Seasonality and forecasting analysis of the South-East Asian container freight market

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Abstract

Purpose – While previous studies focused mainly on East Asia to Europe or United States trade routes, in recent years, trade among South-East Asian countries has increased notably. The price of transporting a container is not fixed and can fluctuate heavily over the course of a week. Besides, extant literature only identified seasonality patterns in the container freight market, but did not explore route-varying seasonality patterns. Hence, this study analyses container freight seasonality patterns of the six South-East Asian routes of the South-East Asian Freight Index (SEAFI) and the index itself and forecasts them.

Design/methodology/approach – Data of the composite SEAFI and six routes are collected from the Shanghai Shipping Exchange (SSE) including 167 weekly observations from 2016 to 2019. The SEAFI and individual route data reflect spot rates from the Shanghai Port to South-East Asia base ports. The authors analyse seasonality patterns using polar plots. For forecasting, the study utilize two univariate models, autoregressive integrated moving average (ARIMA) and seasonal autoregressive neural network (SNNAR). For both models, the authors compare forecasting results of original level and log-transformed data.

Findings – This study finds that the seasonality patterns of the six South-East Asian container trade routes are identical in an overall but exhibits unique characteristics. ARIMA models perform better than SNNAR models for one-week ahead test-sample forecasting. The SNNAR models offer better performance for 4-week ahead forecasting for two selected routes only.

Practical implications – Major industry players such as shipping lines, shippers, ship-owners and others should take into account the route-level seasonality patterns in their decision-making. Forecast analysts can consider using the original level data without log transformation in their analysis. The authors suggest using ARIMA models in one-step and four-step ahead forecasting for majority of the routes. The SNNAR models are recommended for multi-step forecasting for Shanghai to Vietnam and Shanghai to Thailand routes only.

Originality/value – This study analyses a new shipping index, that is, the SEAFI and its underlying six routes. The authors analyze the seasonality pattern of container freight rate data using polar plot and perform forecasting using ARIMA and SNNAR models. Moreover, the authors experiment forecasting performance of log-transformed and non-transformed series.

Keywords Forecasting, Log transformation, Neural networks, Recursive forecast, Seasonality

Paper type Research paper

1. Introduction

Containerization of cargoes is one of the epitomes of globalization. The revolutionary advancement in the technology of carrying cargoes (i.e. containerization) facilitated the development of the global supply chain. Containerization enabled smooth intermodal transfers of cargoes between land (truck, rail) and sea (ships). Therefore, the liberalization waves after the two world wars led containerization to heighten its growth in many economies around the globe while reducing the transactional and labor costs related to handling per unit of cargoes (Weisbrod, 2006; Kaukiainen, 2014). Yet as of today, the container freight market is facing uncertain circumstances in its growth.

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In the “Intra-Asia” trade lanes, many countries, like China, Japan, the Philippines, Singapore, South Korea, Cambodia, etc., alone have accounted for 30% of the total global container trade movement in 2017 (UNCTAD, 2018). According to the freight rate data of Container Trade Statistics Ltd., the freight rate index in Intra-Asia was 106 in February 2012 and dropped to 90 in February 2016 (Kawasaki *et al.*, 2019). Since the 2008 crisis, the container industry and its freight rates are facing a slump or freight depression (Wang *et al.*, 2019) until the COVID-19 crisis. Further, the over-supply of large vessels against the lower global demand for cargoes has led to a continued downfall of freight rates in major container trade routes including the Intra-Asia routes (Kawasaki *et al.*, 2019). However, scenarios changed since March 2021 as freight rates in the container shipping market dramatically increased in the aftermath of post-pandemic industrial activity surge. Furthermore, rises in mergers and alliances among shipping lines (consolidation) played a role to reap benefits such as obtaining the capital for vessels and access to new technologies with a promise of share in the global market (Trace, 2002).

In February 2017, the seventh biggest shipping company at the time – Hanjin Shipping – declared bankruptcy proving yet again that even the big players in the container industry are threatened by the freight rate depression (Kutin *et al.*, 2018). The annual report of UNCTAD (2019) states that the yearly expansion of container trade volumes (TEUs) has relatively slowed down to 2.6% in 2018 from 6% in 2017. Although the idle fleet capacity decreased in recent years, it still was at a relatively high 5.64% internationally in 2017 (Kutin *et al.*, 2018). This indicates the higher financial risks associated with the investment decisions in building or purchasing container vessels (Luo *et al.*, 2009).

Today, the container freight rates vary significantly from week to week. As freight rates dictate the profitability of the shipping business, it influences decisions of the seller of ships to the buyer of shipping services (i.e. shippers) including everyone in between such as ship financing banks, charterers, customs, port/terminal operators, brokers, shippers, and freight forwarders. The complexity within the freight rates development mechanism mainly arises from the fact that such a large number of players are involved. Further, each of the aforementioned market players has different objectives. Hence, the analysis of the freight rates in terms of seasonality patterns identification and selection of the appropriate forecasting model is useful for the major maritime players.

In Section 2, we discuss the existing literature on container freight market analysis. Section 3 presents data and applied methodologies. We present the seasonality and forecasting analysis results in Section 4 along with model diagnostic checks. Finally, concluding remarks and future research directions are presented in Section 5.

2. Literature review

The freight market concerns the prices of shipping cargoes (Duru, 2019). Container freight rates are usually calculated under the freights of all kinds (FAK) approach that does not consider what product is inside the box (Slack and Gouvernal, 2011). According to the United Nations Conference on Trade and Development (UNCTAD, 2018), since 2009, there has been improved growth in the container freight rates. Meanwhile, the center of network for container trade movements seems to have shifted from Europe to Asia (Hoffmann and Hoffmann, 2020). The United States and other countries belonging to the European Union are experiencing marginal growth in their imports and exports, whereas the countries of ASEAN (South-East Asian Nations) such as Singapore, Thailand, Malaysia and Vietnam have been experiencing significant growth in their international trade (UNCTAD, 2018). Furthermore, China now has three ports, namely Nansha, Ningbo and Shekou, that have improved the most (Hoffmann and Hoffmann, 2020). Nine of the top ten ports ranked by TEU volume are in East-Asia mainly dominated by China.

In the early stages of container shipping, the conception was that vessels had a regular and scheduled service of carrying cargoes between ports at fixed prices for transportation (freight rates) with low scope for negotiation (Stopford, 2009). The European shipping conference system and the United States–based Transpacific Stabilization Agreement, for discussion of freight rates among the members, were canceled in 2008 and 2018, respectively, contributing to the fluctuation of container freight rates (Munim and Schramm, 2017, 2020). Meanwhile, such discussion forums do not exist for Inter-Asia routes. Also, freight rates nowadays could be influenced by a range of services offered by the shipping lines (Wang *et al.*, 2019).

