

Forecasting Airline Demand: A Predictive Analysis of Revenue Passenger Miles

Maria I. Gutierrez

Introduction

Problem Statement

 The goal of this project is to forecast revenue passenger miles (RPM) for U.S. air carriers over the next 24 months to assist in predicting demand and identifying trends in the airline industry

BusinessBackground

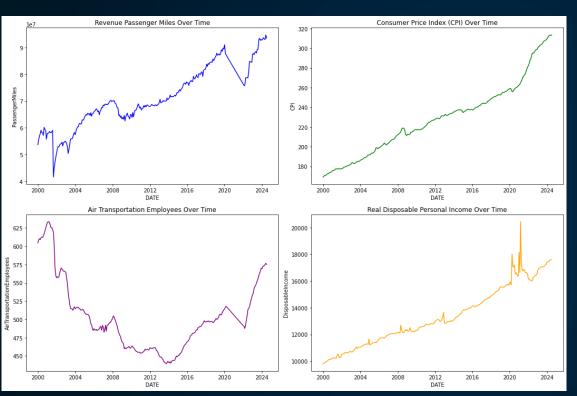
- US Airlines in 2023 generated approximately \$223.31 Billion in revenue (Statista,2024).
- According to the International Air Transport Association (IATA) airlines faced a cumulative net loss of 201 billion in 2020.



Image 1: Airplane(Airplane Images – Browse 3,112,993 Stock Photos, Vectors, and Video, n.d.)

DATA





The primary target variable is Revenue
Passenger Miles (RPM), which measures
the volume of air travel demand and reflects
overall airline industry performance

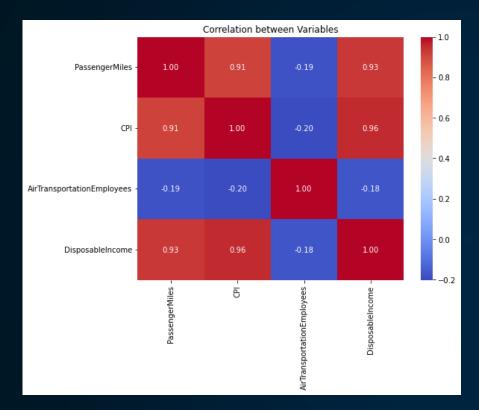
Consumer Price Index (CPI): As an indicator of inflation, higher consumer prices can influence travel costs and demand for air travel

Air Transportation Employees: Reflects workforce levels within the airline industry, indicative of capacity and operational trends

Disposable Income: Higher disposable income typically correlates with greater spending on travel and leisure, including air travel



Monthly Data from Jan 2000 to July 2024



Passenger Miles shows the strongest positive correlations with CPI and <u>Disposable Income</u>, highlighting these economic factors as influential for travel demand. Air Transportation Employees has weak correlations with other variables, indicating that employee numbers might not directly track with travel demand or economic indicators in a straightforward way.

Methodology



Data smoothing and Correlation between variables



Holt-Winters' Seasonal Model: Captures RPM's inherent trend and seasonality for straightforward seasonal forecasting.



SARIMAX Model (Seasonal AutoRegressive Integrated Moving Average with exogenous variables): Integrates seasonality and economic predictors (CPI, employment, income) to improve forecast accuracy by considering external factors.

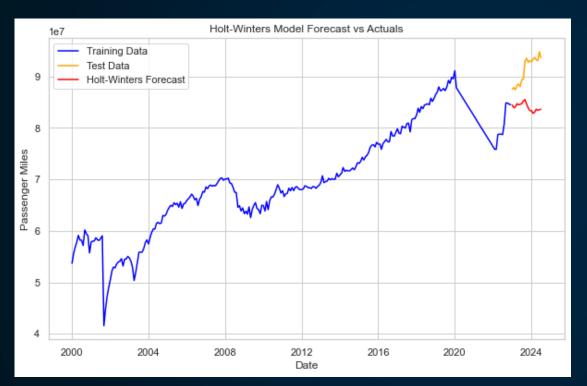


ETS (Error, Trend, Seasonal) Model: Provides flexible decomposition of error, trend, and seasonality to accurately model RPM's seasonal patterns.



