Forecasting accuracy of vector autoregressive model and dynamic factor model for airline passenger traffic

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The choice of appropriate forecasting technique for air transport business is quite challenging and requires comprehensive analysis of empirical results. This paper compares the forecasting accuracy of Vector Autoregressive (VAR) Model and Dynamic Factor Model(DFM)in the determination of air passenger traffic. The aim is to establish through statistical principles, which of the two models outperforms the other by: fitting multivariate time series models of VAR and DFM; comparing the forecasting accuracy of the models; and determining the appropriate model for forecasting monthly passenger flow. Monthly data from January 2015 to December 2019 were utilized for the comparison. The series are trend stationary at all levels based on standard Augmented Dickey Fuller (ADF) unit root tests. Each of these series is found to be integrated of order one [I (1)] on the bases of Akaike Information Criterion (AIC) and the Hannan-Quin information criterion (HQIC). The models were further diagnosed for residual autocorrelation and normality tests followed by models fitness. The results of MAPE, RMSE, and MAD show that values of these three statistics are lower for DFM than the corresponding values for VAR. This study therefore recommends the DFM as a better forecast model for air passenger traffic.

Keywords: accuracy; dynamic; factor; forecasting; vector autoregressive

1. Introduction

The need for appropriate decision making in view of future occurrences of a system has always been the major reason behind time series modeling. As decision makers look for appropriate decision tool (model), they invariably try to identify a predictor which has a minimum associated cost function. In an effort to get the best model, the analyst always tries to explore every relevant information space so as to get a forecast about the future event which will relatively minimize error (Lutkepohl, 2006).

Airlines, economists, and air transport authorities, have had a serious interest in finding the determinants for the demand for air transport. For the airlines, the capability of accurately predicting the air transport demand, and of examining the potential factors that can influence this demand, is critical to their profits and operating strategies. Realistic forecasts of passenger demand are also essential for planning air transport infrastructure. Therefore, the problems of accurately predicting passenger and cargo demand, and of identifying the determinants for this demand, have considerably attracted research interest. Air transportation is a major industry in its own right and it provides important inputs into wider economic, political, and social processes. The demand for its services, as with most transport services, is a derived one which is driven by the needs and desires to attain some other final objective. Air transport can

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facilitate, for example, the economic development of a region or of a particular industry such as tourism. (Saheed and Iluno, 2015)

Generally, forecasters evaluate the projections of aviation activity that result from applying appropriate forecasting methods and its relationships before they are finalized. Other than providing a means for developing quantifiable results, aviation forecasters use forecasting methods and their professional judgment to determine what is reasonable. Thus, making the evaluation forecast results an essential part of the forecasting process (GRA Inc., 2001).

1.1 Statement of the problem

The problem of choosing appropriate forecasting technique to employ in air transport business, is quite challenging and requires comprehensive analysis of empirical results. This paper therefore examines the most efficient forecasting method between vector autoregressive model and dynamic factor model in forecasting monthly passenger flow of an Airline. The aim is to establish through statistical principles, which of the two models outperforms the other by:

i. Fitting multivariate time series models of VAR and DFM,
ii. Comparing the forecasting accuracy of the models using the measures of forecasting accuracy, and
iii. Determining the appropriate model for forecasting monthly passenger flow.

This paper is motivated by the need to comparatively examine the performances of two multivariate time series models, Vector Autoregressive (VAR) Model and Dynamic Factor Model (DFM), as forecasting models for forecasting the air passenger traffic flow of an Airline.

1.2 Operational definitions

Load Factor (LF): The number of Revenue Passenger Miles (RPMs) expressed as a percentage of Available Seat Miles (ASMs), either on a particular flight or for the entire system. Load factor represents the proportion of airline output that is actually consumed. To calculate this figure, divide RPMs by ASMs. Load factor for a single flight can also be calculated by dividing the number of passengers by the number of seats (Hashem and Noor, 2007).
Passenger Revenue (PR): Revenue received by the airline from the carriage of passengers in scheduled operations.
Block Hours (BH): Time from the moment the aircraft door closes at departure of are venue flight until the moment the aircraft door opens at the arrival gate following its landing. Block hours are the industry standard measure of aircraft utilization.
Distance Flown (DF): is a monthly distance covered by all international flights. It is cumulative kilometers flown by each international flight. The study measures this variable in millions of kilometers (Soloman and Sharma, 2020).

