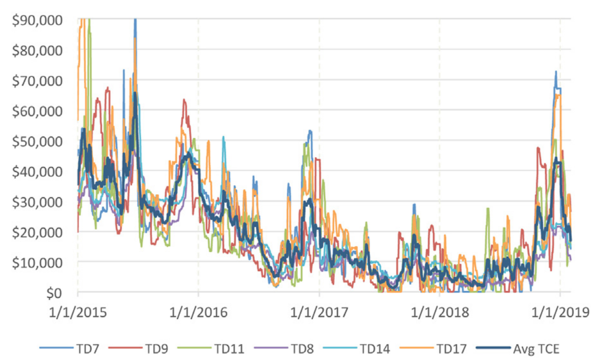

Fig. 2. TCE values on the TD routes in 2015–2019.

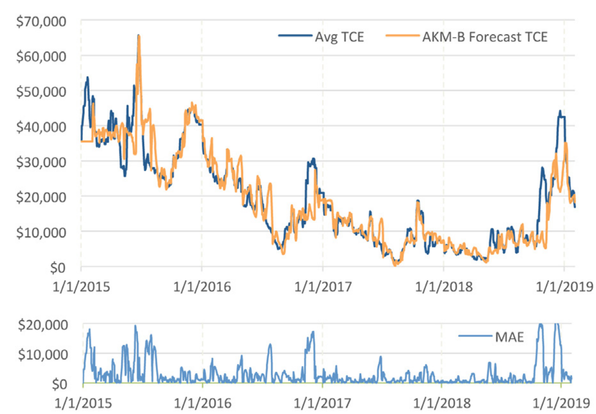

Fig. 3. Forecasted TCE and MAE values by ACM-B model with horizon 30 days.

The resulting forecast function is compiled as the sum of the forecast polynomials of the 0, 1 and 2-degree (7)–(9) multiplied by the weighting coefficients (10)–(12).

$$f_{\tau}(t) = \omega_t^{(1)}\hat{x}_{\tau}^{(1)}(t) + \omega_t^{(2)}\hat{x}_{\tau}^{(2)}(t) + \omega_t^{(3)}\hat{x}_{\tau}^{(3)}(t) \tag{13}$$

The resulting equation is suitable for adaptive forecasting of future values of time series with a forecast horizon τ.

4. Discussion

To assess the forecasting accuracy of the ACM-B method considered above, the values of the average time-charter equivalent were selected for various typical oil transportation routes according to the Baltic International Trade Routes classification: TD7—the North Sea to Continent, TD8—Kuwait to Singapore, TD9—Caribbean to US Gulf, TD11—Cross Mediterranean, TD14—South East Asia to Australia, TD17—Baltic to UK Continent. As we can see in Fig. 2 TCE values of different routes have similar trends, but different kinds of shocks and behavior of the time series. Also, in Fig. 2 shows the average TCE value, which can be used to judge the general trend and behavior of the TCE values of all the routes under consideration. To assess the accuracy, statistics were selected for the period of the crisis in this branch in 2015–2019. In 2015, we see the beginning of the crisis, in 2016—the recession of the oil transportation market, 2017—the main time of the crisis, 2018—the time of gradual recovery from the crisis. Each of these periods is indicative for assessing the accuracy of forecasting TCE values.

In the Q2 of 2015, there were detected high jumps in TCE values with an amplitude from $25,000 to $90,000. Further on, until the end of 2016, the fluctuations in the average amplitude with negative market trend dynamics to fairly low values of about $10,000 were identified. From the beginning of 2017 to the Q2 of 2018, there erupted a deep crisis in the oil transportation market and the average revenue of a tanker per day fluctuated around $0. From Q3 2018 to the beginning of 2019, there was an exponential growth in revenue from transportation up to $70,000 per day.

The results of TCE values forecasting in the various conditions described above using an adaptive combined model with a B-criterion applying the following formula (13) are presented in Fig. 3. The value of errors of forecasting also shown in Fig. 3 as the mean absolute error (MAE). This value is chosen from all forecasting errors as the most important in practice for the real customer. MAE makes it clear how much daily profit in USD will be gained or lost by the tanker charterer.

The figure shows that the MAE has shock values over ±$15,000 during periods of chaotic market and demonstrates fairly stable

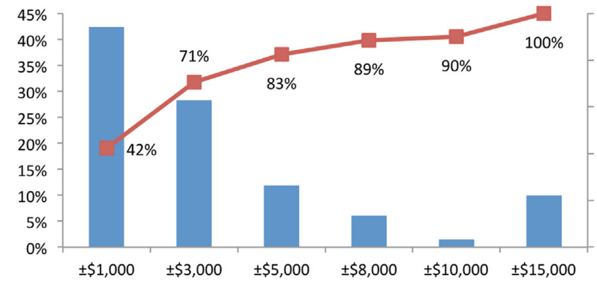

Fig. 4. Histogram of mean absolute errors of AKB-B forecasting of avg. TCE.

behavior ±$3000 during periods of medium and low volatility. It is more convenient to analyze forecast errors in the form of a histogram in Fig. 4.

Vertical bars on it indicate the entry of MAE into the pockets of ±$1000, ±$3000,. . ., ±$15,000, and the graph shows the cumulative percentage of errors in this range. The figure shows that during the 4 crisis years, 42% of forecasts give an accuracy of at least ±$1000, and 71% of forecasts are within the range of ±$3000. This accuracy is sufficient for the practical application of this method in companies of charterers to decide on the choice or rejection of a contract for the transportation of crude oil in a crisis period. We also see that MAE errors of more than ±$3000 account for 19% of cases and decrease exponentially with pocket size. The last 10% are emissions and rough shocks of the MAE market of more than ±$15,000, arising because of unpredictable factors of the crisis period, which should be filtered out and not considered when making a forecast.

Another novelty of this work is the increased accuracy of predicting the TCE values by the ACM-B model in comparison with the existing more modern methods (Table 1). As a result of comparing the accuracy of forecasting ACM-B with the naive method, the autoregressive methods ARIMA and GARCH, the SVR and MLP machine learning models, we see that, according to various metrics, ACM-B prevails in the accuracy of predicting TCE values for each of the TD7–TD17 routes in each year of the crisis period from 2015 to 2019. It should be noted that the naive method competes in accuracy with the SVR and MLP models, while the ARIMA and GARCH methods consistently lose to both. This unusual behavior is the subject of additional research and raises new questions in the forecasting of the TCE of oil tankers.

5. Conclusion

This article explores a gap in the literature on forecasting the tanker market using exponential smoothing techniques. For this, it is proposed to use the ACM-B model based on the Brown model, modified by the author using the Trigg–Leach method. The model studies were carried out on predicting the values of the time-charter equivalent with a horizon of 30 days for several directions of oil transportation in the world ocean for 4 years during the crisis period 2015–2019. The novelty of the research is the high accuracy of predicting ACM-B values of TCE, which is superior to naive and autoregressive methods, as well as machine learning models for all used error metrics. 71% of forecasts have sufficient accuracy for commercial use of ±$3000 in tanker fleet operators and charterers. This research contributes to the growing scientific literature on predicting the tanker freight rate market and expanding the scope of exponential smoothing methods. The results provided are significant for companies operating in the oil and maritime industries, allowing them to respond more effectively to fluctuations in the tanker freight rates market.

Conflict of interest

The authors declare no conflict of interest.

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