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Improving long range forecast errors for better capacity decision making

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IMPROVING LONG – RANGE FORECAST ERRORS
FOR BETTER CAPACITY DECISION MAKING

by

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ABSTRACT

Long-range demand planning and capacity management play an important role for policy makers and airline managers alike. Each makes decisions regarding allocating appropriate levels of funds to align capacity with forecasted demand. Decisions today can have long lasting effects. Reducing forecast errors for long-range range demand forecasting will improve resource allocation decision making. This research paper will focus on improving long-range demand planning and forecasting errors of passenger traffic in the U.S. domestic airline industry. This paper will look to build upon current forecasting models being used for U.S. domestic airline passenger traffic with the aim of improving forecast errors published by Federal Aviation Administration (FAA). Using historical data, this study will retroactively forecast U.S. domestic passenger traffic and then compare it to actual passenger traffic, then comparing forecast errors. Forecasting methods will be tested extensively in order to identify new trends and causal factors that will enhance forecast accuracy thus increasing the likelihood of better capacity management and funding decisions.

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INTRODUCTION

Forecasting is the art and science of taking some of the unknown out of the future. Forecasting is used at almost every organization, in almost all industries ranging from automotive to tourism to food and beverage. In such a competitive market, it is essential for businesses to be readily equipped to handle changes in the environment that may arise in the future. Having an accurate forecast allows an organization to better place itself in a strategic position that will be successful. An accurate forecast is important for airlines to gauge the frequency of flights and number of seats needed from one city to another. It is also important for airport infrastructure planning and airport support services as well to know when the right time is to expand. This thesis will look into the airline industry and build upon current forecasting models being used to forecast domestic airline traffic with the aim of beating and creating a better method to predict future air travel.

Airplane manufacturers need an accurate forecast to foresee when the demand for airplanes will rise. It allows them to manufacture airplanes according to their own schedule (which maximizes profits) rather than responding to a demand that is currently or has already passed. It would be of no benefit for manufacturers to ramp up and expedite their manufacturing if by the time the airplane is finished, demand has slowed down once again. The cost of having to respond to demand immediately would eat away at almost all profits for the manufacturer. There are very high costs for expediting suppliers and the production of parts necessary to complete the final assembly.

Airlines use forecasts to gauge the frequency of flights and number of seats needed from one city to another. Forecasts for airlines become especially important during times of higher

travel such as holidays, when the ability to foresee higher activity allows an airline to use a bigger aircraft to accommodate the demand for travel rather than lose customers to another airline. The need for an accurate forecast comes down to an airport itself as well. The airport must be equipped to accommodate the busiest times of the year. An accurate forecast allows the airport to plan for the future by deciding if/when is the right time to expand infrastructure, both landside and airside facilities.

This leads to the importance of forecasts for support services as well. For example, a rise in demand in air travel would likely affect the rental car business at the airport. If the rental car business could foresee a higher number of passengers flying they could be readily equipped with more inventory to handle the increase in forthcoming demand. An increase in traffic at the airport itself would translate into the increased demand at retailers, restaurants, and lodging.

Given the recent period of skyrocketing prices for fuel and a global recession taking away discretionary income from most households, airlines have had to rethink their business strategies while still being sure to align with customer demands. Airlines have had to adjust pricing policies, eliminate less profitable routes and ground lesser fuel-efficient aircrafts (Fielding). They have also turned to charging customers separately for services that were previously included in the price of a ticket i.e. baggage fees and near elimination of meals and beverages on domestic flights. For these reasons and others, an accurate forecast is needed to provide an organization the ability to make quality decisions for the future. This study will aim to improve upon previous forecast and reduce forecast errors from very well-known private companies and government agencies like the Federal Aviation Authority (FAA). The trickle-down effect of a bad forecast can't be understated. From manufacturers to airlines to airports to

airport support services, a bad forecast may get a company through the current year but it is not a

recipe for long term success and the consequences can be catastrophic.

RESEARCH HISTORY

Studies on air travel demand really began attracting considerable research in the 1940's. Since that time, a lot of research has been done and many studies have been brought to the forefront in examining future trends of air travel demand. According to the article "Air Travel Demand Studies: A Review" (Min, Wang, and Haiyan, 2010), more than 120 journal articles have been published since the early 1950s. While this study will not aim to simply replicate those studies, the goal is to build upon previous findings and continue moving forward with better and more accurate forecast methods.

