A Model to Enhance the Forecasting Efficiency of Suez Canal Revenues Using Combining Methods

Rania Ahmed Hamed Mohamed

Department of Statistics, Mathematics and Insurance.
Faculty of Commerce
Port Said University
Port Said, Egypt
E-mail: rania.hamed@hotmail.com

Abstract

The Suez Canal is a strategic route for world trade, and its revenue is one of the key resources for the Egyptian economy, hence the improving the forecasting of its revenues is very important. This research paper aims to model the Suez canal revenues using the optimal method of combining with a view to overcoming the inefficiencies of individual models, and to develop the forecasting models using the fundamental change that occurs to the future values of the time series, as it has come to be known that these models do not take into account the expected increase in Suez canal revenues after the construction of the new canal running parallel to the old one.

Key words: Autoregressive Integrated Moving Average (ARIMA); Vector Autoregressive model (VAR); Combining forecasts; Forecasting accuracy.

1. Introduction

The Suez canal is the shortest and fastest route for maritime shipping between Europe and Asia. Its revenue is one of the main resources for the Egyptian economy. With this importance , this paper aims to model the Suez canal revenues by using the optimal method of merging to overcome the inefficiencies of individual models, and improve the forecasting accuracy as well as develop the forecasting models to reflect the fundamental change expected to occur to the future values of the time series.

The forecasts are derived from two different forecasting methods: integrated autoregressive moving average (ARIMA) and vector autoregressive model (VAR).

Several forecast combination methods have been developed in the literature. In this paper, five combination methods are used to test the performance of the different forecasting models, as stated above, Simple Average combination method, Variance-Covariance combination method, Ordinary Least Squares combination method, Discounted Mean Square Forecast Error Combination Method, Weighted Averages based on Information Criterion. The rest of the paper is organized as follows: Section 2, Methodology used. Section 3, the Results of the paper, and finally the Summary and Conclusions.

2. Methodology

2.1 Individual Forecasting Methods

2.1.1 ARIMA

ARIMA is the method proposed by Box and Jenkins in 1976 (Box, G. , and Jenkins, 1976) and remained the most popular models for forecasting univariate time series data untill now (suhartono,and Hisyam, M. 2011) It forecasts future values of time series as a linear combination of its own past values and a series of error. It has been applied in many fields and researches. ARMA model is a combination of autoregressive model (AR) and moving average model (MA). In the case seasonal components are included in the model, the model is called SARMA. The general form of seasonal ARIMA models is (Suhartono, 2011; Shabri, A., 2001):

$$\phi_p(B)\,\Phi_P(B^S)\,(1-B)^d\,(1-B^S)^D\,y_t = \alpha + \theta_q(B)\Theta_Q(B^S)e_t \quad (1)$$

Where:

$$\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$$
$$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 \ldots - \theta_q B^q$$
$$\Phi_p(B^s) = 1 - \Phi_1 B^s - \Phi_2 B^{2s} \ldots - \Phi_p B^{ps}$$
$$\Theta_Q(B^s) = 1 - \Theta_1 B^s - \Theta_2 B^{2s} \ldots - \Theta_Q B^{Qs}$$

ϕ, θ: Autoregressive & Moving average coefficients respectively.

Φ, Θ:Seasonal Autoregressive &Seasonal Moving average coefficients respectively.

p, q : are orders of non-seasonal autoregressive and moving average parameters respectively

P, Q: are orders of the seasonal autoregressive and moving average parameters respectively

α : Constant.

y_t : observation at time t.

B : Back shift operator.

e_t : Random error(zero mean& constant variance).

D : Nonseasonal order of differences

D : Seasonal order of differences.

S : Degree of seasonality.

2.1.2 VAR Model

The Vector Autoregression (VAR) model was first suggested by Sims (1980). It is one of the most successful, and flexible to be used for analysis of multivariate time series. The VAR model has proved to be useful for describing dynamic behavior of economic and financial time series and forecasting (Zivot, E.,and Wang,J.,2006). The model treats all the variables as endogenous, and each variable is specified as a linear relationship of the others ,as shown below. (Renani, H., 2011).

