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An Optimal Forecasting Method of Passenger Traffic in Greek Coastal Shipping

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ABSTRACT

Purpose:
The main goal of this study is to exact an optimal forecasting method by answering the research question: which is the best model for capturing short-term seasonal components of passenger traffic in Greek coastal shipping?

Design/methodology/approach:
There are not a lot of scientific efforts in forecasting passenger traffic in Greece. In order to fill this gap, we tried to find an optimal forecasting method, by comparing Box-Jenkins ARIMA, smoothing and decomposition methods. As Greek coastal shipping consists of several concentrated submarkets (lines) we remained in fourteen popular itineraries (including total passenger traffic). Taking into consideration the high seasonality and no stationarity that characterizes those routes we limited our analysis to Winter's triple exponential smoothing, to time series decomposition method, to simple seasonal model and to seasonal ARIMA models.

Findings:
The analysis results show that in fourteen popular coastal routes Winters' multiplicative method, simple seasonal model and decomposition multiplicative trend and seasonal model have the best integration to the time series data. No coastal line led to better results by seasonal Box-Jenkins ARIMA models.

Research limitations/implications:
The results should be treated with caution since COVID-19 pandemic does not allow safe conclusions for the forecasting period 2020-2022 in GCS. However, the forecasting results of the first quarter of 2020, when pandemic had not fully prevailed, gave encouraging results with little deviations between predicted and actual values.

Originality/value:
Greek coastal shipping is one of the biggest in Europe serving a large number of passengers and having a large part of the total shipping fleet. It plays an important role for Greek economy and society, as it connects the majority of inhabited islands to mainland. The finding of an optimal forecasting method of passenger traffic is very significant for both business and government policy. Decisions on the number of routes served by shipping companies, on ships by coastal line (number and size), on companies' pricing policy, on public service obligations, on state port infrastructure policy and on the amount of state funding for barren lines are typical examples.

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1. Introduction

GCS is one of the biggest in Europe and performs an important role connecting mainland to Greek islands[1]. Its contribution to GDP is € 13.6 billion or 7.4% of total GDP (2019). It employs approximately 332,000 people and contributes to public revenues with approximately € 3 billion (IOBE, 2020). It carries over 35 million Greeks and foreigners annually (including ferry lines), with its fleet accounting for about 7% of the global passenger shipping fleet. It covers about 17% of total passenger shipping in Europe, with more coastal lines than other countries (due to the plethora of islands). The sector is characterized by high seasonality with almost half of the transport traffic taking place in the period June-August (IOBE, 2014).

In 2019, the listed shipping companies, employed 2,449 employees, launched 43 ships and served passenger traffic of 7,543,460 people. Respectively, they transported 1,041,574 cars and 555,241 trucks. They served about 36% of total passenger traffic[2] and 46% of total vehicle traffic. The average age of their fleet is high, with 60% being over 22 years old and 25% of the total being over 30 years old (XRTC, 2004-2020).

All the above show that GCS is of great importance for Greek economy and society. The volume of passenger traffic it serves is very high and its forecast is very significant for both business and government policy. Decisions on the number of routes served by shipping companies, on ships by coastal line (number and size), on companies' pricing policy, on public service obligations[3], on state port infrastructure policy and on the amount of state funding for barren lines[4] are typical examples. Indicatively, according to Official Government Gazette B,15/04/20,1426 (article 2), the state funding for the financial support of coastal companies, on barren lines, has a basic precondition. The reduction of average passenger traffic by 80% in relation to the previous year's data. Also, the indisputable existence of scale economies in GCS (because of high fixed costs), is related to economic necessity of achieving high occupancy rates (by using larger ships and reducing routes) (Sitzimis 2021a; 2021b). In any case, both the private and public sector need to know the future passenger traffic in GCS. Forecast is essential to decision making.

The main goal of this study is to exact an optimal forecasting method by answering the research question: which is the best model for capturing short-term seasonal components of passenger traffic in Greek coastal shipping? In particular, it aims to find an optimal forecasting method of passenger traffic in GCS by comparing Box-Jenkins ARIMA, smoothing and decomposition methods (Wardono, et al., 2016; Ahmad & Ahmad, 2013; Trull, et al., 2020). The first methods seem to be effective in predicting passenger traffic in transport and the other two have not been preferred for research (Aivazidou, 2015). The basic assumption in all three of the above methods is that the available observations will continue to behave in the future as in the past (Shim & Siegel, 2001).

In the period 2020-2021, due to covid-19 pandemic, this did not happen and there was a sharp drop in passenger traffic. This is why our forecast will start from 2020, ignoring this decrease so as not to create a problem in time series forecasting for the coming years (and especially for the year 2022 when the situation is expected to return to normalcy).

2. Related work

In relation to transport forecasting efforts in the transport sector, about 60% of publications concern forecasts for passenger transport (Aivazidou, 2015). These mainly concern air, road and urban transport. Similar scientific research on maritime passenger transport is absent from international literature. The main reason is that in a few countries coastal shipping is a means of transport. Remarkable is only the research of Ortuzar and Gonzalez (2002), on the coastal line between the Canary Islands and Tenerife.

In GCS, because it largely connects mainland to Greek islands, the research is more extensive. Attempts in this direction have been made by various authors, such as Psaraftis (1994) who made an attempt to systematically analyze possible scenarios for passenger demand after deregulation of the market. Spathi (2005), attempted to find the function of passenger demand using the dynamic model with the error correction model mechanism (Ramanathan, 2001). A similar study was carried out by Tsekeri (2008) who presented an aggregate analysis of substitution and complementary relationship among all available transport modes for domestic travel in Greece. He proposed a model based on consumer demand theory.

Simplistic efforts were made to forecast the financial statements and passenger traffic of coastal companies, with polynomial and hyperbolic functions having the best application (higher R squared) (Sitzimis, 2012). An important research took place in 2014 (IOBE), which used the regression method for the estimation of demand elasticity for coastal

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[1] It connects about 115 inhabited islands to mainland in Greece.

[2] The remaining 64% for passengers and 54% for vehicles are serviced by smaller companies. In 2019, these companies launched 15 conventional and 21 high-speed vessels on all GCS routes.

[3] Although the market is liberalized and a simple declaration to the Ministry of Maritime Affairs and Insular Policy is required to enter and exit, there are also obligations for shipping companies such as obligatory period of ten-month shipping, prohibition of interruption and change of routes without approval, mandatory crew compositions of ships.

[4] According to Law 2923/2001, the State characterizes as "barren" those lines for which there is no expression of interest for their operation from coastal companies.

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shipping services with respect to ticket prices and household disposable income. Various other forecasting approaches are performed by XRTC on annual basis (2004-2020).

However, according to Aivazidou (2015) the basic forecasting methods used for other passenger transport are mainly time series analysis models and less combined time series and regression analysis models or pure regression analysis models. In fact, the most widely used models are those based on the Box-Jenkins ARIMA methodology, while very few are based on methods of smoothing and time series decomposition. In other words, there is a gap in the relevant literature that we are going to fill with this research.

3. Passenger traffic analysis in GCS

Air, road and urban transport offer useful conclusions about passengers' demand forecasting to a transportation industry (Sitzimis, 2012; Sabry, et al., 2007; Tamber, et al., 2021; Dingari, et al., 2019). We could be based on them and reach to the congruent conclusions about GCS. However, market conditions differ between those industries. In GCS these assumptions cannot be unified and undivided (Goulielmos & Sambrakos, 2002). This market consists of several concentrated submarkets-coastal routes, which should be analysed individually (Sitzimis, 2012; Goulielmos & Sitzimis, 2014; Goulielmos & Sitzimis, 2012). There are many studies that make the mistake of dealing the market GCS as a total (Tsekeris, 2008). We preferred the assiduous review of the real conditions of GCS, by analysing it per coastal route.