The global economy is a main macro factor for the growth of the shipping industry as shipping is a derived demand. Therefore, the demand and supply of cargoes have a significant influence on shipping freight rates (Wang *et al.*, 2019). According to Tvedt (2003), the rise and fall of freight rates across different markets are proportional to demand and over-supply of ships in the market. This holds true in the container shipping market as Jeon *et al.* (2019) found that the container freight cycle is 32.299 months, which is lower than other shipping freight cycles. Such short cycles propel the need to make quick and precise judgments by the ship-owners and brokers.

Moreover, shipping freight rates induce seasonal cyclic effects. Within the time of a year, the rates fluctuate between the highs and lows of the seasonal demand for the cargoes they carry (Kavusssanos and Alizadeh, 2001). The container freight rates peak during the Spring – March to May – and Autumn–August to October – months of the year (Yin and Shi, 2018). The yearly seasonal effect on freight rates is usually long term, influences recovering stage of the shipping cycle and can repeat across freight markets in different geographic locations (Yin and Shi, 2018; Wang *et al.*, 2019).

Despite the relevance of container freight market to the global value chain, there have been a limited number of studies on the seasonality analysis and forecasting of freight rates. Nielsen *et al.* (2014) used an experimental model to forecast freight rates from the exploration of the relationship between a company's freight rates and the market rates. Fan and Yin (2016) applied the traditional econometrics to study the causalities between freight rates and other factors such as ship-building prices as well as second-hand purchases. Munim and Schramm (2017, 2020) used time series (such as ARIMA, VAR) and neural network models for forecasting container freight rates. Except for Jeon *et al.* (2019) and Munim (2022), the majority of the existing studies did not account for seasonal cycles in forecasting container freight rates. Still, seasonality exploration on the route-level freight rate is absent. Hence, this study analyses the seasonal patterns in the South-East Asian Freight Index (SEAFI) composite time series and its six underlying shipping routes and forecasts their freight rates.

3. Data and methodology

3.1 South-East Asian Freight Index (SEAFI)

The SEAFI, published weekly by SSE on Fridays, reflects the spot rate changes of exporting general dry containers (excludes other types like reefer and hazardous). The freight rates are taken from the trade lanes between Shanghai and other South-East Asia base ports (SSE, 2020). The price type is based on the cost insurance and freight (CIF) term with the focus on the mainstream trading price, and the statistical concept "mode" is used for the sporadic, non-batch container space bookings by common carriers excluding the prices of long-term agreements or big customers. The freight rate is calculated in US dollars per TEU that includes ocean freight rate (base price) and surcharges such as fuel or bunker price, exchange rate, container or equipment repositioning and other charges related to the operational cost (like terminal handling, space-booking and document charges). The freight rate of individual trade routes is equal to the arithmetic mean of all freight rates on each route in that respective lane as expressed by equation (1).

$$P_i = \frac{1}{n}\sum_{j=i}^{n} P_{ij} \tag{1a}$$

Here, i refers to a SEAFI route, j a sample company, n is the number of route level sample companies and Pij is the reported freight rates by sample company *(j)* on the route *(i)* for a given period.

The SEAFI composite index is calculated as follows:

$$L = \sum_{j=i}^{n} \frac{P_i}{P_{i0}} \times W_i \times L_0 \tag{1b}$$

Here, Pi reflects the average freight rate of route *(i)*, P_{i0} reflects the average freight rate of route *(i)* in the base period of November 30, 2015, W_i is the weight of the route *(i)* and L_0 is the SEAFI value on the base period. Table 1 presents descriptive statistics of SEAFI composite and for the six routes.

3.2 Polar plots

A time series in general comprises of three main components: a trend-cycle component, a seasonal component and a residual or noise component (Hyndman and Athanasopoulos, 2018). The literature review section discussed the prior studies that demonstrated the seasonal nature of freight rates that are high during March and October. Polar graph has a unique way of showcasing the ups and downs in freight throughout the year. When the freight rates are collected over a period of years, most charts cannot clearly visualize the yearly highs and lows. Polar graphs, unlike the general spot or bar charts, have the nature of plotting circularly around the 52 weeks that depicts the repeated trends of highs during March and October and lows in January and June.

3.3 Forecasting methods

Static forecasts are the common forecasting method used to predict freight rates for practical shipping business operations. As explained by Stopford (2009), momentary equilibrium in shipping is about negotiating deals within hours, days or weeks. Hence, short-term predictions of freight rates are of great interest to charterers and shipbrokers. Although forecasting can be performed using simple methods such as the naïve or moving averages,

Routes	Count	Mean	Median	Mode	S.D.	Minimum	Maximum
SEAFI	167	727.44	751.29	351.08	143.72	351.08	1002.52
Singapore	167	132.85	133	140	24.35	54	188
Vietnam	167	185.53	185	207	55.34	57	372
Thailand	167	140.17	141	141	27.98	71	222
The Philippines	167	−50.95	−42	−51	53.93	−146	51
Malaysia	167	225.58	229	231	45.04	112	327
Indonesia	167	268.87	262	293	42.78	180	384

Note(s): The seven routes' count, respective means, medians, modes, standard deviations, minimum and maximum values are depicted
Source(s): Authors work

Table 1.
Descriptive analysis of each route

when there are certain pre-existing properties like stochastic nature, for example, in the case of the SEAFI composite and its six routes, advanced models such as ARIMA and neural networks are likely to yield better forecast performance (Hyndman and Athanasopoulos, 2018). For estimation of model parameters, the Hyndman and Khandakar (2008) algorithm for automatic ARIMA modeling and automatic SNNAR$(p, P, k)_m$ modeling reported in Hyndman and Athanasopoulos (2018) were utilized. These algorithms suggested non-seasonal ARIMA and seasonal-NNAR models for deployment.

Time series data of 167 weeks of observations are split into two samples: training and test. The training sample consists of 151 weeks starting from 21st October 2016 to 6th September 2019, and the test sample consists of 16 weeks starting from week 152, that is, 12th September 2019 till the end of the observations on 27th December 2019.

3.3.1 Log transformation. The SEAFI composite and its six routes' time series data are heteroscedastic. For data with such properties, a logarithmic transformation is useful. Hence, time series data are transformed using natural log except for the Philippines. The Philippines route has negative data points, and therefore, the time series values are divided by ten instead of taking its natural log. In the following sections, the SEAFI composite and each of its six routes' time series are analyzed twice under different forecast methods – once without the log transformation and once with the log transformation.