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + B_0 x_t + \cdots + B_q x_{t-q} + CD_t + u_t \qquad (2)$$

Where:

$y_t = (y_{1t}, \dots, y_{Kt})'$: is a vector of K observable endogenous variables.

$x_t = (x_{1t}, \dots, y_{Mt})'$: is a vector of M the exogenous variables.

D_t : Includes all pre-determined variables such as the intercept, linear trend and seasonal dummy variables.

u_t : *Is a K*- dimensional unobservable zero mean white noise process with positive definite covariamatrix

A_i, B_j, and C are the coefficient matrices with suitable dimensions.

The optimal lag order for VAR (p) model is chosen by minimizing one of the following information Criteria :"Akaike Information Criterion (AIC)","Schwartz information Criterion (SIC)","Hannan- Quinn Criterion (HQC)"and Final Prediction Error (FPE)" which are defined as follows: (Zivot, E.,and Wang,J.,2006 ; Lutkepoh.H.,Kratzig,M.,and Boreiko,B., 2006 Khim,V.,and Liew,S.,2004):

$$\text{AIC} = -2T[\ln(\hat{\sigma}_P^2)] + 2p \quad (3)$$

$$\text{SIC} = ln\ (\hat{\sigma}_P^2) + pln(T)]/T \quad (4)$$

$$\text{HQC} = ln(\hat{\sigma}_P^2)] + 2T^{-1}p\ ln[\ln(T)] \quad (5)$$

$$\text{FPE} = \hat{\sigma}_P^2(T - p)^{-1}(T + p) \quad (6)$$

Where $\hat{\sigma}_P^2 = (T - p - 1)^{-1} \sum_{t=p}^{T} \hat{\varepsilon}_t^2$, ε_t is the model's residuals and T is the sample size.

2.2 Forecasting Combination

Combining forecasts have been proved by many researchers and practitioners to be an effective way to improve forecasting accuracy (Li, W., Lee , C., and Wong, A., 2012) Bates and Granger (1969) have introduced the combining forecast to overcome the deficiency resulted from using an individual model (Bates,J.M.,and.Granger,C.W.J,1969) , as it is often considered as successful alternative to the use of an individual forecasting model (Hibon,M.,and Evgeniou,T., 2005). Clemen provide an exhaustive review of the combining method applied, and concluded that the combining forecasts should be a part of forecasting practice mainstream (Clemen, R., 1989).The combination concept is widely used in diverse fields , especially useful in case of uncertain about the situation, uncertain about which method is most accurate and to avoid large errors, Combined forecasts were sometimes more accurate than their most accurate components [Armstrong. J, 2001]. In this part, five combination methods are used to test the performance of the forecasting :

2.2.1 Simple average (SA) Combination method

The simple average method is a straightforward combination method, which assigns the equal weight to each individual forecast. The simple average combination method calculates the composite forecasts without taking the historical performance of the individual forecasts into account, the simple average combination method can be expressed as: (Shen.S.,Li,G.,and Song,H.,2008)

$$f_c = \sum_{i=1}^{n} w_i f_i \qquad (7)$$

Where: f_i is the i^{th} single forecast; f_c is the combined forecast generated by the n single forecast f_i , w_i is the combination weight assigned to f_i ; and n is the total number of individual forecasting models. The weights can be specified as (Wong, K., Song, H., Witt, S. F., and Wu, D.C., 2007; Cang, S., 2009):

$$\mathbf{w_i = \frac{1}{n}} \qquad (8)$$

2.2.2 Variance-Covariance(VACO) Method

The variance-covariance method was proposed by Bates and Grager (1969). It calculates the weights by taking the historical performance of the individual forecasts into consideration. Suppose the combined forecasts from two unbiased forecasting models are given as: (Shen,S., Li, G.,and Song,H.,2011 ;Wong, K., Song, H., Witt, S. F., and Wu, D.C., 2007)

$$\mathbf{f_{ct} = wf_{1t} + (1 - w)f_{2t}} \qquad (9)$$

- Where f_{ct} Is the combined forecast based on the individual forecasts of f_{1t} and f_{2t} , w and $(1-w)$ are the weights assigned to f_{1t} and f_{2t} respectively. The weight that minimizes the combined forecast variance is:

$$w = \frac{\sigma_{22}^2 - \sigma_{12}}{\sigma_{22}^2 + \sigma_{11}^2 - 2\sigma_{12}} \quad (10)$$