Coastal lines in Greece are characterized by intense seasonality with the largest percentage of passenger traffic (about 45%) taking place in the third quarter of each year. The months from April to September accounting for about 70% of the total annual number of passengers (Sitzimis, 2012; XRTC, 2004-2020). This fact reflects the strong tourist demand for island destinations (IOBE, 2014). August, is the month with the greatest traffic, leaving behind July, September and June. The lowest traffic of passengers traveling within their national borders, mostly appears during February, January and November (XRTC, 2004-2020).

In order to analyse the passenger traffic in shipping itineraries of Greece, we remained in 13 itineraries, which represented the biggest average percentage of total passenger traffic (diagram 2). Those of Argosaronikos (A), Piraeus-Peloponnese (PP), Piraeus-Creta (PC), Piraeus-Creta-Dodecanese (PCD), Piraeus-Dodecanese (PD), Piraeus-West Cyclades (PWC), Piraeus-East Cyclades (PEC), Piraeus-Mykonos-Tinos-Samos (PMTS), Piraeus-Chios-Mytilene (PCM), Patra-Akarnania-Ionian islands (PAII), Rafina-Euboea-Andros-Tinos (REAT), Volos-North Sporades-Kymi (VNSK) and the rest (L).

The average number of passenger traffic on these lines, between 1970-2000, increased at an impressive rate. Overall, an average increase of 4.2% was observed (Sitzimis, 2012). This was due to: (a) the growth of tourism in insular Greece, (b) the increase in GDP per capita of island inhabitants, (c) the general increase of permanent population in Greece and (d) the greater dependence of islands from the mainland (due to the modern tendency for astyphilia) (Spathi, 2005). The lines with the highest traffic were "A", "PEC" and "PC", while the highest growth rate appeared in line "PEC" (7.2%), followed by lines "PC" (7.1%) and "PWC" (6.5%) (Sitzimis, 2012). It is obvious that "PWC" and "PEC" lines gathered the largest shipping traffic in GCS between 1970-2000. This was mainly due to the great growth of tourist arrivals that occurred in these islands after 1970.

Comparing the years 2001 to 2019 (table 1 and figure 1) it is obvious a very large increase of passenger traffic between the years 2001-2007 (35%), mainly due to liberalization of the market (lifting of cabotage privilege), partly in 2002 and fully in 2006 (Law 2932/01, EU regulation 789/04, Presidential Decree 124/06) (Sitzimis, 2012; Goulielmos & Sitzimis, 2014). Also, in this increase contributed both the Olympic Games in Athens (2004) and the increase of tourist flows to the country. Between 2006-2007 there is stabilization and a small percentage decrease. In the period 2008-2013, passenger transport is significantly reduced due to global financial crisis, with the percentage reduction reaching 25%. The decrease was caused by the descending course of income per capita of Greeks and by the overdraft of Greek households. After 2014 and until 2019 the market is recovering but continues to be at lower levels than it was before the crisis. Despite the sharp increase in tourist traffic[5], Greek coastal shipping does not benefit enough as most foreign tourist arrivals took place by air. Overall, for the years 2001-2019 the average increase was about 10% (table 1).

For 2020, the impact of Covid-19 pandemic was clear. Greek coastal shipping was subjected to a restriction on passengers' transportation from March to May 2020 followed by state ceilings for transported passengers thereafter. If we consider the big drop in tourism, the passenger reduction was significant (about 55%) (IOBE, 2020).

The most popular destination and the greatest average traffic (2001-2019) (Figure 2) is presented in shipping route "A" (having a part of 16.3% of passengers), followed by Piraeus-Cyclades ("PEC" and "PWC", having a part of 15,5% of passengers), "PC" (a part of 13,7%) and "REAT" with 12.9%. This is normal because they constitute very popular touristic destinations. Especially after the deregulation of the market took place «cream skimming». This means that most shipping companies preferred the most lucrative coastal markets, mainly in the summer months. At the same time left non

[5] In 2004 there were 13 million tourist arrivals, whereas in 2019 the number was 34 million.

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profitable markets in winter (Sitzimis, 2012; 2021a; 2021b; Goulielmos & Sambrakos, 2002). Also, the high levels of traffic are interpreted by the fact that these itineraries are based on the part of demand with the least seasonality. So, the higher levels of occupancy rates and exploitation of ships are achieved.

4. Methodology

The main issue in this research was to predict passenger traffic on the main lines of Greek coastal shipping. To do this we had to choose between certain quantitative forecasting methods. Qualitative forecasting methods are based more on human judgment than on the analysis of existing data (Shim & Siegel, 2001). We had quarterly data on passenger traffic between the years 2004-2019, so we chose the quantitative methodology. In each case we processed our data with the statistical package SPSS 22. Exception took place for the calculation of time series decomposition where the Minitab 19 software was used. Also, the calculation of the augmented Dickey-Fuller test was done through EViews 11. The reason was that SPSS did not have these features clearly.

In order to make a prediction for our dependent variable we could use regression analysis (Petropoulos & Asimakopoulos, 2013). In this way we would recognize the quantitative and causal relationship between the variables involved in the interpretation of our problem. Unfortunately, this method is difficult to apply here as the independent variables that affect passenger traffic are not completely clear, it is difficult to find relevant statistic data and time series analysis models seem to be better applied in these cases (Sabry, et al., 2007; Wu, et al., 2013; Tsui, et al., 2014; Rashidi & Ranjitkar, 2015).

For these reasons we could rely on known smoothing methods or Box-Jenkins ARIMA models, taking into account only the existing observations and not the possible relationship with other variables (Ahmad & Ahmad, 2013; Munarsih & Saluza, 2019; Yonar, et al., 2020).

Starting with smoothing methods, they are easy to apply and have a low degree of computational difficulty. The basic logic is that we use time series data, that is, past observations of equal successive time periods. These time series are not affected by the small amount of available data and provide satisfactory forecasts in the short term (Petropoulos & Asimakopoulos, 2013). As is well known, when we do not have a trend and seasonality (stationary time series) for a short forecast range, the simple moving average and simple exponential smoothing models are best applied. Respectively, if there is a trend but not seasonality, for a long range of forecasts, the trend analysis or the exponential smoothing with adaptation to the trend (Holt's method) are suitable. For a smaller range the double exponential smoothing (Brown's method) or the double moving average method (double moving average or linear moving average) are preferable (Chalkos, 2020).

The passenger traffic data available at GCS were quarterly and therefore there were indications of seasonality and no stationarity. As shown in Figure 5 in all examined lines there is a strong increase in traffic in the 3rd quarter of the year, with a slightly decreasing or increasing trend over the years 2004-2019. This means that we could not use prediction techniques such as the above. Repeated seasonal fluctuations and quarterly available observations made the Winters model (Winter's triple exponential smoothing) (indicated when we have seasonality rather than a short-term forecast), the time series decomposition (suitable when we have a trend and seasonality for a long range of forecasts), the simple seasonal model (suitable when we do not have a trend, but only a stable seasonal result) and the seasonal ARIMA models suitable for our case (Chalkos, 2020; Petropoulos & Asimakopoulos, 2013).

Table 1: Total passenger traffic in GCS (for the 13 main itineraries) (2001-2019).

Year	Passengers	Average	% alteration
2001	13,852,000		
2002	13,124,000		
2003	14,905,000		
2004	17,306,000	16,422,862	34.79%
2005	18,257,159		
2006	18,844,396		
2007	18,671,482		
2008	18,068,255		
2009	17,442,121		
2010	16,587,040	15,729,890	-24.72%
2011	15,071,705		
2012	13,608,289		

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2013	13,601,930		
2014	14,463,293		
2015	14,323,032		
2016	14,542,183	15,598,306	20.40%
2017	15,938,427		
2018	16,909,512		
2019	17,413,388		
Average (2001-2019)	**15,943,643**		**10.16%**

Source: Hellenic Statistical Authority (2000-2020). Our elaboration.