The approaches to air travel demand planning in the late 1940's and 1950's centered on the use of gravity models. Gravity models were used to forecast passenger activity between two destinations as opposed to aggregate travel demand (Harvey,1951). The problem with these models was that they did not provide any real insight into understanding the actual causes of air travel demand. Rather, these models were made to just convey the relationships between destinations. In the early 1960's, Dr. Quandt published a research paper titled "The Theory of Travel Demand" in which he proclaimed that travel decisions of an individual emerge from decisions that will optimize his or her behavior (Quandt, Baumol,1966). His research hypothesized that travel demand is positively related to disposable income and negatively related to the cost of travel. While this may seem somewhat elementary to researchers today, this basic underlying thought paved the way for researchers to conduct operational travel demand theories.

Dr. Baumol later built upon this basic premise and included more variables in his research. He attempted to frame travel demand estimation not only in the context of cost, but

also in journey time, departure frequency, and fare packages. He began by looking at the time it took to get from one location to the next and if it had an effect on travel demand. The departure frequency of flights also was examined to see if there was a relationship between the number of possible flights going out and the amount of travel generated as a result of those departures. Finally, he modeled the relationship between the cost of traveling and the demand for travel. The basic idea was that if the cost of travel by air increased too much, passengers would then find other means of transportation and thus decrease overall air travel demand.   Taking these variables into account individually, he estimated volume by ordinary least squares regression model. He furthered his findings by including discriminant analysis as well. Dr. Quandt brought to light the fact that previous models all assumed certain basic universal characteristics of all travelers (Quandt, Baumol, 1966). Prior models had assumed that travelers sharing similar social, demographic, location, and travel options would all make the same choices in regards to travel.

With this understanding, Domencich and McFadden built a model that takes into account such random elements in 1976. Their focus consisted on forecasting to improve service reliability and make it a win-win for both service providers and users (Domencich, McFadden 1975). Domencich and McFadden considered the full range of trip decisions which distinguish travel demand from demand among alternative modes. For example, an increase in parking charges may shift some people to transit, which may re-route some persons to other areas, which may even reduce the total frequency of trips. Their fundamental approach involved understanding the effects of travel time and cost variables through the entire travel decision process. They examined the time of day of travel, trip destination, and trip frequency.

Researcher Atef Ghobrial (1992) made an attempt to estimate travel demand using an econometric model. Ghobrial modeled air travel demand using different combinations of airline operating characteristics as his variables. Some of the variables he used were airline network structure and operating characteristics. A two-stage least-squares procedure was used to come up with the estimated travel demand. The airline network structure regards the makeup of the airline in regards to quality / price; it looks at whether or not an airline is a low cost carrier or a premium carrier. The operating characteristics and firm specific variables obviously vary from airline to airline and the ability to differentiate companies based on their operating characteristics was key to the study. For example some of the operating characteristics / firm specific variables include network size hub dominance, number of flights, capacity of flights, etc. The findings from Ghobrial suggest that demand is elastic to yield and inelastic to network size and hub dominance (Ghobrial, 1992).

Treathaway and Oum (1992)identified 13 main determinants of airline demand, which are the following: price of air travel, income of passengers, price of other transportation modes, frequency of service, timing of service, day of the week, season of the year, safety record, demographics, distance, inflight amenities, customer loyalty and time (Treathaway, Oum, 1992). JW Poore tested the air travel demand forecasts that airline manufacturers and regulators create. His research focused on Boeing, McDonnell Douglas, Airbus, and the International Civil Aviation Organization. His findings indicate that these forecasts are indeed accurate and representative of actual passenger counts. (Poore,1993).

The study from Alperovich, and Machnes (1994) also focused on understanding air travel. Alperovich and Machnes found that air travel to foreign destinations is elastic to income

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and inelastic to price. A time series was used to analyze the data (Alperovich, Machnes,1994). Abed, Jasimuddin, and Jeddah (2000) developed many models to analyze and forecast the demand for air travel in Saudi Arabia. They used different explanatory variables in stepwise regression to create their model. Their findings suggest that it is necessary to have total expenditures of the country and population size as the explanatory variables in order to model domestic passenger air travel most accurately in Saudi Arabia (Fail, Abed, and Jasimuddin, 2000). Most researchers define demand for air transport into two main groups of drivers (Jorge-Calderón,1997). The first driver defined involves geo-economic factors. These factors are determined by the economy and local characteristics. For example, the income and population of an economy are key factors of this type. Next are service related factors, the most important of which are quality and price.