Where σ_{11}^2 and σ_{22}^2 are the unconditional individual forecast error variance and σ_{12} is the covariance. In practical Bates and Granger (1969) suggested the next Formula to combine the forecasts:

$$w_i = \frac{\sum_{t=1}^{T} e_{1t}^2}{\sum_{t=1}^{T} e_{1t}^2 + \sum_{t=1}^{T} e_{2t}^2} \quad (11)$$

Where e_{1t} , e_{2t} are individual forecast errors, and T is the sample size, and for more than two individual forecasts the weights can be calculated, according to Fritz, Brandon, and Xander (1984), by :(Shen.S.,Li,G.,and Song,H.,2008)

$$w_i = \frac{[\sum_{t=1}^{T} e_{it}^2]^{-1}}{\sum_{i=1}^{n}[\sum_{t=1}^{T} e_{it}^2]^{-1}} \quad (12)$$

It is noted that w_i in (12) satisfies the constraint $\sum_{i=1}^{n} w_i = 1$.

2.2.3 Ordinary Least Squares Combination Weights

Granger and Ramanathan (1984) suggest to use ordinary least squares to estimate the optimal combination weight (Genre,V.,Kenny,G.,Meyler,A.,and Timmermann,A.,2010). In this method the individual forecasts are used as regressors in an ordinary least squares regression (OLS). The weights computed using the historical sample data. Hence, the expectation equation is shown as follows (Zhang,F.,and Roundy,R.,2004;Hsiao,C.,and Wan,S.,2011):

$$Y = X\beta + \varepsilon \quad (13)$$

Where y is an $n \times 1$ vector of actual demand in periods 1....n, X is an n×k forecast matrix, β is a k × 1 vector of unknown weights and ε is an $n \times 1$ vector of errors with distribution $N(0,\sigma^2 I)$.

2.2.4 Discounted Mean Square Forecast Error (DMSFE) Combination Method

The discounted MSFE method was proposed by Bates and Granger (1969) for a two individual forecast case and subsequently generalized by Newbold and Granger (1974) for n-individual-forecasts combination. The combination of n-individual forecasts for period (t) is given as below:(Cang, S., 2009;Shen,S., Li, G.,and Song,H.,2011; Stock ,J.,and Watson, M.-,2004)

$$f_{ct} = \sum_{i=1}^{n} w_i f_{it} \tag{14}$$

Where f_{it} is the forecast for period t from forecasting method i, w_i is the weight assigned to individual forecast i and n is the number of individual forecasts. The weight of the DMSFE of the combined forecasts is defined as:

$$w_i = \frac{\left[\sum_{t=1}^{T} \beta^{T-t+1} e_{it}^2\right]^{-1}}{\sum_{i=1}^{n}\left[\sum_{t=1}^{T} \beta^{T-t+1} e_{it}^2\right]^{-1}} \tag{15}$$

β is selected discounting factor with $0 < \beta < 1$. (Shen.S., Li,G.,and Song, H.,2008).In practice, a few values of β close to 1 (such as 0.80, 0.90 and 0.95) are pre-selected to calculate the weights and the one that produces the most accurate combination forecasts would be selected. T and n denote the observation lengths used to obtain the weights and the number of combined single forecasts, respectively, and the e_{it}^2 forecast error obtained from the model i for observation t.

2.2.5 Weighted averages based on Information Criterion.

- In this method the Akaike's Information Criterion (AIC) or Bayesian Information Criteria (BIC) is computed for each model, mentioned before (Acquah,H,2012; Burnham,k.p.,and Anderson,D.R.,2004):

Let IC_i denote the AIC or BIC for the *i*-th model and

$$\Delta\, IC_i = IC_i - min_j IC_j \qquad (16)$$

where $min_j IC_j$ is the lowest IC value across the models , the weights are: (Hsiao,C.,and Wan,S.,2011;Clark,T.E., and McCracken,M.W.,2006)

$$\mathrm{w_i} = \frac{\exp(-0.5\Delta \mathrm{IC_i})}{\sum_{\mathrm{j=1}}^{\mathrm{N}} \exp(-0.5\Delta \mathrm{IC_i})}, \mathrm{i} = 1, \dots \dots \dots \dots, \mathrm{N} \qquad (17)$$