4.1. Measures of forecasting accuracy

The basic selection criterion we followed is which method best suited our data, that is, it led to the smallest values ofdiscrepancies between predicted ($\overline{Y}t$) and actual values (Yt) of the time series (forecast error). By studying the time behavior of forecast error values, we were able to arrive at both the evaluation of our forecasting methods and the choice between alternatives (Agiakloglou & Oikonomou, 2019; Karmaker, et al., 2017).

We used the following precision measures:

a) The mean absolute percentage error (MAPE), which expresses the percentage accuracy. Defined as:

$$MAPE = \frac{\Sigma\left|\frac{Yt-\bar{Y}t}{Yt}\right|x100}{n} \qquad (1)$$

where n is the number of measurements.

b) The mean squared deviation (MSD or MSE) calculated as:

$$MSD = \frac{\Sigma(Yt-\bar{Y}t)^2}{n} \qquad (2)$$

Mean squared error expresses the mean value of the squared deviations and is considered statistically more reliable, so it is used more often. Because its interpretation is difficult to understand we mainly used the root mean squared error (RMSE) (Agiakloglou & Oikonomou, 2019).

Figure 1: Fluctuations of total passenger traffic in GCS (2001-2019)	**Figure 2: Average passenger traffic per route in GCS (2001-2019)**

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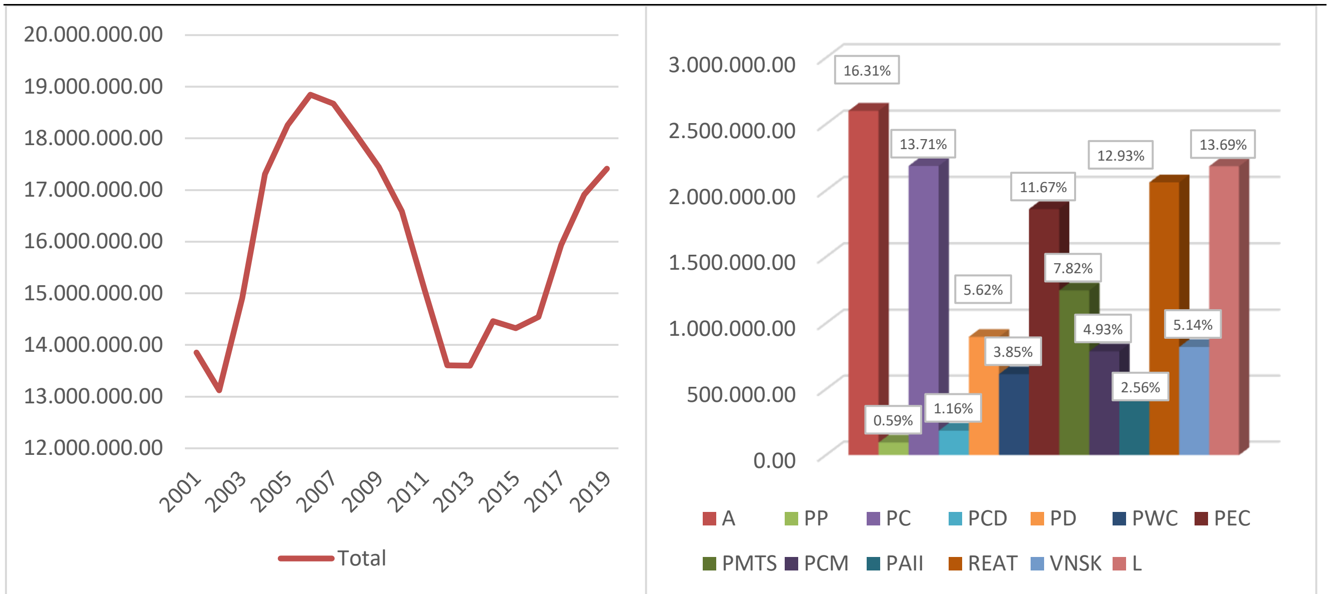

Source: Hellenic Statistical Authority (2000-2020). Our elaboration.

c) The mean absolute error (MAE), which expresses a measure of the accuracy of the forecast against the actual values, maintaining the units of measurement of the original time series. It is set as:

$$MAE = \frac{\Sigma |Yi - Fi|}{n} \tag{3}$$

and its high values show bias of the method.

d) The Bayesian information criterion, developed by Schwarz (1978) (or BIC) selects the model that minimizes:

$$BIC = \ln \sigma^2 + \frac{\ln n}{n} r \tag{4}$$

where σ^2 is the sum of the squares of the residuals, n is the number of observations and r is the total number of parameters with the constant term.

For all forecasting accuracy measures we considered that the lower the price the better the model in terms of estimation (Chalkos, 2020). We also accepted that MAPE values below 10% describe an extremely accurate forecast, below 20% a relatively good forecast and below 30% a marginally accurate forecast (Dingari, et al., 2019).

4.2. Winter's triple exponential smoothing

Winter's triple exponential smoothing has three smoothing parameters. The parameter α for the smoothing of time series values (level), the parameter β for the smoothing of trend (slope) and the parameter γ for seasonality smoothing. These components are either additive or multiplicative. The multiplication model is selected when the seasonal pattern in the data depends on the size of the data. In other words, the size of the seasonal pattern increases as the series goes up and decreases as the series goes down. The additive one is selected when the seasonal pattern in the data does not depend on the size of the data. In other words, the size of the seasonal pattern does not change as the time series goes up or down (Hansun, et al., 2019; Dingari, et al., 2019).

The smoothing of the time series values in the additive model is done through the function:

$$A_t = a(Y_t - S_{t-L}) + (1-a)(A_{t-1} + T_{t-1}) \tag{5}$$

whereas in the multiplicative through the function:

$$A_t = a\frac{Yt}{S_{t-L}} + (1-a)(A_{t-1} + T_{t-1}) \tag{6}$$

where α is the smoothing constant (0≤α≤1), At the smoothed values of time series, St is the seasonal factor of the period t and L is the periodicity of the seasonality.

In the additive model the smoothing of the trend follows the equation:

$$T_t = \beta(A_t + A_{t-1}) + (1-\beta)T_{t-1} \tag{7}$$

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where β is the trend smoothing constant ($0 \le \beta \le 1$) and T_t the smoothed values of trend. The equation in multiplicative model is transformed as:

$$T_t = \beta(A_t/A_{t-1}) + (1-\beta)T_{t-1} \quad (8)$$

The seasonality smoothing in additive model follows the equation:

$$S_t = \gamma[Y_t - A_t] + (1-\gamma)S_{t-L} \quad (9)$$

and in multiplicative the equation:

$$S_t = \gamma\frac{Yt}{A_t} + (1-\gamma)S_{t-L} \quad (10)$$

where γ is the smoothing constant of seasonality ($0 \le \gamma \le 1$).

The forecast is:

$$\bar{Y}_{t+h} = (A_t + hT_t)S_{t+h-L} \quad (11)$$

where h=1,2,3…L is the future periods of first year and

$$\bar{Y}_{t+h} = (A_t + hT_t)S_{t+h-2L} \quad (12)$$

where h=L+1,L+2,L+3…2L is the future periods of second year etc.

Initialization of the method according to Chatfield (2003) is required. For t=1,2,..,L-1 the values At are not determined, while for t=L the A_L is defined as:

$$A_L = \frac{Y_1 + Y_2 + \cdots + Y_L}{L} \quad (13)$$

For t=1,2,…,L-1 the values Tt are not determined, for t=L we set T_L=0 and for t=1,2,…,L the values of the seasonal coefficients St are calculated as:

$$S_t = \frac{Y_t}{A_L} \quad (14)$$

The optimal values of α, β and γ were calculated automatically by minimizing the RMSE criterion in SPSS and for all possible combinations of parameter values in the time series data (Chalkos, 2020; Dhali, et al., 2019; Ravinder, 2013; Tamber, et al., 2021).