2. Literature Review

Srisaeng *et al*. (2015) proposed genetic algorithm optimization models for modelling Australia's domestic airline passenger demand using enplaned passengers (GAPAXDE model) and revenue passenger kilometres performed (GARPKSDE model). Their results show that both the quadratic GAPAXDE and GARPKSDE models are more accurate, consistent, and have superior predictive capability as compared to the linear models.

Lim and McAleer (2001) predicted monthly tourist arrivals to Australia from three destinations: Hong Kong, Malaysia and Singapore. They used the single Exponential Smoothing model, Brown's double exponential smoothing model, the additive and multiplicative Seasonal Holt-Winters models as well as the non-seasonal exponential smoothing model. Their performance is evaluated with the RMSE (Root Mean Squared Error) criterion. They found that for the series in levels, the multiplicative Holt-Winters model offers the best performance for Hong Kong and Singapore whereas in the case of Malaysia, the additive Holt-Winters model is the most accurate.

Bahram *et al.* (2002) employed vector error correction model (VECM) to examine the long-run dynamic relationship between air carrier firms' capacity (CAP) measured by the available seat miles and their profits (PRF) for US airline industry. They used quarterly observations on nine US carriers (Alaska, American, America West, Continental, Delta, Northwest, Southwest, Trans World and United) from quarter 3 of 1983 to quarter 3 of 1998. The objective was to investigate whether CAP is related to profitability. If size and profits demonstrate a positive long-run relationship, then there is a market incentive for carrier acquisitions and a move toward an oligopoly market structure. Their result showed that there is a long-run positive relationship between the available seat miles and profits. Granger causality tests also verified that for all carriers the capacity variable causes profits.

Emiray and Rodriguez (2003) on their long study in Canada, provided monthly forecast of enplane/deplane air passengers flow for three market segments (domestic, international and trans-border flights), based on data covering the period stretching from January 1984 to September 2002. The study considered six-time series models (Autoregressive AR(p), AR(p) with seasonal unit roots, Seasonal Autoregressive Integrated Moving Average (SARIMA), Periodic Autoregressive Model (PARM), Structural Time Series Model (STSM) and the Seasonal Unit Roots Model). They concluded that forecasting performance depends on two key elements: the market segment considered and the forecasting horizon. They revealed that short memory models are better for short term forecasting whereas long memory models are better for long term forecasting.

Kulendran and Witt (2003) generated one, four and six quarter ahead forecasts of international business passengers to Australia from the following four countries: Japan, New Zealand, the United Kingdom and the United States. They considered different forecasting models: the error correction model (ECM), the structural time series model (STSM), the basic structural model (BSM), no change models as well as various ARIMA models. They concluded that forecasting performance varies with the forecasting horizon and depends on the adequate detection of seasonal unit roots. Consequently, ARIMA and BSM models were the most accurate for short term forecasting (one-quarter ahead) whereas the seasonal no change model outperformed the other models for medium term forecasting (four and six quarters ahead).

Coshall (2006) examined the performance of ARIMA and SARIMA models for predicting air passenger traffic flows. The study forecasted air travel from the United Kingdom to twenty destinations using quarterly data of UK outbound air travelers with several models, which include: Naïve 1 model, Naïve 2 model, the Holt-Winters model and a variety of ARIMA models. It was concluded that, the Root Mean Square Error (RMSE) established that the ARIMA model was dominant.

Andreoni and Postorino (2006) used the yearly data of planed/enplaned passengers at Reggio Calabria airport in the South of Italy to forecast air transport demand. Two univariate ARIMA models and a multivariate ARIMAX model with two explanatory variables (mainly per capita income and the number of movements both to and from Reggio Calabria airport) were used to generate forecasts. The authors concluded that all three models offer accurate forecasts.