The majority of the forecasting techniques used in prior studies were quantitative in nature. Many simple time series models were used in addition to advanced time series approaches such as generalized autoregressive conditional heteroscadesticity (GARCH) (Adrangi, Chatrath, & Raffiee,2011). Another method tested was regression analysis using econometric variables. The econometric approach measures the relationship between demand and economic factors using regression analysis on historical data.

In addition to the FAA, the airplane manufacturer Boeing creates its own forecast which they call "The Current Market Outlook". It is a long-term forecast of air traffic volumes and demand. The forecast serves many important purposes.. First and foremost, it allows the company to plan for the long term and provides very useful information and guidance to shape their strategic decisions. Each year they create their forecast from scratch so that they are able to

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capture any changes in the business environment. They create their forecasts on the basis of analyzing what they perceive to be key indicators of airline volume, including but not limited to, Gross Domestic Product (GDP), fuel prices, market liberalization, airline capabilities, airline strategies, emerging markets, economic growth, growth/decline of high-speed rail, and the environment. The demand forecast is ultimately created by using a top down-bottom up analysis approach.

Bottom-up analysis begins with forecasting the travel demands between countries. These forecasts are based on many different economic projections, historical trends, and regulatory policies. Trends in airline demand are identified by analyzing government statistics on visitors coming in and going out of the country. Tourism receipts are also analyzed with the purpose of trying to identify potential trends. Finally, countries are grouped into categories based on their geographic location and the travel between and within regions is analyzed. In the top-down approach, projections are first made on a global level and then trickle down to country and then to regional travel demand. The two approaches are then reconciled to come up with one final number. Any changes in population, transportation methods, and even new competitors within the airline industry are factored in. The final data is put together to develop the complete demand forecast.

The contribution to the field that this paper aims to make is to compare forecasted with actual amounts and calculate forecast errors. Prior studies have all focused on the ability to model passenger travel demand as accurately as possible but have neglected to provide a means of comparison in order to validate the accuracy of the model built. This study will build a model

to better predict air travel demand and then compare those predicted passenger counts with actual

counts. These errors will then be compared to the forecast errors of the industry standard (FAA).

METHODOLOGY

In this study, it was decided that the best and most accurate model to build upon was the study done in 2000 by Fail, Abed, and Jasimuddin. Their model used the total expenditures of the country and population size as the explanatory variables to represent demand for domestic travel in Saudi Arabia. . Using this idea as a base, the decision was made to explore and understand the relationships between different macro-economic factors and passenger demand. The following variables were analyzed in this study.

Dependent Variable: Annual Passenger Count (Passenger Enplanements)

Independent Variables: GDP Growth, Unemployment Rate, Change in CPI, Personal Income, Population

These macro-economic variables were chosen because the total expenditures of a country are highly dependent on these variables. Obviously the GDP growth is a direct measure of the consumption / expenditures of a country. The unemployment rate is also important because if people are out of work they will not be spending as much. Changes in the Consumer Price Index (CPI) and Personal Income affect expenditures directly because these changes affect the amount of purchasing power that individuals have. Finally the population of a country would seem to have a linear relationship with its expenditures, that is, one would expect the expenditures of a country to increase as its population increases as well. The data is collected from reputable organizations, a summarization of the variables and their sources is below

Variable	Source
Annual Passenger Count	Bureau of Transportation Statistics
GDP Growth	World Bank
Unemployment Rate	Bureau of Labor Statistics
Change in CPI	Bureau of Labor Statistics
Personal Income	Bureau of Economic Analysis
Population	World Bank

Table 1: Variable Sources

We begin our analysis of this data by inputting the dependent and independent variables into statistical software SAS version 9.2. We would like to begin making our predictions for passenger count from 2006 forward using model reflective of actual data from 1990-2005. A regression is run on this data to provide a statistical model of best fit. Estimates of regression coefficients of variables with all five independent variables mentioned above are included in the model in Proc Reg (a SAS procedure for regression analysis) and are displayed below in Table 2.