4.3. Time series decomposition and Simple seasonal exponential smoothing

The objective of time series decomposition is to identify the mechanism by which time series values are formed. The decomposition method is used to separate a time series into the trend component, the seasonality component, the cyclical component and the irregular component to make predictions (Chalkos, 2020).

It is necessary to choose whether the seasonality works addictively or multiplicatively to the trend. If it works addictively, the model has the form:

$$Yt = Tt+St+Ct+It \quad (15)$$

where Yt is the real observation in time t, Tt is the trend, St is the seasonality, Ct is the circularity and It is the randomness. This model is more difficult for further computational analysis and assumes independence between the factors. This assumption applies to natural phenomena, but not to business or economic applications, where the trend also affects seasonal fluctuations (Agiakloglou & Oikonomou, 2019). In the case of the multiplicative model the above relation is transformed as:

$$Yt = Tt \cdot St \cdot Ct \cdot It \quad (16)$$

It works well when the fluctuations depend on the level of values, which is usually the case (Kyriakidis, 2018).

The simple seasonal exponential smoothing is suggested for series with no trend and a seasonal effect that is constant over time. It has two smoothing parameters, level (α) and season (δ). It is very similar to an ARIMA model with zero orders of autoregression, one order of differencing, one order of seasonal differencing, and orders 1, p, and p + 1 of moving average, where p is the number of periods in a seasonal interval (for quarterly data, p = 4) (IBM, 2021). The model equation is:

$$Y_t = \mu_t + S_{t,p} + a_t \quad (17)$$

and the smoothing equations are:

$$L_t = a(y_t - S_{t-P}) + (1-a)L_{t-1} \quad (18)$$

$$S_t = \delta(y_t - L_t) + (1-\delta)S_{t-P} \quad (19)$$

The h-stem-ahead equation is:

$$\bar{Y}_{t+h} = L_t + S_{t-P+h} \quad (20)$$

h=1.2…, where μ_t is the mean of the observed time series at period t, S_{t-P+h} is the seasonal component, p is the seasonality periodicity, h is the number of periods in forecasting and a_t is the forecast error at period t.

4.4. ARIMA: Auto-Regressive Integrated Moving Average

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In relation to the Box-Jenkins ARIMA models, we would say again that in all coastal lines appear seasonal data that have a distinct pattern which is repeated every year (Figure 5). Our data are quarterly, so the length of the seasonal period is S = 4. This means that there are observations that are correlated both within the year and between different years. In these cases, seasonal ARIMA (SARIMA) models that contain non-seasonal and seasonal autoregressive and moving average terms are applied (Wardono, et al., 2016; Ma, et al., 2018; Sim, et al., 2019). In fact, in non-stationary series, a seasonal difference is usually used to completely determine the model. (Wardono, et al., 2016; Ma, et al., 2018; Sim, et al., 2019).

These models are denoted as ARIMA (p,d,q)(P,D,Q)s where: p are non-seasonal autoregressive terms, d are regular differences, q are non-seasonal moving average terms, P are seasonal autoregressive terms, D are seasonal differences, Q are the seasonal terms of moving average and s is seasonality. Indicatively a SARIMA model is written:

$$\Phi_p(\mathrm{B})\Phi_p(B^S)(1-B)^d(1-B^s)^D y_t = \theta_q(\mathrm{B})\Theta_Q(B^S)\varepsilon_t \tag{21}$$

where ϕ and θ, are parameters of autoregressive (AR) and moving average (MA), while Φ and Θ, are parameters of seasonal autoregressive (SAR) and seasonal moving average (SMA) respectively. B is lag operator which defined as $B^K Y_t = Y_{T-K}$ (18) (Wang, et al., 2013; Suhartono, 2011).

In particular, to implement SARIMA modeling and forecasting in GCS we followed 4 basic steps (table 2). The first stage was the "recognition" of the model whenever we initially ascertained the existence or not of stationarity in the time series data. When the series were not stationary (in the sequence chart the values were not around zero) we applied the method of differences. In some cases, both first regular differences (ΔYt = Yt-Yt-1) and seasonal quarterly differences (ΔYt = Yt-Yt-4), that is of order S = 4, were needed. After the differences if the autocorrelation function of the time series were declining rapidly and were zero, we considered this to be a sign of stationarity. In order to determine whether the time series actually became stationary we applied the augmented Dickey-Fuller test, which had as null hypothesis that the data are not stationary (p-value <5% in order to reject the null hypothesis) (Hasudungan & Pulungan, 2021; Makatjane & Moroke, 2016). We used EViews software for this unit root test.

In the resulting stationary time series, through Minitab 19 we checked the importance of the time series autocorrelation coefficients per lag. We used the t-student distribution, with n-1 degrees of freedom, 95% confidence interval for one-tailed test and null hypothesis that the coefficients are not autocorrelated (Gujarati & Porter, 2018). The autocorrelation of the coefficients is desirable, so our goal was to accept the alternative hypothesis (that is approximately for values t <2). At the same time, we checked the autocorrelation for all Lags, where we used the Ljung - Box Q statistics through the chi-square distribution, with the same degrees of freedom as the lags, 95% confidence level, one-tailed test and null hypothesis that the data is random and without apparent trend (LBQ>chi-squared). That is, not all autocorrelation coefficients are statistically different from zero (Gujarati & Porter, 2018). The same test was performed through SPSS where the p-value <5% for the Box-Ljung statistic criterion was required.

The final identification of the appropriate model per coastal line was made by comparing the ACF and PACF calculated from the data with the theoretical ACF and PACF for the various ARIMA models. The general logic was that if the sample autocorrelations exponentially drop to zero and some are interrupted, the model will require autoregressive terms. If the sample autocorrelations are interrupted and some of them decrease the model will also require moving average terms (Kyriakidis, 2018). By counting the number of significant sample autocorrelations and the partial autocorrelations we determined the classes of MA and AR terms.

For instance, in itinerary "A" we got a regular and a seasonal difference, because through the sequence chart and the ACF diagram of the original series we found no stationarity in the data. After the differences, the autocorrelations of the time series decreased rapidly and were zero, which was a sign of stationarity for us. The Augmented Dickey-Fuller test statistic gave a p-value<5%, which means that the null hypothesis is rejected and indeed the time series was stationary. Because we wanted our data to have the desired autocorrelation, using the t-statistic for a significance level of 5%, one-tailed test, and n-1 degrees of freedom, we found that the autocorrelation coefficients were statistically different from zero. The same conclusions were emerged by the chi-squared statistic (zero hypothesis rejection), showing that the time series data as a whole were not random.

So, we decided to proceed with the modeling of the seasonal ARIMA model. We definitely had 1 nonseasonal difference (d) and 1 seasonal difference (D). In nonseasonal AR (p) we tested values 1 and 2 because we had lags which are significantly correlated and in seasonal AR (P) the value 1 as it is sufficient for most seasonal patterns (IBM, 2021). Considering that sample autocorrelation ceases after the 1st lag and partial autocorrelation decreases, we used values 1 and 2 as nonseasonal MA (q) and obtained value 1 as seasonal MA (Q) as it is sufficient for most seasonal patterns (IBM, 2021).

The second stage concerned the "assessment" of the model and specifically its parameters. Based on the previous analysis for line "A" we checked several models, keeping the differences constant. The model with the lowest RMSE, MAE, MAPE and normalized BIC was the SARIMA (0,1,1) $(1,1,0)_4$.