Coshall (2009) studied tourist departures from the United Kingdom to twelve destinations. He concluded that the performance of different combination methods depends on the forecasting horizon. In this particular case, the variance-covariance method outperformed simple averaging for one and two years ahead forecasts while the reverse is true for three years ahead forecasts.

Ghomi and Forghani (2016) submitted that demand forecasting for available seats in airlines is essential to maximize the expected revenue by setting the proper fare levels for those seats. They argued that the product in airline industry is the seat, which is expensive, and cannot be stocked. They stated that the demand for the seats is almost indeterminate, the capacity is fixed and difficult to increase and the variable costs are very high. They used data from a major airline company in Turkey comprising past five years daily passenger data for a flight. The techniques of Box-Jenkins and artificial neural networks were used for the forecasting.

Fildes *et al.* (2011) made use of a wide variety of multivariate models to study air traffic flows between the United Kingdom and five other countries: Germany, Sweden, Italy, the USA and Canada. They used the following econometric models: an autoregressive distributed lag model (ADL), a pooled ADL model, a time-varying parameter model (TVP) as well as an automatic method for econometric model specification. They also considered the previous four models augmented by a world trade explanatory variable (which measures the total trade of all industrial countries). In addition, they applied the following (mostly univariate) models: a Vector Autoregressive(VAR) model, a vector autoregressive model with the world trade variable, an exponential smoothing model, an autoregressive model of order three, AR(3), as well as Naive I and Naive II benchmark models. Forecasting performance was evaluated according to the following four criteria: (i) Root Mean Square (Percentage) Error (RMSE), (ii) Geometric Root Mean Square Error (GRMSE), (iii) Mean Absolute Scaled Error (MASE), and (iv) Geometric Mean Relative Absolute Error (GMRAE). They found that ADL models with the inclusion of a world trade variable outperformed overall the univariate models (exponential smoothing and AR(3) models) but that the difference in forecasting performance was usually small, although it varied depending on the forecasting performance criterion used (usually larger when using RMSE).

Banerjee *et al*. (2020) provided a synoptic and critical evaluation of the wide-ranging research that has been performed in demand forecasting in the scheduled passenger transportation industry. They assessed the forecast methodologies with recommendations on different methodologies that industry practitioners can adopt to suit their specific needs. They concluded that there is a lack of standardization in the way in which methods are defined and tested. They therefore, proposed open source testbeds to streamline benchmarking of new models.

According to Zivot and Wang (2003), the vector autoregressive (VAR) model is one of the most effective, flexible and easy to use models for the analysis of multivariate time series. It isa natural extension of the univariate autoregressive model to dynamic multivariate time series. They opined that the model has demonstrated to be especially useful for relating the dynamic behavior of economic and financial time series and for forecasting. The model frequently delivers superior forecasts to those from univariate time series models and elaborate theory-based simultaneous equations models.

Soloman and Sharma (2020) utilized a monthly Ethiopian airline's data for international flights from January 2009 up to December 2013 to construct vector autoregressive (VAR) and VECM models, and also to see the result of a dependent variable Load Factor (LF) to Passenger Revenue (PR), Block Hours (BH), and Distance Flown (DF) at international level and concluded that in the long run, a one million dollar increase in the monthly Passenger Revenue accounts for an average increase of about 0.54% in the monthly Load Factor.

Dynamic factor models are parsimonious representations of connections among time series variables. With the flow in data availability, they have proven to be vital in macroeconomic forecasting (Doz and Fuleky, 2019).

Miranda *et al.* (2021) analyzed the practical significances on factor estimation, in-sample forecasts and out-of-sample forecasting of using other estimators of the DFM under different sources of likely misspecification. They measured factor extraction when assuming diverse number of factor dynamics and concluded that lack of consensus is only marginally critical when it comes to factor extraction, but matters when the objective is out-of-sample forecasting.