Table 2: Parameter Estimates with 5 variables

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	-142046277	715321578	-0.2	0.8466
PersonalIncome	1	22063	24677	0.89	0.3923
Population	1	1934317	3240289	0.6	0.5638
GDPGrowth	1	9495230	3084998	3.08	0.0117
Unemployment	1	-11488129	4247585	-2.7	0.0221
ChangeinCPI	1	4230328	5047148	0.84	0.4215

It is not necessary to use statistically insignificant variables. For this reason, the most insignificant variable "population" which has the highest p-value is taken out of the model.

After taking the population variable out of the model, the regression was re-run in SAS with the remaining four variables (Personal Income, GDP Growth, Unemployment, and Change in CPI). The SAS output for thus run is displayed below in Table 3.

Table 3: Parameter Estimates with 4 variables

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	284265857	39867477	7.13	<.0001
PersonalIncome	1	36738	2091.6845	17.56	<.0001
GDPGrowth	1	10450171	2559511	4.08	0.0018
Unemployment	1	-11779415	4094157	-2.88	0.015
ChangeinCPI	1	1885872	3075987	0.61	0.5523

Continuing the same process, the variable that was the most statistically insignificant was kicked out. In this model, the variable "change in CPI" with the highest p-value is most insignificant. The next running of the regression model excluded this variable and was re run using the three remaining variables (Personal Income, GDP Growth, and Unemployment). The SAS output for this model is provided below in Table 4.

Table 4: Parameter Estimates with 3 variables

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	294865923	34976752	8.43	<.0001
PersonalIncome	1	36342	1936.9543	18.76	<.0001
GDPGrowth	1	10206098	2461735	4.15	0.0014
Unemployment	1	-12068410	3959760	-3.05	0.0101

It can be seen from the above table that there are not any statistically insignificant variables in the model and therefore all of the variables can stay in our model. The adjusted R-squared value for this model is .9778 which means that 97.78% of the variation in Passenger Count is explained by the variation in the three independent variables (Personal Income, GDP Growth, and Unemployment Rate). With these three significant variables, we obtain the following prediction equation to predict the mean passenger count for given values of independent variables.

Passenger Count = 294,865,923 + 36,342*PI + 10206098*GDPGrowth - 12068410*Unempl.

Before we use the above equation for prediction purposes, it is important to check that the statistical assumptions required for the validity of tests used in the above regression analysis are satisfied.

STATISTICAL ASSUMPTIONS

We have looked at normal probability plot of residuals which is approximately a straight line and Shapiro-Wilks Test (W =0.93, p-value =0.2397) for normal distribution assumption of residuals. It appears that there is no significant departure from normal distribution. The Breusch-Pagan test (chi-square =0.54, p-value =0.7644) for heteroscedasticity indicates that the constant error variance assumption is satisfied. To see if the data has any outliers or influential observations, we have looked at both the studentized and studentized deleted residuals. For our data, abs (studentized residuals) do not exceed 1.781 (more than three indicates no outliers) and abs (studentized deleted residuals) do not exceed 1.9876 (more than $t_{11, (1-\alpha/(2n))} = 3.76544$ indicates outlier). Thus there is no indication of any outlier in our data. Next we look to see if there are any influential observations in our data using Cooks D method. If Cooks D is greater

than the 50th percentile of the $F_{4, 12}(\alpha)$ distribution, then we will have influential data. However,

all Cooks D from our data are below $F_{4, 12}(\alpha) = .8848$ (the 50% percentile number). In fact, the

largest Cook D value is only approximately .54. Multi-colinearity is checked using Variance

Inflation Factor (VIF) which turns out to be less than 1.66 for all three independent variables of

our model. A VIF value greater than 10 is an indication of excessive multi-coliniearity. Finally

the Durbin Watson Test (D= 1.21, p-value = 0.0061) for trend is checked. The test indicates

that there may be some trend in the data, a possible violation of independence assumption. It is

somewhat expected for trends to occur in the passenger count because it mirrors business cycles

very closely. For this reason, the decision was made that it was still okay to continue with our

regression model. It should be noted that all of the assumptions were calculated using SAS.