In the third stage and before using the models for prediction, we checked them for their "adequacy". Adequate is the model whose residuals are random and independent (Gujarati & Porter, 2018). Through Minitab 19 we relied on a chi-square test, based on Ljung-Box statistics with number of lags minus number of parameters degrees of freedom. If p-value>5% for all individual values (lags), the residual autocorrelations were considered to express consistent and random

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errors (white noise). At the same we performed a comprehensive check of the adequacy of the model, through the chi-square test based on Ljung-Box statistics (SPSS). For line "A" it appeared that the errors had white noise behavior. Then, the statistical significance of the parameters of the selected model was checked. In line "A" because p-value<5% the coefficients were statistically significant and were maintained in the model. Finally, the interpretive power of the model was investigated through stationary R squared. Given the adequacy of the models, we adhered to the principle of parsimony and on every case, we chose the simplest model that provided an adequate description of the main characteristics of the data (Kyriakidis, 2018).

Table 2: Basic steps for SARIMA forecasting in GCS (2004-2019).

STEP 1: Model recognition		**STEP 2: Model estimation**	**STEP 3: Model adequacy**	**STEP 4: Model forecasting and feedback**
1. Are data stationary?	2. Now the data are stationary:	1. Which is the best fitted model per route?	1. Is the best fitted model statistically adequate?	1. Which are the quarterly forecasts of passenger traffic for years 2020-2022?
a. Check sequence chart	a. Are the autocorrelation coefficients statistically different from zero?	a. Check which model has the lowest result in MAPE, RMSE, MAE and normalized BIC	a. Check the residuals whether are random and independent.	a. We must forecast passenger traffic only for year 2022 cause COVID-19.
b. Check ACF, PACF diagrams	b. Are time series data as a whole random?		b. Check model interpretive power	b. Compare the predictive values to the actuals
c. If there is no stationarity take a normal or both a normal and a seasonal difference	c. Which are the possible values of SARIMA trend and seasonal components?			
d. Check again sequence chart				
e. Check again ACF, PACF diagrams				
f. Use augmented Dickey-Fuller test				

Source: (Researcher, 2020)

In the last stage and after determining the adequacy of the models, we made forecasts for the years 2020,2021,2022 per quarter and we compared the predictive values to the actuals.

5. Analysis and results

As we said, the quarterly data for most of the coastal lines show a marginally decreasing or increasing trend and a relatively stable seasonality (repeated) (Figure 1). Using SPSS statistical software, we calculated Winters 'additive and multiplicative model and the additive and multiplicative model of decomposition in every significant route of GCS. Also, we analysed SARIMA models and simple seasonal exponential smoothing models per route. Especially for decomposition method we calculated both trend and seasonality or only seasonality. So, the results concluded a linear trend and seasonal indices per quarter.

The time series on the coastal lines of Greece were examined for the first time, so we considered it expedient to find the optimal parameters for each method used. That is, those values that minimize the RMSE criterion (table 3). With SPSS finding the best values of α, β, γ is no longer the problem (Tamber, et al., 2021). An exception was the SARIMA method where the approach was done step by step, as described in the methodology. In this case too, however, the exported model was compared with the excellent one via SPSS (through SPSS modeler). In case of conflicting results our main selection criteria were RMSE and normalized BIC. Moreover, through the stationary R squared we performed the

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interpretation power of the selected model and with the use of the Ljung - Box test we checked its adequacy. Then we made a forecast for the year 2022, which was our final goal, as under positive conditions there will be a return to normalcy (after COVID-19 pandemic).

Most forecasts gave us MAPE below 20%, so the best fitted methods describe relatively good forecasts. Particularly, our analysis revealed that surprisingly eight of fourteen itineraries (including total passenger traffic) integrated better to Winters 'multiplicative method (figure 6 and table 3). It proved the better model for the short - term quarterly seasonality as many researchers have shown (Makatjane & Moroke, 2016; Dingari, et al., 2019). Other itineraries fitted better to SS model and only in "PD" the best method was DMTS. No line led to better results through the SARIMA models. The choice of SS and WM methods shows that smoothing methods show satisfactory accuracy rates in relation to SARIMA models and in general in relation to more complex forecasting methods (Petropoulos & Asimakopoulos, 2013). This is because they are not affected by the peculiarities of the data patterns or by occasionally occurring extreme values.

What we noticed is that in all lines selected by WM method the trend parameter β was almost zero, which means that the passenger traffic trend does not change over time. The slope of the trend line was constant during the observation period. In some lines the value of the parameter α (level) was quite large (eg "PAII") which shows that in this case more weight is given to the most recent observations and very little weight to the most remote ones (Agiakloglou & Oikonomou, 2019; Trull, et al., 2020). In lines where the value of α was lower, the smoothing of time series was more intense, with the respective forecasting models fluctuating around the initial level and being slow to follow large changes in the historical data. The high weighting parameter γ for seasonal components showed for the majority of itineraries that seasonal factor has great influence. This is reasonable because of the observed seasonality in GCS. An exception is "PC" line where the low value of γ indicates a stable seasonal effect (Vujko, et al., 2018). For all coastal lines the Ljung - Box statistical criterion showed that the errors had white noise behavior and the models were adequate. Also, in all lines the coefficient of determination R squared was relatively high, which shows the good interpretive power of the models.

The lines that SPSS showed SS as the best model, the conclusions vary. The rule is that the seasonal factor has a significant influence, except for "VNSK" line where there is a constant seasonal effect. The smoothing parameter of level differs per route, considering the importance of older or newer data. The resulting models, outside the "VNSK" line, are adequate and with relatively high data adaptability. "PD" line was the only one that gave DMTS as the best model. The -2287 slope of the linear trend equation shows an average decrease of 2287 passengers per quarter. The corresponding values of seasonal indices show that passenger traffic is increased in the second and third quarters and decreased in the first and fourth. However, the MAPE clarifies a marginally good forecast.

In conclusion, by comparing predictive values to the actuals, interesting results emerged. For the first quarter of 2020, when covid-19 pandemic had not fully prevailed, in eight to fourteen lines the percentage deviation was under 30% (figure 3 and 4) and the average deviation in all lines was 36.7% (including "T"). Indicatively, in "PDM" line was -0.72%, and in "T" (total passenger traffic) was 34.6% (figure 4). Also, in all lines the actual passenger traffic was inside the upper and low bound of the forecast. Considering firstly that the forecasting methods gave more positive results than the real ones, because of the long-term upward trend of tourist arrivals and secondly that the Greek government took the first restrictive decisions for passenger traffic in March of 2020 (a month of the first quarter), we have to do with a relatively good forecasting result.

Figure 3: Average deviation between real data and forecast on 13 coastal lines in GCS (1st quarter of 2020).	**Figure 4: Deviation between real data and forecast of tota traffic ("T") in GCS (1st quarter of 2020).**