Most papers reviewed on modeling air passenger traffic have not focused on identifying a single model which is efficient in forecasting air passenger traffic. This paper seeks to fill that gap.

3. Methodology

3.1 Data source

This study considered monthly Max Air's data for international flights over the time period January 2015 – December 2019. The data were obtained from the Head Office of Max Air located in Kano, at Mallam Aminu Kano International Airport.

3.2 Method of data analysis

Vector Autoregressive (VAR) Model and Dynamic Factor Model (DFM) are the two forecasting techniques to be deployed in this paper. The models will be used to forecast future air passenger traffic. The R and STATA12 software will be used for data analyses.

3.3.1 Vector Autoregressive Model

Let $Y_t = (Y_{1t},\ Y_{2t},\ Y_{3t},\ + \cdots + Y_{nt})^T$ denote a $(n \times 1)$ vector of time series variables. A VAR model with p lags can then be expressed as follows:

$$Y_t = c + \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + \cdots + \Pi_p Y_{t-p} + \varepsilon_t \quad t = 1, 2, \cdots, T \tag{3.1}$$

where c denotes an (n x 1) vector of constants and Π_i, for $for\ i = 1, 2, \cdots, p$, is an $(n \times n)$ coefficient matrix of autoregressive coefficients; ε_t is an $(n \times 1)$ unobservable zero mean white noise vector process (serially uncorrelated) with time invariant covariance matrix Σ, i.e.,

$$E(\varepsilon_t) = 0\ and\ cov(\varepsilon_t, \varepsilon_s) = E(\varepsilon_t, \varepsilon_s^T) = \begin{cases} \Sigma, & \forall t = s \\ 0, & \forall t \neq s \end{cases} \tag{3.2}$$

with Σ an $(n \times n)$ symmetric positive definite matrix (Soloman and Sharma, 2020).

3.3.2 Dynamic Factor Model (DFM)

Dynamic Factor Model (DFM) is a very powerful and popular tool to reduce the dimension of large systems of economic and financial variables by assuming that their dynamic dependence relies on a relatively small number of underlying unobserved common factors. It is given as follows:

$$x_t = \Lambda_0 f_t + \Lambda_1 f_{t-1} + \Lambda_2 f_{t-1} + \cdots + \Lambda_s f_{t-s} + e_t \qquad (3.3)$$

$$f_t = A_1 f_{t-1} + A_2 f_{t-2} + \cdots + A_p f_{t-p} + u_t \qquad (3.4)$$

$$e_t = De_{t-1} + v_t, \qquad (3.5)$$

where x_t is the $N \times 1$ vector of observations at time $t = 1, 2, \cdots, T$, which is assumed to be stationary, f_t is the $q \times 1$ vector of unobserved factors at time t and e_t is the corresponding $N \times 1$ vector of idiosyncratic components, which are assumed to be weakly cross-sectional and serially correlated (Poncela and Ruiz, 2020).

4. Results and Discussion

In this section, the results of the data analyses are presented and discussed.

4.1 Descriptive statistics

Table 1: Descriptive Statistics of the Max Airline Passenger Traffic Data

Variable	Mean	SEM	StDev	CV	Min	Median	Max	Skewness
LF	49.695	0.680	2.357	.0474	45.762	49.432	55.012	0.73
BH	8.584	0.502	1.738	0.2025	5.766	8.433	10.997	0.12
DF	6.614	0.337	1.166	0.1763	5.166	6.500	8.582	0.52
PR	48.18	3.11	10.77	0.2235	30.18	48.76	68.62	0.45

Table 1 shows the descriptive statistics results of the response and decision variables. A total of 60 observations were recorded. Block Hours has the least coefficient of variation of 4.74%, making it the most stable, while Passenger Revenue has the highest coefficient of variation of 22.35%, making it the most dispersed. Hence, all the variables can be considered stable with regard to their coefficients of variation, since none of them is too far from 20%.