2.3 Forecast Evaluation .

There are several error measures to compare the forecasting performance of different forecasting methods, the most frequently used measures are:(Moghaddasi,R., and Badr,B.R.,2008; Pattranurakyothin T., and Kumnungkit, K. ,2012)

- Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{n}} \qquad (18)$$

- Mean Absolute Error (MAE)

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|y_t - \hat{y}_t| \qquad (19)$$

- Mean Absolute Percentage Error (MAPE).

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \times 100\% \qquad (20)$$

- A simple relative accuracy measure is the Theil Inequality Coefficient (U) defined as follows:

$$U = \frac{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}}{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t)^2} + \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\hat{y}_t)^2}} \qquad (21)$$

Where $\hat{y}_t$& y_t are the forecasted and actual values respectively; n is the number of data forecasted values.

3. Empirical results

3. 1 Data

In this paper, data are collected from Suez Canal Authority. The time-series data used in this paper is monthly data and covers a period from January 1990 to November 2013 (288 observations). The data have been divided in two parts: first part, from January 1990 to December 2010 (252 observations), is used for building a model and second part, from January 2011 to December 2013 (36 observations), for testing the model.

3.2 Individual forecasting models.

In this paper, one time series method (seasonal ARIMA) and one econometric method (VAR) are used to generate the *ex post* forecasts. The selection models applied in this paper is based on the ground that these methods have been widely and successfully used in forecasting.

3.2.1 ARIMA modeling

The aim of this part is to construct adequate Seasonal ARIMA models, using Box-Jenkins method, and to implement them in order to forecast short run of the Suez Canal revenues. However, the existing literature on forecasting the Suez Canal revenues so far, had not adopted SARIMA modelling. Therefore, this paper intends to fill this gap.
Preparation of data: at this point, emphasize is made on data characteristics to see whether any transformation is needed. The original time series plot is shown in figure (1). The first thing noted is general increasing trend and seasonal pattern, which implies a seasonal ARIMA model; values increase over time, which is referred to as non-stationarity in the variance of the data. Further, no extreme and unusual specificities are present in the data.