3.3.2 Stationarity. For identifying the stationarity of the data, the two unit root tests used are Phillips-Perron (1988) and augmented Dickey–Fuller test (ADF) (Dickey and Fuller, 1979). The ADF test evidently showcases that the seven data series level as well as log-transformed time series could not reject the null hypothesis with the p-value higher than 0.05, which implies that all the series had a unit root. But with the first order of difference, the p-value has fallen below 0.01 for all the series thereby rejecting the null hypothesis and also indicating stationarity. This also indicates that the d component for the seven series for ARIMA modeling. The results of Phillips–Perron test are identical to the ADF test. Moreover, the first order differenced time series for both level and log-transformed routes showcase the p-value to be lower 0.01, which supports the alternative hypothesis indicating stationarity in the seven time series. While stationarity is a perquisite to ARIMA models, SNNAR models do not require such modeling of data before forecasting.

3.3.3 ARIMA. ARIMA is made up of three modeling approaches with AR standing for auto-regressive; I for differencing and MA for moving average. The integrated or d component is utilized for achieving stationarity of the time series. ARIMA applies the differencing on the time series, and therefore can be written as:

$$y'_t = \phi_1 y'_{t-1} + \ldots + \phi_p y'_{t-p} + \theta_1 \mathrm{e}_{\mathrm{t}-1} + \ldots + \theta_q \mathrm{e}_{\mathrm{t}-\mathrm{q}} + \mathrm{e}_{\mathrm{t}} \tag{2}$$

Here, y'_t is the differenced series. The "predictors" on the right-hand side include both lagged values of y_t and lagged errors. Equation (2) is an expression of ARIMA (p, d, q) model.

3.3.4 SNNAR. The main reason for forecasting data with the SNNAR method is that SNNAR also allows complex nonlinear relationships between the response variable and its predictors (Hyndman, 2008). In the case of the seven time series, the neural networks have a supervised learning process wherein a particular point in time t equaling to 52 weeks is considered.

The network responds by starting a random prediction using the input variables, helps in the process of modifying the weights and bias in its different layers, and therefore considered as a learning process. Further, in the output or final layer, the difference, i.e. error term between the network's predicted values (starting at week 53) and the actual or desired output values is calculated and returned to begin the process again. This propagates the network forward with new predictions made each time by the modified weights and bias until the difference or error term is reduced to its least. In essence, SNNAR is a process of forecasting that runs multiple times in an iterative process to find the best fit for prediction. Therefore, the formula for a seasonal SNNAR$(p, P, k)_m$ that is utilized in this study's seven series can be expressed as:

$$y_j = \beta_j + \sum_{i=1}^{p} W_{i,j} y_{t-i} + \sum_{i=1}^{p} W_{i,j} y_{t-m} \tag{3}$$

Here, y_j is the estimated value of output node j, βj represents a constant for node j, Wi,j is the weight from the input node i to output node j, $y_{t\text{-}i}$ represents the inputs from ith previous weeks until lag p. Further m showcases the seasonal period of observations, i.e. yearly or monthly.

4. Results and discussion

4.1 Seasonality

Seasonality patterns are evident for the SEAFI composite and its six routes as demonstrated by the polar graphs in Figure 1(a–g). Taking the example of SEAFI composite, it is clearly visible that the index points in week 1 of every year start low at about the range between 600 and 900. Similarly, each of the different routes – Singapore, Thailand, the Philippines, Vietnam, Indonesia and Malaysia – all start and end with low index points for any given year. Another interesting point is the sudden drop of points across all routes in the year 2019 on week 30, which falls in the summer month of July. The onset of tariffs by the US on Asia, especially on Chinese manufactured goods, could have triggered this fall (UNCTAD, 2019).

Although the seasonal fluctuations in freight rates fall at the same time for all the six routes as well as the SEAFI composite, the intensity of the growths and falls varies largely among the routes. Considering the case of Thailand and Vietnam, in the year 2019, there has been a severe dip around the weeks of 36, but the sharp peak from this fall has been seen in these two routes during week 44. It is not the case for a hub port like Singapore or Malaysia. Similarly, there is small peak of rates in Indonesia, Malaysia and Vietnam in the 2nd week of 2017, but the SEAFI composite could not reflect its magnitude and showed a small growth only. Although the big picture, i.e. the average of all six routes, the SEAFI composite, gives a rough estimate on how seasonality plays out for all the routes, there are still variations from route to route.

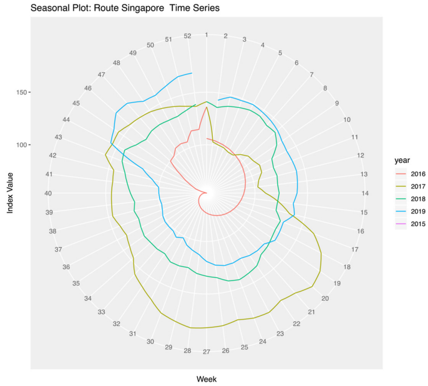
4.2 ARIMA and SNNAR estimations

The best fitting ARIMA and SNNAR models for the seven series that are estimated based on their respective training samples are reported in Table 2. The table presents the selected ARIMA(p,d,q) and SNNAR$(p, P, k)_m$ models for both the level and log-transformed series' training samples. The lag and differencing properties of ARIMA models vary for the different time series. The SNNAR is employed for the seven series for a period of 52 weeks. The most common model for the routes is the SNNAR $(2,1,2)_{52}$ except for the Philippines and log-transformed series of Singapore. The SNNAR$(2,1,2)_{52}$ model has two autoregressive lag inputs *(p)*, one seasonal component *(P)* and two hidden layers *(k)* for 52 weeks. The fitted plots that include the new series from both SNNAR and ARIMA models for the seven series at one-step forecast are plotted in Figure 2(a–g). The graphs on the left are on the level series while the graphs on the right are on the log-transformed series.

Coming to the fit of the models, visually the fitted values for both the forecasting models coincide with the actual training samples of the time series in both level and log-transformed cases. In the case of test samples for the level and log-transformed series, there is a sign of a

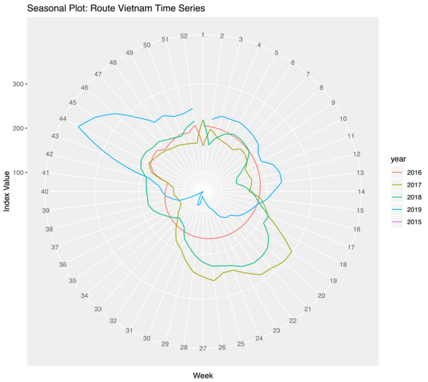
SEAFI Composite

(a)