4.2 Unit root test

Unit root tests are confirmatory strive for stationarity detection. Augmented Dickey-Fuller test is employed to test stationarity and determine the maximum order of integration of each series as presented in Table 2. The results of the unit root test for the LF, BH, DF and PR demonstrate that the series are trend stationary based on the Augmented Dickey-Fuller unit root test in Table 2. Comparing the ADF test statistics with their corresponding critical values, it shows that all the level series have unit roots, however the first difference of all series are stationary at least at 1%, 5% and 10% significant levels.

Table 2: Augmented Dickey-Fuller Unit Root Test

z_t	Test stat	1%	5%	10%
LF	-5.985	-3.567	-2.923	-2.596
BH	-6.454	-3.567	-2.923	-2.596
DF	-6.454	-3.567	-2.923	-2.596
PR	-4.925	-3.567	-2.923	-2.596
			p-value for Z(t) =0.0000	

4.3 Specification of VAR Order

In this paper, determination of optimal lag length for the VAR/DF model is performed using the Akaike Information Criterion (AIC) and Hannan-Quin Information Criterion (HQIC). In each criterion, the lag with a minimum criterion value is selected as an optimum lag length for the model. The results are shown in Table 4.3.

Table 3: Selection – Order Criteria

Lag	LL	LR	df	P	FPE	AIC	HQIC
0	-402.611					14.1969	14.2247
1	-396.15	12.921	4	0.012	4605.35	**14.1105***	**14.1941***
2	-395.12	2.0595	4	0.725	5114.85	14.2148	14.3541
3	-389.047	12.146	4	0.016	4763.55	14.142	14.337

The optimal lag length is determined by the least values of both information criteria. From Table 3, the least values for both AIC and HQIC occurred at lag 1. Hence, the optimal lag length for the unrestricted VAR model is 1.

4.4 Test of residual autocorrelation

Table 4: Breusch-Godfrey LM Test for Residual Autocorrelations

Lag	Chi-Squared	LM Test (P-Value)
1	9.6558	0.79358

Table 4 presents the results for the Breusch-Godfrey LM test for the residual autocorrelation of VAR (1) model. The result shows that there is no residual autocorrelation since the associated p-value (0.79358) is greater than the conventional significance level of 0.05.

4.5 Normality test (Residual Analysis)

The Jarque-Bera test based on the sample skewness and sample kurtosis is presented in Table 5. Table 5 shows that the p-values for LF and PR are 0.3747 and 0.1988which are greater than 0.05. Thus, the data are normally distributed.

Table 5: Jarque-Bera Test for Normality

S	Chi-Squared	Degree of freedom	P- Value
LF	1.963	2	0.3747
PR	3.231	2	0.1988

4.6 Vector autoregressive results

Table 6: The Vector Autoregressive Results

		Coefficient	Standard Error	Z	P > |Z|	95% confidence Interval	
LF	L1	0.2397746	0.1259113	1.90	0.057	-0.007007	0 .4865561
PR	L1	0.3528221	0.1185443	2.98	0.003	0.1204796	0.5851647
BH	L1	1.615018	0.7498151	2.15	0.031	0.145407	3.084628
DF	L1	-0.0182312	0.1965761	-0.09	0.926	-0.4035132	0.3670508
Constant		24.35965	25.67229	0.95	0.343	-25.95711	74.67641
Sample		2015m2 - 2019m12					
Log likelihood		-407.337					
FPE		4464.363					
Det (Sigma_ml)		3402.545					
Number of obs		59					
AIC		14.07922					
HQIC		14.18918					
SBIC		14.36092					

From the results in Table 6, since the p-values of PR and BH are below the significance level of 5%, then the coefficients of PR (0.3528) and BH (1.6150) are significant in determining lapse rates. The coefficient of PR implies that an increase in PR will increase lapse rates. It can be observed that PR is significantly affected positively by 35% when there is one unit change in its lagged values and also affected by a constant term of 24.3596.