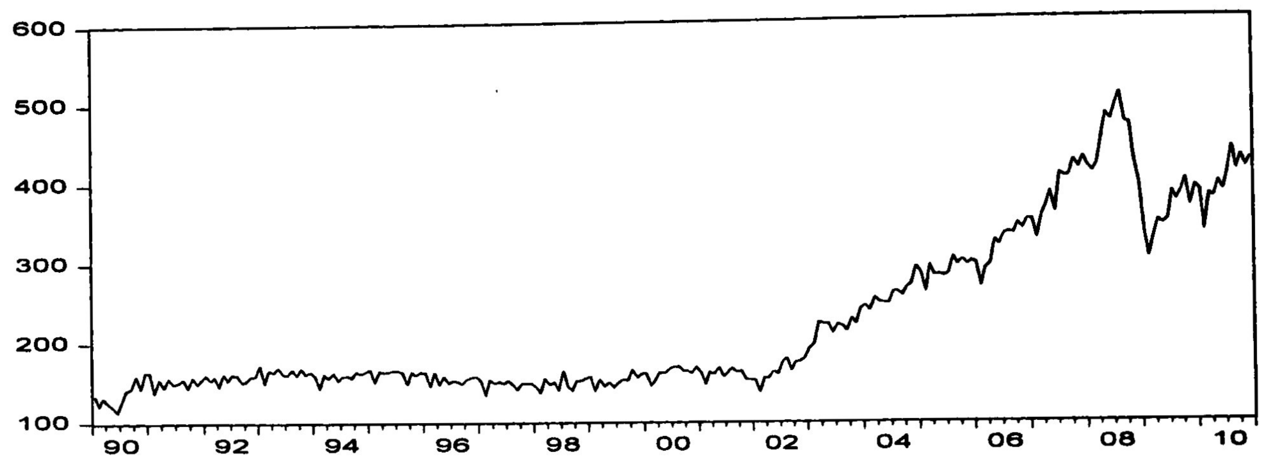

Fig (1) the Suez Canal revenue data from January 1990 to December 2010

The logarithmic transformationis used to get a time series stationary in its variances, and then applied Augmented Dicky-Fuller (ADF)is applied to test stationary of time series. What is needed to ensure that they stationarity assumption is satisfied as shown in table (1) is to put order differencing first. Then, seasonal difference at lag 12 is used to obtain stationary series.

Table (1) : Results of ADF test for Revenues data

ADF			
Level		First difference	
Test	Prob	Test	Prob
-1.2816	0.8783	-7.6271	0.01

* Using R package

Once stationarity and seasonality have been addressed, the next step is to identify the suitable model. Here comes the selection of SARIMA model based on Akaike's Information Criterion and Bayesian information Criteria. Throughout examining several proposed models, it is found that the suitable model in the datasetis SARIMA (2,1,2) $(1,1,0)_{12}$.The results of estimated SARIMA model are presented in the table (2).

Table (2): Estimation SARIMA $(2,1,2)(1,1,0)_{12}$

Coefficients:

	ar1	ar2	ma1	ma2	sar1
	-0.6339	-0.0098	-0.1763	-0.8236	-0.6173
s.e.	0.1532	0.0735	0.0677	0.0652	0.1499

sigma^2 estimated as 0.003083: log likelihood = 364.74, AIC = -717.48

* Using R package

3.2.2 VAR Model

In the VAR model, loading influence variable is taken as inter-effect variable to do the structural model ,After that ,the steps of the process VAR method are done as mentioned before.

In order to study the relations between variables for the time under study, the optimum lag is determined. For this purpose, the model selection criteria are used: Akaike information criterion, Schwartz criterion, Hannan- Quinn criterion and final prediction error. The results show that the optimum lags, according to SC criterion, is 2 lags, whereas the FPE, HQ & AIC criterion indicate the optimal lag number is p=4.

Here one of them is determined based on the diagnostic tests. The absence of serial correlation, heteroscedasticiy and if the error process is normally distributed. Asymptotic portmanteau test is used: Autoregressive conditional heteroscedasticity (ARCH) LM test, Breusch-Godfrey LM serial correlation test and Jarque-Bera (JB) normality test. Considering the results, data in lag 4 is proved to be good as shown in table (3).

Table (3) VAR Estimation

rev = rev.l1 + load.l1 + rev.l2 + load.l2 + rev.l3 + load.l3 + rev.l4 + load.l4 + const + trend

	Estimate	Std. Error	t value	Pr(>|t|)	
rev.l1	0.82489	0.07779	10.605	< 2e-16	***
load.l1	-0.71763	0.29769	-2.411	0.01668	*
rev.l2	0.37160	0.09380	3.962	9.84e-05	***
load.l2	0.03218	0.30387	0.106	0.91575	
rev.l3	0.05310	0.09334	0.569	0.56995	
load.l3	0.09679	0.30318	0.319	0.74981	
rev.l4	-0.32387	0.08004	-4.046	7.03e-05	***
load.l4	0.84449	0.29499	2.863	0.00457	**
const	0.23380	3.41589	0.068	0.94549	
trend	0.04836	0.02339	2.068	0.03974	*

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 13.55 on 238 degrees of freedom

Multiple R-Squared: 0.9821, Adjusted R-squared: 0.9814

F-statistic: 1450 on 9 and 238 DF, p-value: < 2.2e-16

* Using R package

3.3 Forecasting Combining.

This part aims to examine whether combining Suez canal revenue forecasts generated from different models can improve forecasting accuracy.

The combined weights related to the variance-covariance combination and discounted MSFE methods are calculated from the previous performance of the single model forecasts. Optimal weights calculated from the previous 20 forecasts were assigned to the 21th forecast. This step was then continuously moved one-step ahead until the combination series included all 16 observations. In terms of discounted MSFE combination, the values of 0.8 and 0.9 were imposed on β in this study. The combination assessment results with β= 0.9, the discounted MSFE combination yields good results.