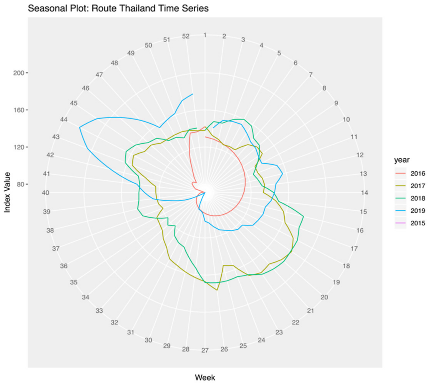
Singapore

(b)



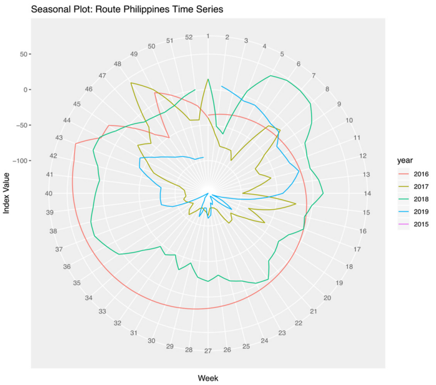
Vietnam

(c)



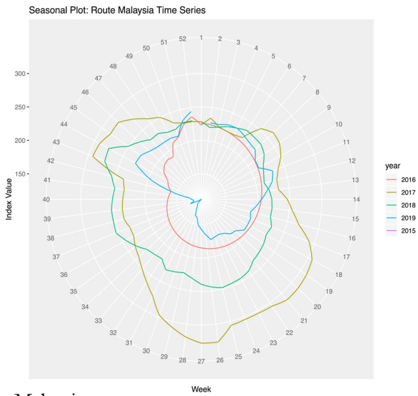
Thailand

(d)



The Philippines

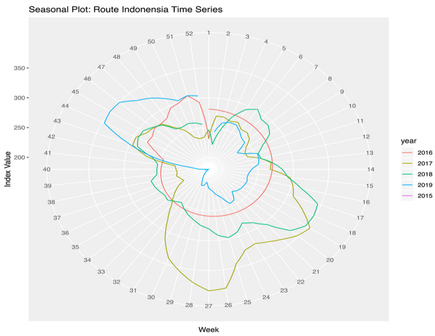
(e)



Malaysia

(f)

Figure 1.
(a–g): Polar plots of the seven time series depicting seasonality



Indonesia

(g)

Source(s): Authors work

Figure 1.

Table 2. Selected ARIMA and NNAR Models for forecasting

Routes	ARIMA-level series	ARIMA-log-transformed series	NNAR- level series	NNAR- log-transformed series
SEAFI composite	ARIMA(3,1,2)	ARIMA(0,1,3)	SNNAR$(2,1,2)_{52}$	SNNAR$(2,1,2)_{52}$
Singapore	ARIMA(1,0,3)	ARIMA(5,0,0)	SNNAR$(2,1,2)_{52}$	SNNAR$(1,1,2)_{52}$
Vietnam	ARIMA(0,1,4)	ARIMA(1,1,0)	SNNAR$(2,1,2)_{52}$	SNNAR$(2,1,2)_{52}$
Thailand	ARIMA(1,1,0)	ARIMA(1,1,0)	SNNAR$(2,1,2)_{52}$	SNNAR$(2,1,2)_{52}$
The Philippines	ARIMA(0,1,2)	ARIMA(0,1,2)	SNNAR$(7,1,4)_{52}$	SNNAR$(7,1,4)_{52}$
Malaysia	ARIMA(1,1,0)	ARIMA(1,1,0)	SNNAR$(2,1,2)_{52}$	SNNAR$(2,1,2)_{52}$
Indonesia	ARIMA(3,1,2)	ARIMA(3,1,2)	SNNAR$(2,1,2)_{52}$	SNNAR$(2,1,2)_{52}$

Note(s): As estimated models are based on training samples, they are the same for both one-step and four-step forecasting. Model parameters of the ARIMA models are available on request
Source(s): Authors work

lack of fit between the forecasted values and actual test sample values. Overall, at one-step forecast for level and log-transformed series, there is no significant lack of fit. Both models seem to be in concurrence with the data, although ARIMA is better in a few cases.

The following Figure 3(a–g) has the fitted and forecast plots of ARIMA and SNNAR models for the seven series at four-step forecasts. Similar to the previous charts, the left side includes the level plots, whereas the right side includes the log-transformed.

In Figure 3, there is an uncanny resemblance in the performance of both the forecasting models when compared between the level and log-transformed series. Considering the SEAFI composite as an example, it is seen that although the ARIMA model properties differ, the forecasts have similarities. The SEAFI composite route level series has ARIMA(3,1,2) as the best fit while the log-transformed has ARIMA(0,1,3).

In most routes' (level and log-transformed) training samples, the fit of both the forecasting models to the actual series seems appropriate, whereas the test sample showcases some degree of inadequacy. In SNNAR models for almost all the routes, predictions are often underperforming to actual. Whereas ARIMA model's forecast values for most routes (for