RESULTS

Now that a model has been created from data between 1990-2005 and the assumptions have been discussed, the next step involves further analysis of the individual variables themselves. For the purpose of prediction, we need values of all independent variables for the next 5 years. To do this we created individual forecasts for each independent variable. This was done using the 'proc autoreg' procedure in SAS. It does not use year as an independent variable but rather uses the time orders in the data. Different scenarios were exercised in regards to the duration of the lag from 1-5. After looking at all the different scenarios and the associated adjusted R-squared value, lag 3 was used to predict each individual independent variable. A higher lag would have eliminated more data points from our set. With a lag of 3, the regression is run on the prior 3 years only. For example, in the year 2006, with a lag of 3, the regression in SAS is being calculated from data in 2003, 2004, and 2005. Likewise, in the year 2007, regression in SAS is being calculated from the data in 2004, 2005, and 2006. The forecast values of the three independent variables were then plugged into the regression equation created earlier. Table 5 below gives a snapshot of the results.

Table 5: 3 variable Model Data

	P Count Actual	PI Predicted	GDP Grwth Predicted	Unemp.	Predicted P Count	Model Error	FAA Error
16	660642163	10,975.15	3.34101	5.0083	667,380,919.92	1.02%	0.70%
17	681492975	11,412.23	2.98454	5.1802	677,552,915.90	0.58%	4.50%
18	653822858	11,791.85	3.05088	5.4315	688,993,709.10	5.38%	9.30%
19	620277076	12,112.84	2.93622	5.5932	697,537,675.96	12.46%	10.00%
20	632129027	12,374.02	3.04455	5.6042	708,002,353.60	12.00%	11.30%

Table 4 above shows that the only errors that have been predicted better than the FAA was the 2nd and 3rd Year projections. Due to the relative lack of success with this model, further

analysis was conducted to see if an additional variable could be included in the model to help

create better results. After some analysis it was seen that the inclusion of the variable 'year'

reduced model error. Year was chosen to be included because of its relatively high R squared

value against passenger count. It was very highly correlated and thus it was hypothesized that it

could improve our overall model accuracy.

Returning to SAS, regression was re-run to include year with our previous variables. The

adjusted R-squared value for this regression which included year was .9762. While this is a very

slight increase from the adjusted r squared of the model without year (.9751), we will see a little

bit later that it improves out errors. All of the assumptions as stated earlier have also held when

year is included but VIF for personal income and year increases substantially due to the high

correlation between these two variables. We will continue using this model even though this co

linearity exists in order to see if our final results are better with this model. The new model with

Year, Personal Income, GDP Growth, and Unemployment Rate is

$$Passenger\ Count = 341973606 + 3644838*Year + 26881*PI + 9589476*GDPGrwth -$$

$$12554955*UnemploymentRate.$$

Table 6 below shows the errors when using this model and the forecast values of the independent

variables displayed above in Table 4.

Table 6: Error Analysis for Regression Model with Year included

Year	PC Actual	PI Predicted	GDP Growth Pred.	Unemp.	Reg Predicted PC	My error	FAA Error
16	660,642,163.00	10,975.15	3.34101	5.00833	664,473,198.59	0.58%	0.7%
17	681,492,975.00	11,412.23	2.98454	5.1802	674,291,003.44	1.06%	4.5%
18	653,822,858.00	11,791.85	3.05088	5.43147	685,621,888.96	4.86%	9.3%
19	620,277,076.00	12,112.84	2.93622	5.59315	694,765,844.70	12.01%	10.0%
20	632,129,027.00	12,374.02	3.04455	5.60415	706,332,185.71	11.74%	11.3%

It can be seen that the errors have indeed decreased with this model; however it only beats the FAA forecast for period 1, 2, and 3. In order to try and come up with an even better model, we now incorporate some qualitative research findings in regards to forecast errors. In a research project done in 2007 titled "Gauging the Uncertainty of the Economic Outlook from Historical Forecasting Errors" (Reifschneider,Tulip 2007), researchers collected data on the forecast errors made from a variety of forecasters of economic interest. They collected forecast error on data from 1986-2006 and table 7 below shows their projections for unemployment forecast errors in 2008, 2009, and 2010.