Forecasts of all methods from 2011:01 to 2013:12 using performance measures were evaluated as shown in table (4).

Table.4 forecast results (Out of sample period)

Model	ARIMA	VAR	SA	VACO	OLS	DMSFE	AIC
RMSE	43.1	23.21	31.15	35.98	21.45	28.14	23.31
MAE	34.58	17.99	24.20	28.53	17.11	21.59	18.04
MAPE	8.27%	4.29%	5.82%	6.84%	4.06%	5.21%	4.31%
U	0.048	0.027	0.035	0.041	0.025	0.032	0.027

The empirical results show that:

- Combining methods based on ordinary least squares outperform all other combining methods in general and the best individual forecasts.
- The Weighted averages based on Akaike's Information Criterion (AIC) Came in second place after OlS method.
- The Discounted Mean Square Forecast Error combination methods, which take historical performance of individual forecasts into account, perform better than Variance-Covariance and Simple average method.
- The forecast Combinations do not always outperform the best single forecasts.
- The relative performance of combination versus single model forecasts varies across methods.
- Whether or not combination forecasts outperform single model forecasts, it depends on the combination technique used.
- The minimum and maximum values of the revenues are 375.3 , 472.9 respectively ,and the forecasted values from OLS, AIC and VAR methods are between the minimum and maximum values as shown in table 5.

No	Actual	ARIMA	VAR	SA	VACO	OLS	DMSFE	AIC
Jan 2011	416.6	422.9300	421.0633	421.9992	422.5046	432.8573	422.5046	421.0820
Feb 2011	388.7	424.5535	419.9420	422.2477	423.4928	430.0094	423.4928	419.9881
Mar 2011	413.5	427.9267	421.6778	424.8022	426.4894	430.7872	426.4894	421.7402
Apr 2011	434.6	428.3455	422.4183	425.3819	426.9822	431.7492	426.9822	422.4775
May 2011	436.6	431.7791	422.2878	427.0334	429.5961	429.4133	429.5961	422.3827
Jun 2011	445.2	432.6327	423.3846	428.0086	430.5056	430.6941	430.5056	423.4770
Jul 2011	449.2	435.5519	423.704	429.6279	432.8268	429.4175	432.8268	423.8224
Aug 2011	**472.9**	436.9261	424.367	430.6465	434.0375	429.6616	434.0375	424.4925
Sep 2011	438.3	439.4478	425.016	432.2319	436.1284	429.1739	436.1284	425.1603
Oct 2011	447.9	441.1655	425.5858	433.3756	437.5821	429.0522	437.5821	425.7415
Nov 2011	435.5	443.4642	426.2463	434.8552	439.5040	428.7212	439.5040	426.4184
Dec 2011	443.7	445.3765	426.917	436.1467	441.1308	428.6457	441.1308	427.1015
Jan 2012	445.8	447.5700	427.5771	437.5735	442.9716	428.3790	442.9716	427.7770
Feb 2012	381.4	449.5886	428.2873	438.9379	444.6893	428.3029	444.6893	428.5003
Mar 2012	428.0	451.7419	429.0048	440.3733	446.5123	428.1556	446.5123	429.2321
Apr 2012	433.1	453.8215	429.7455	441.7835	448.2840	428.0921	448.2840	429.9862
May 2012	435.2	455.9663	430.5123	443.2392	450.1118	428.0314	450.1118	430.7668
Jun 2012	415.9	458.0842	431.2984	444.6913	451.9234	428.0191	451.9234	431.5662
Jul 2012	433.1	460.2367	432.1085	446.1726	453.7672	428.0250	453.7672	432.3897
Aug 2012	446.6	462.3827	432.942	447.6623	455.6113	428.0734	455.6113	433.2364
Sep 2012	435.3	464.5499	433.7974	449.1736	457.4768	428.1449	446.7150	434.1049
Oct 2012	443.1	466.7198	434.6759	450.6978	459.3497	428.2528	447.8164	434.9963
Nov 2012	407.7	468.9049	435.5767	452.2408	461.2394	428.3880	448.9080	435.9099
Dec 2012	424.6	471.097	436.4994	453.7981	463.1395	428.5551	448.9560	436.8453
Jan 2013	405.1	473.3012	437.4438	455.3725	465.0539	428.7504	449.6324	437.8023
Feb 2013	**375.3**	475.5143	438.4092	456.9617	466.9801	428.9749	449.9110	438.7802
Mar 2013	407.4	477.7387	439.3954	458.5670	468.9197	429.2266	450.9020	439.7788
Apr 2013	406.1	479.9731	440.4017	460.1874	470.8716	429.5053	451.8753	440.7974
May 2013	438.1	482.2183	441.4275	461.8229	472.8364	429.8095	452.8512	441.8354
Jun 2013	404.6	484.4736	442.4723	463.4729	474.8133	430.1388	453.3900	442.8923
Jul 2013	429.2	486.7400	443.5354	465.1377	476.8029	430.4914	454.7746	443.9674
Aug 2013	455.4	489.0164	444.6164	466.8164	478.8044	430.8673	455.7200	445.0604
Sep 2013	442.0	491.304	445.7145	468.5092	480.8184	431.2644	457.1300	446.1703
Oct 2013	466.0	493.6017	446.8291	470.2154	482.8440	431.6826	458.7748	447.2968
Nov 2013	442.4	495.9108	447.9596	471.9352	484.8820	32.1199	459.4680	448.4391
Dec 2013	439.6	498.2301	449.1055	473.6678	486.9314	432.5763	460.4076	449.5967