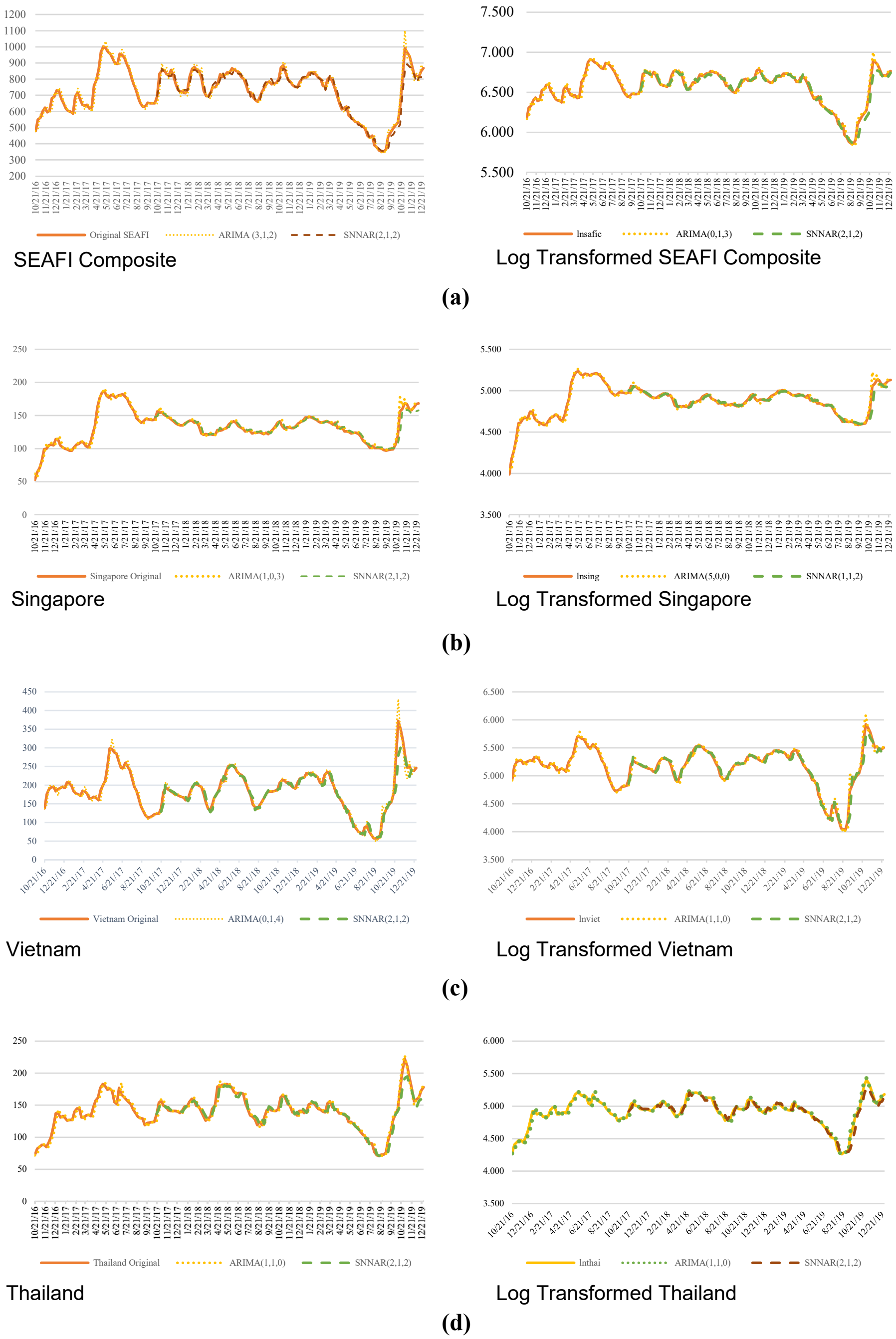


Figure 2.
SEAFI one-step forecasting (level and log-transformed series) using ARIMA and SNNAR

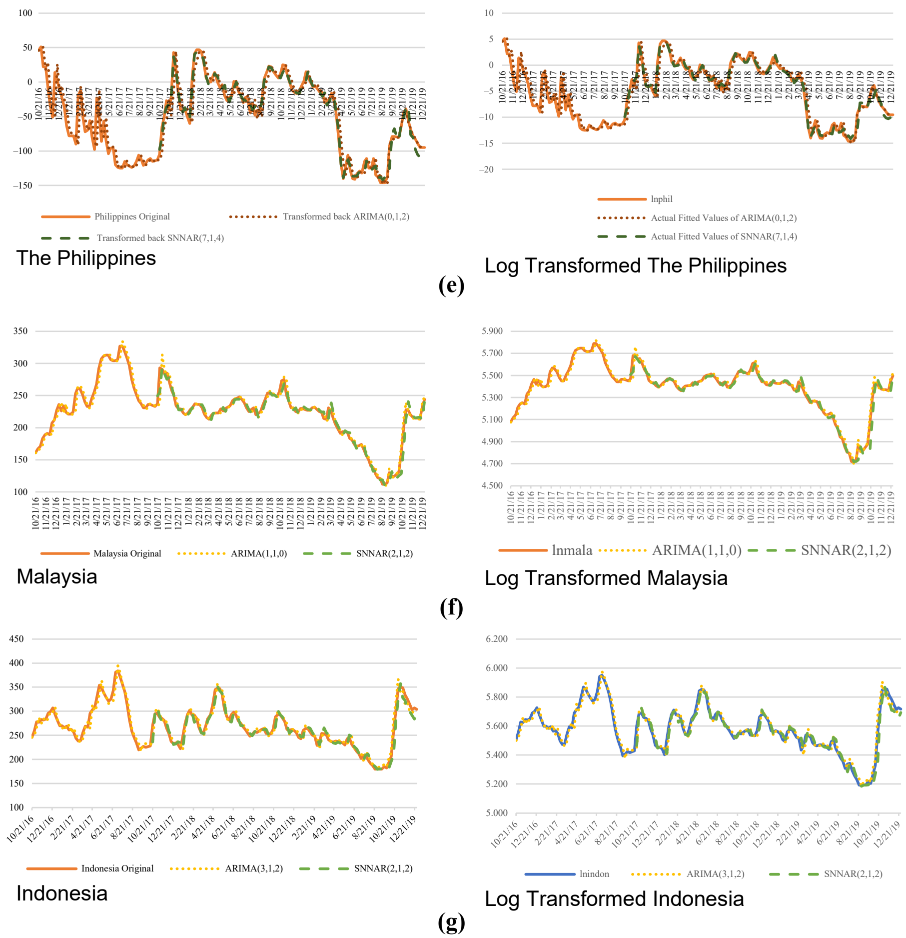


Figure 2.

Source(s): Authors work

level and log-transformed) are relatively volatile compared to the actual with the exception to the Philippines.

From Figure 3, it is understood that for a given route, the fitted values derived from the ARIMA model do not always exactly coincide with the actual. However, to tangibly realize a model's fit, the residuals for the routes (both level and log-transformed series) have been analyzed utilizing residual diagnostics measures. Three tests, namely, the Box–Ljung test on residuals, Box–Ljung test on squared residuals and Jarque–Bera tests on residual are applied to identify autocorrelations, conditional heteroscedasticity and normality, respectively (results available on request). It is found that most routes have low p-values and high statistic values in the Jarque–Bera test, indicating that the residuals of all the seven series are not normally distributed. On the other hand, both the Ljung–Box tests showcase promising results with high p-values with low values of the Q^* implying of the nonexistence of auto-correlations and changing variances in the residuals. Some exceptions include the residuals of the Philippines which in both level and log-transformed