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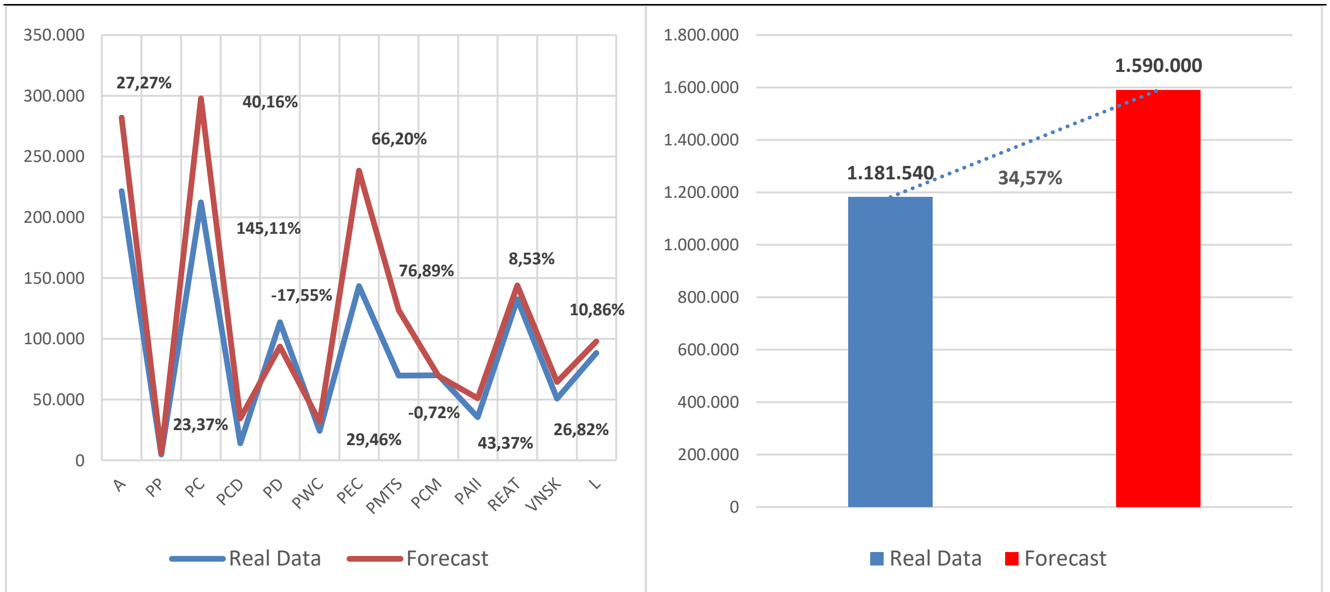

Source: Researcher (2020)

6. Conclusions and discussion

GCS is one of the biggest in Europe and covers about 17% of total passenger shipping. It plays an important role for Greek economy and society. There are not a lot of scientific efforts in forecasting passenger traffic in Greece. In order to fill this gap, the main goal of this study was to find an optimal forecasting method, by comparing Box-Jenkins ARIMA, smoothing and decomposition methods. As GCS consists of several concentrated submarkets (lines) we remained in fourteen popular itineraries (including total passenger traffic). Taking into consideration the high seasonality and no stationarity that characterizes those routes we limited our analysis to Winter's triple exponential smoothing, the time series decomposition method, the simple seasonal model and the seasonal ARIMA models.

Even if we followed a careful step by step approach for SARIMA models ("recognition", "assessment", "adequacy", "forecasting and feedback") no coastal line led to better results by this method. In fact, eight of fourteen itineraries integrated better to WM, five of fourteen to SS and only one to DTMS. Especially for WM it emerged from the analysis that traffic trend did not change over time, in some lines the smoothing of the time series was more intense, and the seasonal factor had great influence. The suggested models were adequate with relatively high interpretative power. About SS method the smoothing parameter of level differed per route and seasonality was of great significance. The resulting models presented high data adaptability. In "PD" line, where DTMS model seemed the best one, the -2287 slope of the linear trend equation shew an average decrease of 2,287 passengers per quarter.

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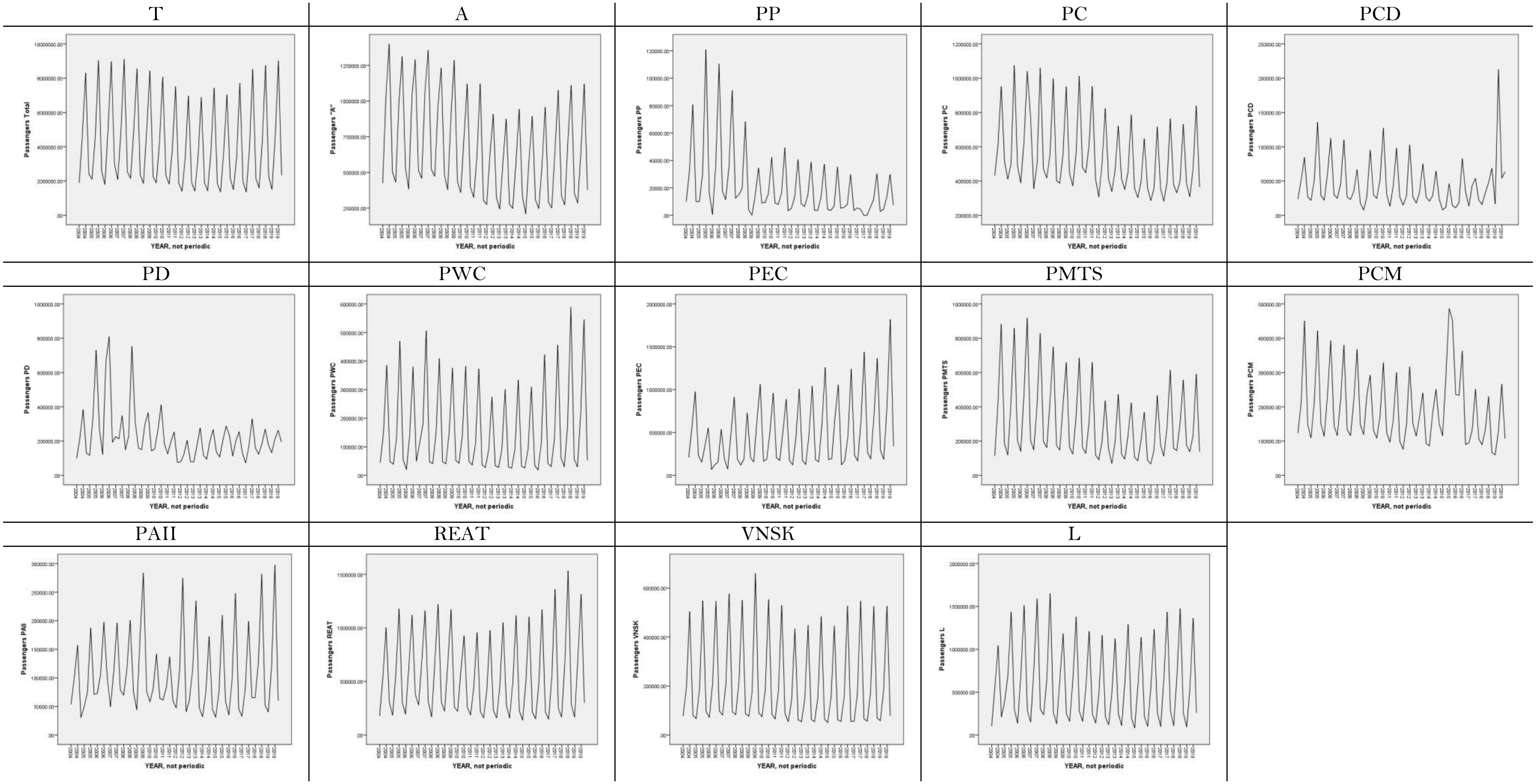

Figure 5: Sequence charts of passenger traffic of the main coastal itineraries in Greece (2004-2019) (data on quarterly basis).

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Table 3: Best fitted forecasting methods for all lines in GCS (2004-2019).