Table 5: the forecasted values and the real observations for 36 out-of-sample data

3.4 Develop forecasting models

This paper focuses on attempting to develop the forecasting methods dealing with time series so as to take into account the occurrence of any fundamental change that may affect the future values of the series. The purpose is to increase efficiency of the forecasting process, e.g., taking into account the expected change in Suez canal revenues after the construction of the new canal, which according to the Suez Canal Authority is expected to increase the Suez Canal revenues by 259 percent due to the following factors:[1]

i. Passage of ships with a draft of up to 66 feet in both directions while currently the canal allows the passage of 8 ships with a draft of 45 feet.
ii. Reducing the time of ship passage through the Canal to 11 hours instead of 18 hours currently.
iii. Elimination of waiting time.
iv. Increasing the passage of ships with different shipments from 49 to 97 ships per day on average.

The previous models did not take into account the expected increase in Suez Canal revenues after digging the new canal, which is expected to increase revenues by 259% according to Suez Canal Authority. Therefore, this section aims to develop forecasting models for the significant change expected to the future values of the time series as a result of new factors or a significant change in the current factors influencing the series values.

The hypothesis that the ARIMA used model is Y_{t1} and the VAR used model is : Y_{t2}, and the percentage of significant change to the future values of the series is R,

Where:

$R = 1$ in case no significant change to the future values of time series occurs and in case any significant change to time series values occurs:

R=percentage of change × probability of its occurrence (22)

Thus, the combining model used in forecasting Suez canal revenues after digging the new Suez canal according to the Ordinary Least

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[1] Suez Canal Authority

after digging the new Suez canal according to the Ordinary Least Squares Combination Weights will take the following form:

$$Y_{tR} = \beta_1 RY_{t1} + \beta_2 RY_{t2} + \varepsilon \qquad (23)$$

Where Y_{tR} : vector of combiend values , Y_{t1} : forecast from ARIMAmodel , Y_{t2} : forecast from VAR model, β is a k × 1 vector of unknown weights and ε : vector of errors distribution.

4. Summary&Conclusions

The paper investigates the performance of forecast combination methods in comparison with individual forecasts in modeling Suez Canal revenues. The combination of forecasts is based on forecasting derived from ARIMA and VAR models.

Results concluded that the Combining methods based on ordinary least squares outperform all other combining methods, and in general, outperform the best individual models used for modeling Suez canal revenues.

The forecasting models of the significant change to future values of the time series were developed after noting that such models did not take into account this change. In the future, it can be concluded that more advanced forecast models can be combined to achieve more accurate results and more effective combination methods can be developed. Research should continue in order to find out the best strategy to improve the forecast accuracy.

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