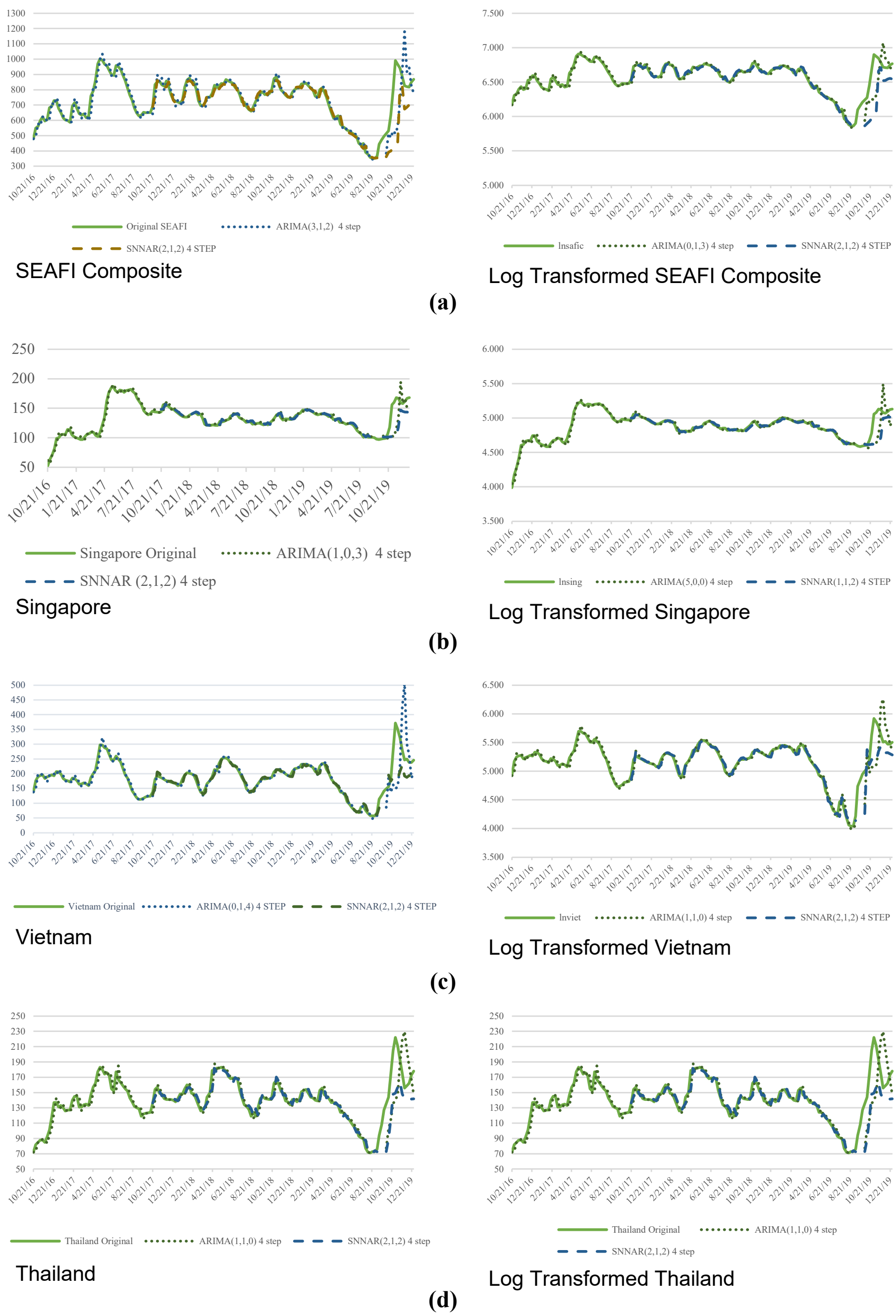


Figure 3.
SEAFI four-step forecasting (level and log-transformed) with ARIMA and SNNAR

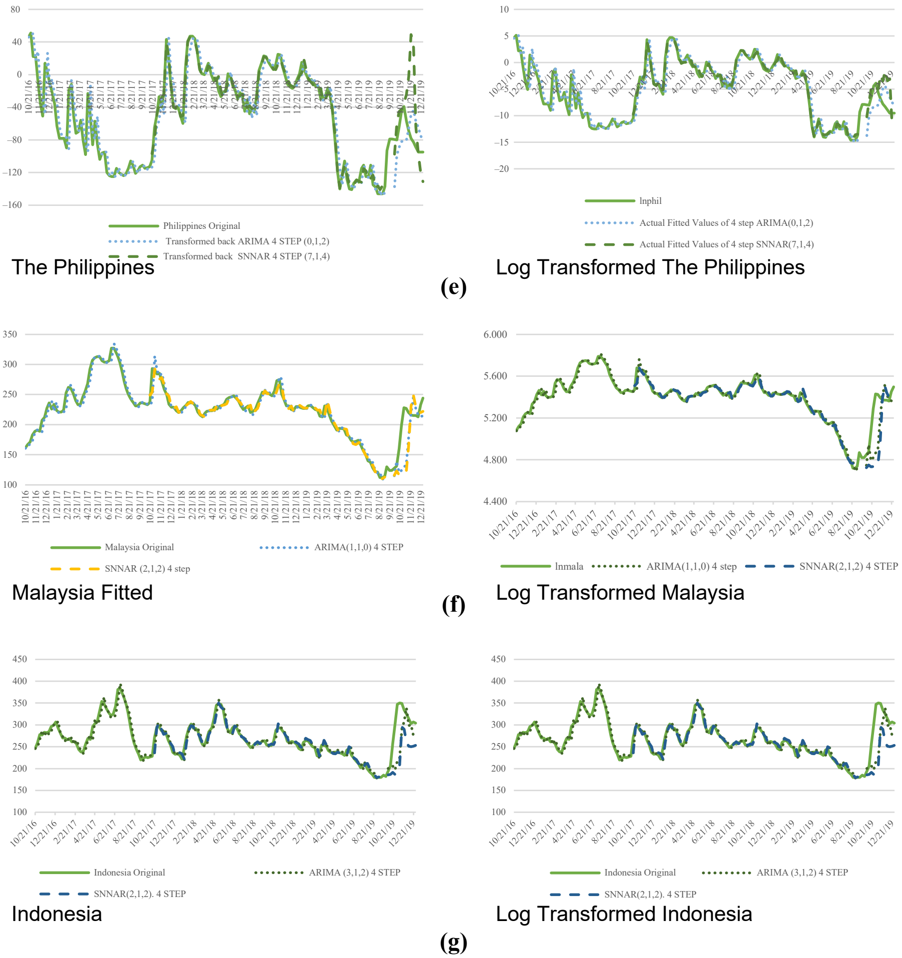


Figure 3.

Source(s): Authors work

cases have a low p-value (<0.05). Similarly, Singapore's residuals of the log-transformed training sample showcase the ARCH effect as in the Philippines. This indicates the need for GARCH modeling that could be studied in the future research. Considering residuals diagnostics on SNNAR method is not necessary since the network on its own trains the models to fit the data as parsimonious as possible.

4.3 Forecast accuracy

The evaluation of each forecasting models has been done by the training and test sample forecast accuracy. The need for doing such is to validate estimated forecast methods. In essence, a forecasting method that has a lower error is considered the most accurate (Ruppert and Matteson, 2015).