VAR (Vector AutoRegression) Model: Models interdependencies among RPM and economic variables to capture mutual influences and predict multi-variable impacts.

Holt-Winters Seasonal Model

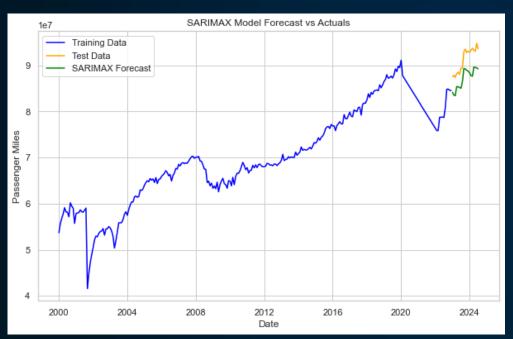


Holt-Winters Model Metrics
MAE: 7176105.244299201
MAPE: 7.78%
MSE: 60558629160459.04
RMSE: 7781942.505599681
R ² : -8.11887354417765



While the Holt-Winters model provided a baseline forecast, it struggled to align closely with actual values, especially during periods of fluctuation. This outcome indicates that the model may not be the best fit for forecasting Passenger Miles, possibly due to the complexity and non-linear behavior of the data that it couldn't fully capture.

SARIMAX: Model (Seasonal AutoRegressive Integrated Moving Average with exogenous variables)



SARIMAX Model Metrics:

MAE: 4044456.4643969624

MAPE: 4.42%

MSE: 17131819258734.256

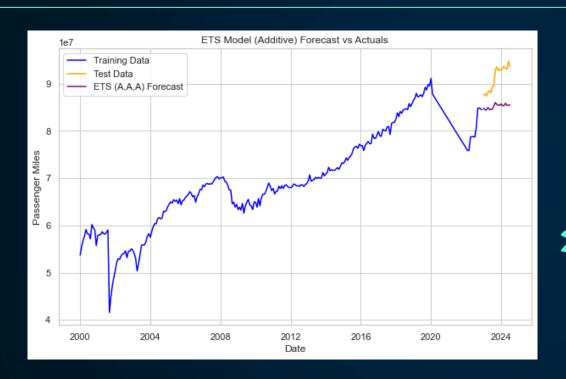
RMSE: 4139060.1902768044

R²: -1.579696660374681



SARIMAX model gives a better accuracy (indicated by MAE and MAPE), but the negative R² implies room for improvement in capturing long-term patterns. The model performs well in the short term, its accuracy may decline over longer periods,

ETS (Error, Trend, Seasonal) Model



ETS (A,A,A) Model Metrics:

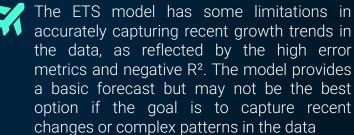
MAE: 6026367.692601673

MAPE: 6.54%

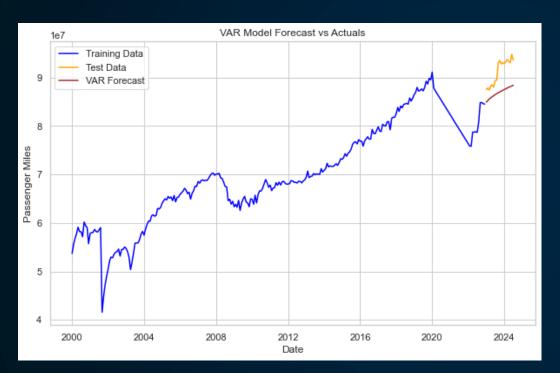
MSE: 41070377166863.76

RMSE: 6408617.414611653

R²: -5.184346987181255



VAR (Vector Auto Regression) Model

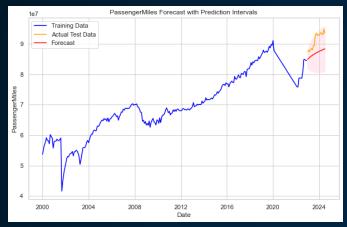


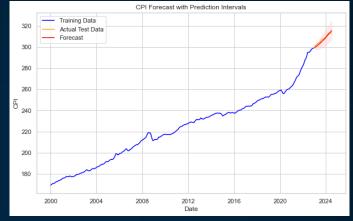
VAR Model Metrics
MAE: 4321140.178914916
MAPE: 4.69%
MSE: 21497768365420.43
RMSE: 4636568.598157524
R ² : -2.2371180445129744