Table 7: Historical Projection Errors

Average Historical Projection Error Ranges			
(Percentage Points)			
	2008	**2009**	**2010**
Unemployment rate	±0.5	±0.8	±1.0

The Institute of Economic Competitiveness at the University of Central Florida provides complete economic forecast and analysis every quarter on both a national and state level. In their publication from 1st quarter 2007, they project national unemployment rates to stop falling by 2007 and begin rising for the next 2-3 years. This slight increase in unemployment, according to the institute, will be fueled by projected continued job loss in the manufacturing, information, financial and construction industries; the latter two of which are part of the fallout from the cooling housing sector. In addition, they project unemployment to increase slightly due to changes in global competition from information technology advancements. The Congressional Budget Office (CBO) makes yearly projections of the unemployment rate as well. In their 2007 annual report, the CBO anticipates that job growth will slow down for the next few years due to

the decline in housing activity, as jobs in residential construction and industries related to
housing have been declining. One of the things that many economic forecasters have ignored in
making their projections for unemployment is the actual new job growth rate. Many have just
taken a look at the unemployment rate staying low and have been pleased with that result.
However, the warning signs for a coming higher unemployment are apparent when looking at the
rate of job growth declining every month in 2006. A job creation study done by the Labor
Department shows that while jobs created was still positive, the decline in growth from month to
month suggests trouble to come as mentioned in a journal on CNN criticizing then President
Bush for only touting jobless figures and ignoring job creation data (CNN). Using all this
information, the projected unemployment rate from the time series was increased by .5 for 2008,
.8 for 2009, and 1 for 2010 rather than decreased. The errors were then recalculated and
summarized below in Table 8, which shows better errors for nearly all periods.

Table 8: Errors for Model with Increased Unemployment

Year	PC Actual	PI Predicted	GDP Growth Pred.	Unemp.	Reg Predicted PC	My error	FAA Error
16	660,642,163.00	10,975.15	3.34101	5.00833	664,473,198.59	0.58%	0.70%
17	681,492,975.00	11,412.23	2.98454	5.1802	674,291,003.44	1.06%	4.50%
18	653,822,858.00	11,791.85	3.05088	5.93147	679,344,411.46	3.90%	9.30%
19	620,277,076.00	12,112.84	2.93622	6.39315	684,721,880.70	10.39%	10.00%
20	632,129,027.00	12,374.02	3.04455	6.60415	693,777,230.71	9.75%	11.30%

It is important to understand the FAA errors for comparisons purpose. The next section will
discuss these in detail.

FORECAST ACCURACY

Given the volatile nature of the U.S. airline industry, it does not come as a surprise that the forecast for each year contains a certain degree of variance from actual count. This variance will be measured by the Mean Absolute Percentage Error (MAPE) to stay consistent with the variance measure of the FAA. Every fiscal year the FAA publishes their forecast for the coming years. At the same time, the FAA looks back and conducts an analysis from historical results to see how accurate their forecasts are. The FAA measures the mean absolute percent errors for the projected values versus the actual results for U.S. carrier's domestic operations. The metric called "Passenger Enplanements" is important in our study; it is a measure of the number of scheduled passengers. This metric shows the relative forecast variance by the number of years in advance the forecast took place. For example, in the table below, the "3 Years" column for Pax Enplanements shows that the mean absolute percent error was 9.3% for the forecast prepared 3 years prior.

Forecast Variable	Mean Absolute Percent Error				
	1 Year	2 Year	3 Year	4 Year	5 Year
Pax Enplanements	0.70%	4.50%	9.30%	10.00%	11.30%

When the FAA makes its forecast for the coming year, it is then that they publish their forecast errors of the prior years. This is important to note because, though the FAA published their latest forecasts in 2011, the errors were looking back on the projections from 2006, 2007, 2008, 2009, and 2010. In other words, the FAA was making a projection in 2006 of what they believed passenger travel would be in 2010. This corresponds to the 5 year MAPE of 11.30%. In 2007, the FAA made a projection of what they believed to be passenger travel in 2010 and this

error came out to the 4 year MAPE of 10.00% just for illustrative purposes. The same process

continues throughout.

LIMITATIONS/FURTHER RESEARCH

As discussed prior in this paper, the model that I have built seems to be a better overall approximation for passenger count than that of the FAA. However, there may be some limitations with this project. First of all, the individual independent variable forecasts were all predicted using 'proc autoreg' in SAS. If this software is not a good method in reality, this could provide erroneous forecast for these variables which leads to a bad forecast. Another drawback to the approach used is that some of the conditions for statistical assumption were not met. These conditions could lead to inaccurate conclusions and provide a misleading forecast. In the final model built, the variance inflation factor is relatively high for year and personal income. The research that was incorporated into this study may also not be as accurate as it claims. The average prediction errors for unemployment for example, may be off. It is also difficult to gauge whether to increase the rate in the positive direction or rather in a negative direction. Even with these limitations, we are fairly confident that the model built is a good predictor for annual passenger enplanements in the United States of America.

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