Three types of forecast accuracy measures are calculated that include root mean squared error (RMSE), mean absolute percentage error (MAPE) and autocorrelations at lag 1 (ACF1). While RMSE and MAPE are widely used, the ACF1 is considered as a forecast accuracy measure because autocorrelations are a definitive measure showcasing the magnitude of effect of the previous values over the current predicted ones. Based on the number of steps like four-step or one-step, the correlation between the past values and future forecasted values should reduce since the rule of thumb is that the inaccuracy of the forecasts increases with time. Therefore, in the case of four-step ahead forecasts, the ACF1 values are not produced by the software package in R. The ACF1s are only calculated at one-step ahead forecasts using the function *accuracy()* under forecast package. Table 3 reports the forecast performance for one-step ahead training sample forecasting.

Comparing the RMSE of both the forecasting methods for all the log-transformed series, it is evident that the models of ARIMA have higher forecast errors than SNNAR. However, ACF1 for both methods under the same series, it is seen that the routes of SEAFI, Singapore and Vietnam have high positive autocorrelations values under SNNAR. This could explain the reason behind the comparatively accurate predictions of SNNAR with low forecast errors. Nonetheless, considering all three measures, it is evident that SNNAR is forecasting better than ARIMA in the training sample.

Now considering the level series, the RMSE for the SEAFI composite under both forecasting methods stands out. Nonetheless, considering other measures, both MAPE and ACF1 are quite low for the SNNAR model compared ARIMA. Several routes display similar results of low forecast errors under the measures of RMSE and MAPE for the neural network model. It could be said that for the seven series' training samples for both level and log-transformed series under one-step forecast, SNNAR models seem to have greater forecast accuracy. Table 4 reports the forecast performance for one-step ahead test sample forecasting.

Table 4 presents the forecast errors of ARIMA and SNNAR models, calculated for the seven series' test samples (both level and log-transformed). The forecast errors for almost all the routes in the level and log-transformed series reveal contrasting results from the training samples. Except for ACF1 in the routes of Thailand, Malaysia and Indonesia, the rest two errors have a higher value under the SNNAR models. Hence, under one-step forecasting, ARIMA model is better with more forecast accuracy and fewer errors compared to SNNAR.

Considering the multi-step forecast, it is often argued that forecasting one-step, i.e. one day or one week ahead is never sufficient to sustain the business operations. Even in case of freight rates, the view with a bigger reach, i.e. a bigger forecast horizon consisting of four weeks ahead, is preferred (Nielsen *et al.*, 2014). For a given route, the training sample for forecasting under steps 4 and 1 is the same. SNNAR has an iterative estimation process of the fitted values; hence, for the same sample, the model estimates might differ each time they are estimated (available upon request). As mentioned earlier, only MAPE and RMSE are utilized for four-step ahead test sample. Table 5 reports the test sample forecasting performance under four-step ahead forecast. Only the routes of Vietnam and Thailand have lower values for their respective SNNAR models compared to ARIMA. The RMSE values for all routes are high with SEAFI composite going above 200 for both the ARIMA model (at 234.042) and SNNAR model (at 267.39). The high values of forecast errors diminish when the series are under-forecasted under log-transformed, although the Philippines is a slight exception.

Although the log-transformed series have a smaller scale for the forecast errors, they follow the level series by showcasing a superior performance of ARIMA models over the SNNAR models for the same number of data series (5 out of 7) and exceptions (2 out of 7). In its entirety under four-step forecast, ARIMA models forecast precisely for the level and log-transformed series of 5 routes, i.e. SEAFI composite, Singapore, the Philippines, Malaysia and Indonesia. Only for the route of Vietnam and Thailand, the models of SNNAR forecast more reliably than ARIMA models.

Table 3.
Forecast accuracy for the 7 series' level and log-transformed training samples under one-step forecast

Forecast method 1 – ARIMA for training sample of level series at one-step forecast

	Routes							
Accuracy measure	SEAFI composite ARIMA(3,1,2)	Singapore ARIMA(1,0,3)	Vietnam ARIMA(0,1,4)	Thailand ARIMA(1,1,0)	The Philippines ARIMA(0,1,2)	Malaysia ARIMA(1,1,0)	Indonesia ARIMA(3,1,2)	Average
RMSE	30.23	4.006	10.255	6.852	18.669	8.629	9.902	12.649
MAPE	3.095	2.281	4.517	3.491	33.784	2.442	2.855	7.495
ACF1	0.021	−0.061	−0.059	2.22E−05	−0.005	−0.001	0.007	−0.014

Forecast method 2 – NNAR for training sample of level series at one-step forecast

	Routes							
Accuracy measure	SEAFI composite SNNAR(2,1,2)	Singapore SNNAR(2,1,2)	Vietnam SNNAR(2,1,2)	Thailand SNNAR(2,1,2)	The Philippines SNNAR(7,1,4)	Malaysia SNNAR(2,1,2)	Indonesia SNNAR(2,1,2)	Average
RMSE	21.787	2.818	8.387	5.423	6.366	6.886	8.768	8.634
MAPE	2.393	1.546	4.049	2.88	29.454	2.122	2.469	6.416
ACF1	−0.009	−0.073	0.006	−0.125	−0.222	−0.14	0.051	−0.073

Forecast method 1 – ARIMA for training sample of log-transformed series at one-step forecast

	Routes							
Accuracy measure	SEAFI composite ARIMA(0,1,3)	Singapore ARIMA(5,0,0)	Vietnam ARIMA(1,1,0)	Thailand ARIMA(1,1,0)	The Philippines ARIMA(0,1,2)	Malaysia ARIMA(1,1,0)	Indonesia ARIMA(3,1,2)	Average
RMSE	0.045	0.032	0.065	0.05	1.867	0.036	0.037	0.305
MAPE	0.494	0.475	0.904	0.723	16.935	0.456	0.508	2.928
ACF1	−0.009	−0.094	0.006	−0.016	−0.005	−0.019	−0.006	−0.020

Forecast method 2 – NNAR for training sample of log-transformed series at one-step forecast

	Routes							
Accuracy measure	SEAFI composite SNNAR(2,1,2)	Singapore SNNAR (1,1,2)	Vietnam SNNAR (2,1,2)	Thailand SNNAR (2,1,2)	The Philippines SNNAR(7,1,4)	Malaysia SNNAR(2,1,2)	Indonesia SNNAR(2,1,2)	Average
RMSE	0.031	0.022	0.058	0.039	0.657	0.029	0.034	0.124
MAPE	0.37	0.332	0.798	0.587	9.176	0.384	0.446	1.728
ACF1	0.017	0.15	0.012	−0.084	−0.097	−0.083	0.047	−0.005

Source(s): Authors work

Table 4. Forecast accuracy for the 7 series' level and log-transformed test samples under one-step forecast