ROUTE	BEST METHOD	OPTIMAL PARAMETERS OR FORECASTING EQUATIONS	Decision Criteria				Stationary R^2		Forecast (2022)			
			MAPE	MAE	RMSE	BIC		Ljung-Box (sig)	Q1	Q2	Q3	Q4
T	WM	α (level)=0.306 β (trend)=0.000 γ (seasonal)=0.686	6.039	215260.3	294890.3	25.384	0.482	0.913	1540000	4370000	8710000	2220000
A	WM	α (level)=0.357 β (trend)=0.000 γ (seasonal)=0.686	6.749	39243.2	53079.5	21.954	0.538	0.748	259080	623203	1020000	324689
PP	SS	α (level)=0.110 δ (seasonal)=0.872	82.142	6054.2	10448.6	18.638	0.403	0.840	5822	13977	30044	6825
PC	WM	α (level)=0.285 β (trend)=0.001 γ (seasonal)=0.020	8.019	42879.3	61744.5	22.256	0.733	0.412	278050	388919	688388	348976
PCD	SS	α (level)=0.118 δ (seasonal)=0.596	27.673	12782.6	27146.1	20.548	0.493	0.977	34561	146343	62183	65877
PD	DMTS	☑ Yt=303722-2287t ☑ Seasonal indices per quarter: 1: 0.60398 2: 1.08655 3: 1.63551 4: 0.67396	29.765	-	108750.6	-	-	-	82617	146142	216239	87566
PWC	WM	α (level)=0.152 β (trend)=0.000 γ (seasonal)=0.566	15.982	19917.6	32556.8	20.976	0.646	0.359	31786	195435	552708	55475
PEC	WM	α (level)=0.341 β (trend)=0.000 γ (seasonal)=0.375	23.695	80663.3	115526.3	23.509	0.595	0.769	253116	942605	1960000	349748
PMTS	WM	α (level)=0.228 β (trend)=0.000 γ (seasonal)=0.768	12.544	31153.9	44033.5	21.580	0.568	0.051	111435	205063	478801	121487
PCM	SS	α (level)=0.800 δ (seasonal)=0.940	20.379	34210.7	50724.4	21.798	0.437	0.966	69395	122896	257577	107133
PAII	WM	α (level)=0.800 β (trend)=0.001 γ (seasonal)=0.899	24.531	21330.1	28319.9	20.698	0.630	0.426	51579	128663	281568	60866
REAT	SS	α (level)=0.211 δ (seasonal)=1.000	10.632	47950.9	70316.0	22.451	0.416	0.972	144073	684704	1340000	297672
VNSK	SS	α (level)=0.299 δ (seasonal)=0.000	12.430	17012.7	26667.9	20.512	0.573	0.008	64477	177411	525451	77157
L	WM	α (level)=0.209 β (trend)=0.000 γ (seasonal)=0.411	13.749	58622.3	86110.2	22.922	0.702	0.831	95890	588148	1310000	242620

Source: Research Data (2020)

In general, most forecasts gave as MAPE below 20%, so the best fitted methods described relatively good forecasts. Of course, the results should be treated with caution since COVID-19 pandemic does not allow safe conclusions for the forecasting period 2020-2022 in GCS. However, the forecasting of the first quarter of 2020, when pandemic had not fully prevailed, gave encouraging results with little deviations between predicted and actual values.

Further research could be done by using and testing time series data of this analysis against different data tools and methods. By this way the effectiveness of our forecast could be tested and challenged, and possibly higher levels of accuracy achieved.

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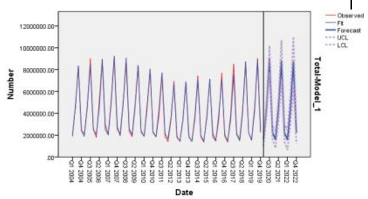
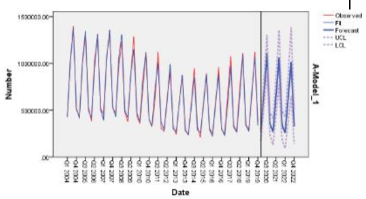
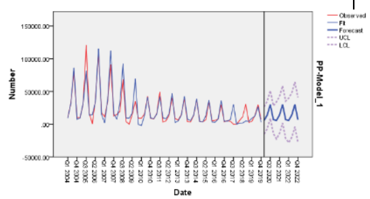
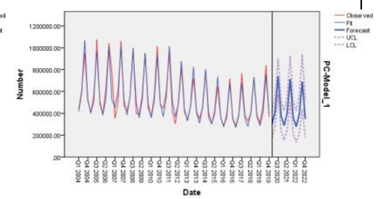
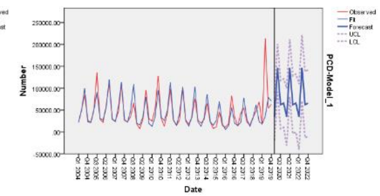
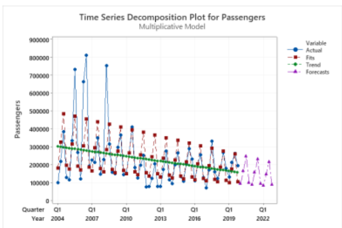
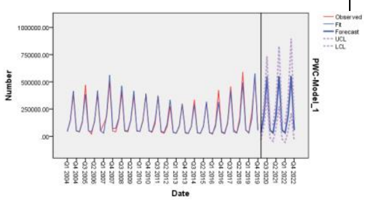
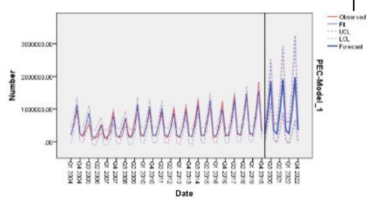
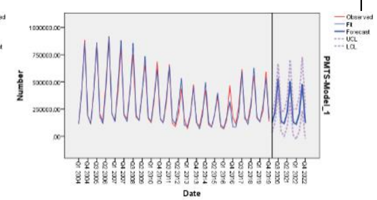
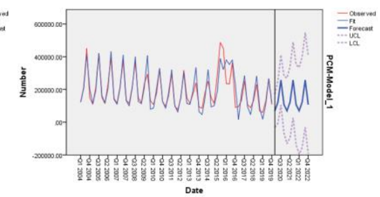
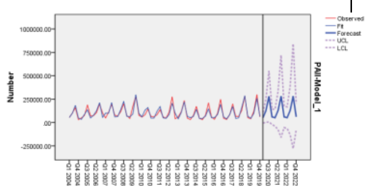
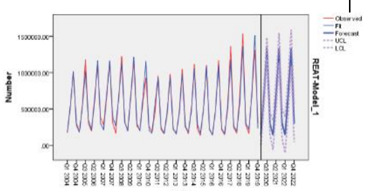
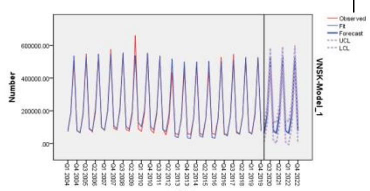
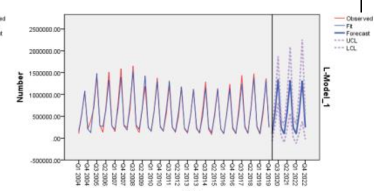
T (method: WM)	A (method: WM)	PP (method: SS)	PC (method: WM)	PCD (method: SS)
				
PD (method: DMTS)	**PWC (method: WM)**	**PEC (method: WM)**	**PMTS (method: WM)**	**PCM (method: SS)**
				
PAII (method: WM)	**REAT (method: SS)**	**VNSK (method: SS)**	**L (method: WM)**	
				

Figure 6: Best fitted method and forecasting results for the main coastal itineraries in Greece (2020-2022) (data on quarterly basis).

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Nomenclature

GCS	Greek Coastal Shipping
WM	Winters' Multiplicative method
DTMS	Decomposition Multiplicative Trend and Seasonal method
SS	Simple Seasonal method
SARIMA	Seasonal ARIMA models
ACF	Autocorrelation
PACF	Partial autocorrelation
GDP	Gross domestic product

References

Agiakloglou, C. N. & Oikonomou, G. S. (2019). *Forecasting methods and decision analysis*. Athens: Benou.

Ahmad, W. & Ahmad, S. (2013). *Arima model and exponential smoothing method: a comparison*. s.l., Department of Mathematics, Faculty of Science and technology.