Forecasting model for Load Factor using VAR:

The predictive VAR model for Load Factor shows that both PR and BH have positive impact on LF, per unit increase while DF has negative impact on LF. The forecasting model is:

$$LF_t = 24.35965 + 0.3528PR_t + 1.6150BH_t - 0.018231DF_t \qquad (4.1)$$

indicating that, a unit increase in the monthly Passenger Revenue will account for an average increase of about 0.35in the monthly Load Factor. Likewise, a unit increase in Block Hour will result in an average increase of about 1.62 in the monthly Load Factor of the Max Airline, in the long run. In contrast, a unit increase in the monthly Distance Flown, will cause a decrease of about 0.02 in the Load Factor per month.

4.7 Dynamic factor model results

Table 7: The Dynamic Factor Model Results

	Coef.	Std. error	Z	P > |Z|	95% conf. interval	
e.lf						
L1	.2700637	.1301634	2.07	0.038	.014948	.5251793
L2	-.1191061	.1301202	-0.92	0.360	-.3741369	.1359248
LF						
BH	.6129653	.7361413	0.08	0.934	-.3923871	.3665343
DF	0	(omitted)				
PR	.0121681	.0878768	2.25	0.025	.2185619	3.196866
-cons	45.16605	3.579513	6.27	0.000	25.46642	48.6293
Vare. lf	4.238478	1.730352	2.45	0.007	9.809942	20.74347
Range	2015 m1 – 2019 m12					
Coy log-likelihood	-413.48247					
Wald chi 2(2)	21.62					
Prob>chi 2	0.0014					
No of obsn	60					

From Table 7, the result of the Dynamic Factor Model, the output describes the estimation sample, reports the log-likelihood function at the maximum, and gives the results of a Wald test.

The null hypothesis that all parameters except for the variance parameters are zero is rejected at all conventional levels since the Wald statistic of 21.62 has a p-value of 0.0014 (<0.05). The variable, DF, was dropped from the analysis due to collinearity issues. The results in the estimation table indicate that the impact of BH on LF has a coefficient of 0.6129653 with a p-value of 0.934 (>0.05). The results further show, from the estimation table, that the impact of PR on LF has a coefficient of 0.0121681 with a p-value of 0.025 (<0.05). The factor is very persistent on DF and thus, is a significant predictor for LF. It has a Z-score of 2.25.
The DFM model is represented as:

$$LF_t = 45.16605 + 0.0121681PR_t + 0.6129653BH_t,$$

indicating that a unit increase in the monthly Passenger Revenue will account for an average increase of about 0.01 in the monthly Load Factor. Likewise, a unit increase in Block Hour per month will result in an average increase of about 0.61 in the monthly Load Factor of the Max Air, in the long run.

4.8 Model comparison using the measures of forecast accuracy

Table 8 presents the results for the forecasting accuracy of the Dynamic Factor Model and the Vector Autoregressive Model using the MAPE, RMSE, and MAD.

Table 8: Model forecasting accuracy using MAPE, RMSE and MAD

	LF	
	VAR	DFM
MAPE	0.001345	0.001115
RMSE	1.044646	0.514846
MAD	.068368	0.055432

The results show that values for MAPE, RMSE and MAD are lower for DFM than the corresponding values for VAR. Thus, the DFM is a better forecast model for Load Factor than the VAR model.

5. Conclusion

The forecasting accuracy of two multivariate time series models, VAR and DFM was assessed on the bases of data from Max Airline. Data on Load Factor, Passenger Revenue, Block Hour and Distance Flown covering the period from January 2015 to December 2019 were used for the analysis. Using MAPE, RMSE and MAD to check the forecasting accuracy of the two models, the results show that DFM outperformed VAR. For DFM, MAPE = 0.001115; RMSE = 0.514846; MAD = 0.055432 while for VAR, MAPE = 0.001345; RMSE = 1.044646; MAD = 0.068368. Furthermore, the DFM forecast model shows that Distance Flown is not very useful in forecasting the Load Factor for Max Airline. This study therefore recommends the Dynamic Factor Model as a better forecast model over the Vector Autoregressive Model for forecasting air passenger traffic.

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