Forecast method 1 – ARIMA for test sample of level series at one-step forecast

Accuracy measure	Routes SEAFI composite ARIMA(3,1,2)	Singapore ARIMA(1,0,3)	Vietnam ARIMA(0,1,4)	Thailand ARIMA(1,1,0)	The Philippines ARIMA(0,1,2)	Malaysia ARIMA(1,1,0)	Indonesia ARIMA(3,1,2)	Mean
RMSE	41.919	6.458	27.598	5.348	2.612	5.917	12.994	14.692
MAPE	4.239	2.718	8.912	2.983	2.632	2.15	3.826	3.923
ACF1	0.158	0.2	0.432	0.69	−0.066	0.509	0.605	0.361

Forecast method 2 – SNNAR for test sample of level series at one-step forecast

Accuracy measure	Routes SEAFI composite SNNAR(2,1,2)	Singapore SNNAR(2,1,2)	Vietnam SNNAR(2,1,2)	Thailand SNNAR(2,1,2)	The Philippines SNNAR(7,1,4)	Malaysia SNNAR(2,1,2)	Indonesia SNNAR(2,1,2)	Average
RMSE	64.379	11.843	36.811	15.006	14.135	14.314	19.091	25.083
MAPE	7.314	5.475	10.497	7.657	18.386	5.925	5.397	8.664
ACF1	0.437	0.284	0.537	0.442	0.219	0.341	0.001	0.323

Forecast method 1 – ARIMA for test sample of log-transformed series at one-step forecast

Accuracy measure	Routes SEAFI composite ARIMA(0,1,3)	Singapore ARIMA(5,0,0)	Vietnam ARIMA(1,1,0)	Thailand ARIMA(1,1,0)	The Philippines ARIMA(0,1,2)	Malaysia ARIMA(1,1,0)	Indonesia ARIMA(3,1,2)	Average
RMSE	0.048	0.0562	0.113	0.042	0.261	0.035	0.047	0.086
MAPE	0.527	0.754	1.475	0.719	2.326	0.451	0.675	0.990
ACF1	0.453	0.397	0.413	0.672	−0.066	0.453	0.559	0.412

Forecast method 2 – SNNAR for test sample of log-transformed series at one-step forecast

Accuracy measure	Routes SEAFI composite SNNAR(2,1,2)	Singapore SNNAR (1,1,2)	Vietnam SNNAR (2,1,2)	Thailand SNNAR (2,1,2)	The Philippines SNNAR(7,1,4)	Malaysia SNNAR(2,1,2)	Indonesia SNNAR(2,1,2)	Average
RMSE	0.113	0.087	0.167	0.11	1.393	0.094	0.072	0.291
MAPE	1.416	1.102	2.113	1.818	13.06	1.267	0.964	3.106
ACF1	0.432	0.372	−0.087	0.37	0.105	0.39	−0.042	0.220

Source(s): Authors' work

Table 5.
Forecast accuracy for the 7 series' level and log-transformed test samples under four-step forecast

Forecast method 1 – ARIMA for test sample of level series at four-step forecast

Accuracy measure	SEAFI composite ARIMA(1,1,0)	Singapore ARIMA(1,0,3)	Vietnam ARIMA(0,1,4)	Thailand ARIMA(1,1,0)	The Philippines ARIMA(0,1,2)	Malaysia ARIMA(1,1,0)	Indonesia ARIMA(3,1,2)	Average
RMSE	234.042	31.273	128.082	52.169	31.675	48.020	63.297	84.080
MAPE	22.057	15.030	36.540	26.662	41.050	17.328	14.184	24.693

Forecast method 2 – SNNAR for test sample of level series at four-step forecast

Accuracy measure	SEAFI composite SNNAR(2,1,2)	Singapore SNNAR(2,1,2)	Vietnam SNNAR(2,1,2)	Thailand SNNAR(2,1,2)	The Philippines SNNAR(7,1,4)	Malaysia SNNAR(2,1,2)	Indonesia SNNAR(2,1,2)	Average
RMSE	267.293	34.779	92.508	45.406	54.650	53.202	79.639	89.639
MAPE	27.263	17.113	28.354	23.635	56.684	19.249	21.715	27.716

Forecast method 1 – ARIMA for test sample of log-transformed series at four-step forecast

Accuracy measure	SEAFI composite ARIMA(0,1,3)	Singapore ARIMA(5,0,0)	Vietnam ARIMA(1,1,0)	Thailand ARIMA(1,1,0)	The Philippines ARIMA(0,1,2)	Malaysia ARIMA(1,1,0)	Indonesia ARIMA(3,1,2)	Average
RMSE	0.32	0.256	0.496	0.326	3.168	0.278	0.244	0.727
MAPE	3.764	4.036	7.669	5.563	36.174	3.881	2.995	9.155

Forecast method 2 – SNNAR for test sample of log-transformed series at four-step forecast

Accuracy measure	SEAFI composite SNNAR(2,1,2)	Singapore SNNAR (1,1,2)	Vietnam SNNAR (2,1,2)	Thailand SNNAR (2,1,2)	The Philippines SNNAR(7,1,4)	Malaysia SNNAR(2,1,2)	Indonesia SNNAR(2,1,2)	Average
RMSE	0.46	0.262	0.417	0.375	3.725	0.354	0.303	0.842
MAPE	5.674	3.824	6.301	6.192	42.407	4.878	4.461	10.534

Source(s): Authors' work

5. Conclusion and future research

Carrying cargoes in a box revolutionized the thinking of many and brought in the improvement for transporting different kinds of cargoes. Thus, the price of carrying containerized cargoes forms the basis of the study. Forecasting freight rates has been a topic of interest for decades, and in that the segment of container freight rates is relatively new. In recent years, the growing trade opportunities from East Asia have grown the need for predicting container freights rates from this particular region. Considering past freight rates as an input, this study has utilized two univariate forecasting methods ARIMA and SNNAR for forecasting the SEAFI composite and its six routes. This index was chosen because it includes the routes of almost all South-East Asia base ports from Shanghai, China, to nations such as Singapore, Vietnam, the Philippines, Thailand, Malaysia and Indonesia (SSE, 2020). It was found that ARIMA had better forecast accuracy for majority of the seven data series for both the level as well as log-transformed series under one-step and four-step forecasts. Only the routes of Vietnam and Thailand under four-step forecasts had better accuracy with their respective models of SNNAR.

Further studies on the index may also include the investigation of the GARCH effect, as indicated by the existence of ARCH effects for the Philippines and Singapore series. The current study utilized polar graphs for seasonality pattern demonstration; future studies may apply statistical tests such as the HEGY test for the analyzed data series. Since the COVID-19 pandemic, the container freight rates skyrocketed. The SEAFI value stood at 6731.05 in the first week of December 2021, which was only 820.01 in the first week of December 2019. Hence, analysis of structural breaks in the SEAFI composite and its six routes due to COVID-19 is worth investigating.

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