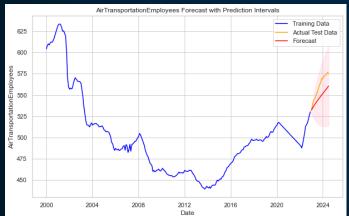


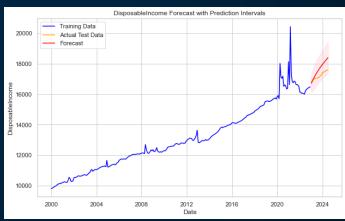
The VAR model effectively captures interdependencies among economic indicators. While not as aggressive in predicting rapid growth, it provides a realistic scenario where modest increases across economic indicators support a gradual recovery in passenger miles, aligning with economic condition

VAR Model Graphs

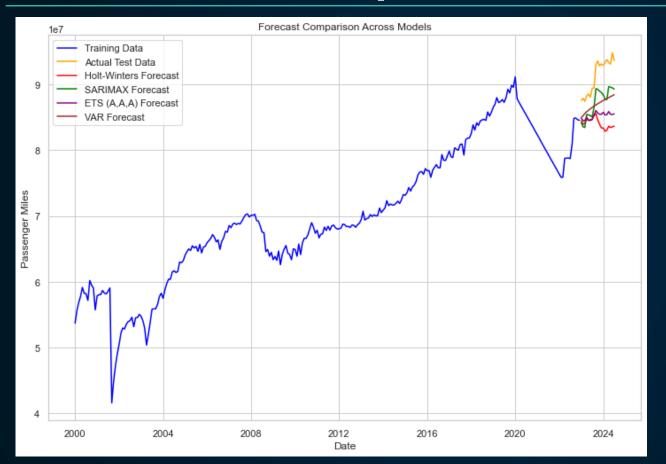








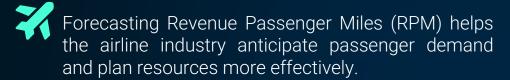
Forecast Comparison Across Models





Based on the MAE, MAPE, MSE, RMSE, and R², the SARIMAX model performs the best overall. It has the lowest error metrics and the least negative R², making it the most reliable for forecasting Passenger Miles in this context.

Conclusion



Including economic and labor variables like CPI, Air Transportation Employees, and Disposable Income enhances forecast accuracy by reflecting external influences on RPM.

The SARIMAX model proved to be the most effective, showing that accounting for exogenous variables leads to a more accurate and actionable forecast.



Image 2: Airplane(Chatgpt Generated)

REFERENCES

- Airplane Images browse 3,112,993 stock photos, vectors, and video. (n.d.). Adobe Stock.
 https://stock.adobe.com/search?k=airplane
- All employees, air transportation. (2024, November 1). https://fred.stlouisfed.org/series/CES4348100001
- Consumer Price Index for all urban consumers: All items in U.S. city average. (2024, November 13).
 https://fred.stlouisfed.org/series/CPIAUCSL
- Kenton, W. (2022, August 19). Revenue Passenger Mile (RPM): defining a transportation metric. Investopedia.
 https://www.investopedia.com/terms/r/revenue-passenger-mile-rpm.asp
- Revenue Passenger miles for U.S. air carrier domestic and international, scheduled passenger flights. (2024, October 30). https://fred.stlouisfed.org/series/RPMD11
- Total operating revenues of the U.S. airline industry 2023 | Statista. (2024, May 7). Statista.
 https://www.statista.com/statistics/197680/total-operating-revenues-in-us-airline-industry-since-2004/