Aivazidou, E. (2015). *Development of time series and regression models for the assessment of the effects of the economic crisis on maritime passenger and freight traffic in Greece*, Thessaloniki: UTH.

Chalkos, G. E. (2020). *Statistics: Theory and Practice*. Thessaloniki: Disigma.

Chatfield, C. (2003). *The analysis of time series: An introduction*. New York: Chapman and Hall.

Dhali, N., Barman, N. & Hasan, B. (2019). Determination of optimal smoothing constants for Holt-Winter's multiplicative method. *Dhaka Univ. J.*, July, 2(67), pp. 99-104.

Dingari, M., Reddy, M. & Sumalatha, V. (2019). Air traffic forecasting using time series models. *International journal of recent technology and engineering*, November, 8(4).

Goulielmos, A. & Sambrakos, E. (2002). *Ferry and short-sea shipping*. Piraeus: Stamoulis.

Goulielmos, A. & Sitzimis, I. (2012). Measuring market concentration in the Aegean Ferry System. *Spoudai Journal*, 62(1-2), pp. 7-27.

Goulielmos, A. & Sitzimis, I. (2014). The Liberalization process of the Ferry System in Greece, 2001-2009: What have been the benefits to users of Aegean Sea Transportation?. *Spoudai Journal*, 64(4), pp. 39-66..

Gujarati, D. & Porter, D. (2018). *Econometrics: Principles and applications*. Thessaloniki: Tziolas.

Hansun, S., Vincent, C. & Subanar, C. (2019). Revitising the Holt-Winters' additive method for better forecasting. *International journal of enterprise information systems*, 2(15), pp. 43-57.

Hasudungan, A., Pulungan, A. (2021). An Analysis of the Monetary Transmission Mechanism of M&A, Greenfield FDI, Domestic Investment, and GDP Per Capita Growth: The Structural Vector Correction Model in Indonesia. *International journal of business and economic sciences applied research (IJBESAR)*, 14(2), pp. 29-42.

IBM. (2021). *IBM SPSS Forecasting: Build expert forecasts in a flash*. [Online] Available at: https://www.ibm.com/downloads/cas/OP3RLVLR

IOBE. (2014). *The contribution of passenger shipping to the Greek economy: performance and prospects*, Athens: Foundation for economical and industrial research.

IOBE. (2020). *The Greek coastal shipping during period 2016-2020: Performance, contribution in economy and prospects*. Athens: Foundation for economic and industrial research.

Karmaker, C., Halder, P. & Sarker, E. (2017). A study of time series model for predicting Jute Yarn demand: Case study. *Hindawi, Journal of Industrial Engineering*.

Kyriakidis, M. (2018). *Telecommunications market analysis and forecasting techniques*. Athens: National and Kapodistrian university of Athens.

Makatjane, K. & Moroke, N. (2016). Comparative study of Holt-Winters triple exponential smoothing and seasonal ARIMA: Forecasting short term seasonal car sales in South Africa. *Risk governance: financial markets & institutions*, 6(1).

Ma, L., Hu, C. & Han, Y. (2018). *ARIMA model forecast based on eviews software*. s.l., IOP conf. series: earth and environmental science 208.

Munarsih, E. & Saluza, I. (2019). *Comparison of exponential smoothing method and autoregressive integrated moving average (ARIMA) method in predicting dengue fever cases in the city of Palembang*. s.l., Journal of Physics: conference series.

Ortuzar, D. & Gonzalez, M. (2002). Inter-island demand response with discrete choice models. *Journal of transport economic and policy*, January, 46(1).

Petropoulos, F. & Asimakopoulos, V. (2013). *Business forecasting*. Athens: Symmetria.

Psaraftis, C., 1994. *Greek coastal shipping system: impact of market deregulation and new technologies on modal split*. Capri, Italy, s.n.

Ramanathan, R. (2001). The long-run behavior of transport performance in India: a cointegration approach. *Transportation research*, 35(A).

Rashidi, S. & Ranjitkar, P. (2015). Estimation of bus dwell time using univariate time series models. *Journal of advanced transportation*, Issue 49, pp. 139-152.

Ravinder, H. (2013). Determing the optimal values of exponential smoothing constants - does solver really work?. *American journal of business education*, May/June, 6(3), pp. 347-360.

Sabry, M., Abd-El-Latif, H. & Badra, N. (2007). Comparison between regression and arima models in forecasting traffic volume. *Australian journal of basic and applied sciences*, 126-136, 2(1).

DOI: 10.25103/ijbesar.143.05

Schwarz, G. (1978). Estimating the dimension of a model. *The annals of statistics*, 2(6), pp. 461-464.

Shim, J. K. & Siegel, J. G. (2001). *Managerial economics*. Athens: Kleidarithmos.

Sim, S., Tay, K., Huong, A. & Tiong, W. (2019). Forecasting electricity consumption using SARIMA method in IBM SPSS software. *Universal journal of electrical and electronic engineering*, 6(5B), pp. 103-114.

Sitzimis, I. (2012). *Aegean coastal market: the consequences of cabotage removal by microeconomic tools*. Thesis. Peiraus: University of Peiraus.

Sitzimis, I. (2021a). Economies of scale in Greek coastal shipping. A survivor analysis, Under review in *European Transport/Transporti Europei journal*.

Sitzimis, I. (2021b). An implementation proposal of innovative pricing in Greek coastal shipping. *Oradea journal of business and economics (OJBE)*, 6(2), pp. 69-77.

Spathi, S. (2005). *A comparison between air and coastal services in internal routes: An econometric estimation of demand*, Athens: Center of programming and economical research.

Suhartono. (2011). Time series forecasting by using seasonal autoregressive integrated moving average: Subset, multiplicative or additive model. *Journal of mathematics and statistics*, 1(7), pp. 20-27.

Tamber, Jighjigh, A., Michael, O. & Ojowu, O. (2021). The Holt-Winters multiplicative model of passengers' traffic forecast of the Nigeria airports. *Internationa journal of engineering in computer science*, 3(1), pp. 35-40.

Trull, O., Garcia-Diaz, J. & Troncoso, A. (2020). Stability of multiple seasonal Holt-Winters models applied to hourly electricity demand in Spain. *Applied Sciences*, February, Volume 10.

Tsekeris, T. (2008). Consumer demand analysis of complementarity-substitution relationships among passenger transport modes in Greece. *International journal of transport economics*, 35(3), pp. 415-449.

Tsui, W., Balli, H., Gilbrey, A. & Gow, H. (2014). Forecasting of Hong Kong airport's passenger throughput. *Tourism management*, Issue 42, pp. 62-76.

Vujko, A., Papic-Blagojevic, N. & Gajic, T. (2018). Applying the exponential smoothing model for forecasting tourists' arrivals - example of Novisad, Belgrade and Nis. *Ekonomika Poljoprivrede*, July, pp. 757-473.

Wang, S., Feng, J. & Liu, G. (2013). Application of seasonal time series model in the precipitation forecast. *Mathematical and computer modelling*, Issue 58, pp. 677-683.

Wardono, Arief, A. & Siti, R. (2016). Arima method with the software minitab and eviews to forecast inflation in semarang indonesia. *Journal of theoritical and applied information technology*, December, 94(1).

Wu, J., Zhong, L., Li, L. & Lu, A. (2013). *A prediction model bases on time series data in intelligent transportation system*. Berlin: Springer.

XRTC, B. c. (2004-2020). *Annual survey on Greek coastal shipping*. Athens: s.n.

Yonar, H., Yonar, A., Tekindal, M. & Tekindal, M. (2020). Modeling forecasting for the number of cases of the COVID-19 pandemic with the curve estimation models, the Box-Jenkins and exponential smoothing method. *EJMO*, 4(2), pp. 160-165.

DOI: 10.25103/ijbesar.143.05