Iowa State University
Digital Repository

Industrial and Manufacturing Systems Engineering Conference Proceedings and Posters

Industrial and Manufacturing Systems Engineering

2017

Probabilistic Methods for Long-Term Demand Forecasting for Aviation Production Planning

Minxiang Zhang
Iowa State University

Cameron A. MacKenzie
Iowa State University, camacken@iastate.edu

Caroline Krejci
Iowa State University

John K. Jackman
Iowa State University, jkj@iastate.edu

Guiping Hu
Iowa State University, gphu@iastate.edu

See next page for additional authors

Follow this and additional works at: https://lib.dr.iastate.edu/imse_conf

Part of the Operational Research Commons

Recommended Citation

Zhang, Minxiang; MacKenzie, Cameron A.; Krejci, Caroline; Jackman, John K.; Hu, Guiping; Hu, Charles Y.; Burnett, Gabriel A.; and Graunke, Adam A., "Probabilistic Methods for Long-Term Demand Forecasting for Aviation Production Planning" (2017). *Industrial and Manufacturing Systems Engineering Conference Proceedings and Posters*. 176.
https://lib.dr.iastate.edu/imse_conf/176

This Conference Proceeding is brought to you for free and open access by the Industrial and Manufacturing Systems Engineering at Iowa State University Digital Repository. It has been accepted for inclusion in Industrial and Manufacturing Systems Engineering Conference Proceedings and Posters by an authorized administrator of Iowa State University Digital Repository. For more information, please contact digirep@iastate.edu.

Probabilistic Methods for Long-Term Demand Forecasting for Aviation Production Planning

Abstract
The aviation industry represents a complex system with low-volume high-value manufacturing, long lead times, large capital investments, and highly variable demand. Making important decisions with intensive capital investments requires accurate forecasting of future demand. However, this can be challenging because of significant variability in future scenarios. The use of probabilistic methods such as Brownian motion in forecasting has been well studied especially in the financial industry. Applying these probabilistic methods to forecast demand in the aerospace industry can be problematic because of the independence assumptions and no consideration of production system in these models. We used two forecasting models based on stochastic processes to forecast demand for commercial aircraft models. A modified Brownian motion model was developed to account for dependency between observations. Geometric Brownian motion at different starting points was used to accurately account for increasing variation. The modified Brownian motion and the geometric Brownian motion models were used to forecast demand for aircraft production in the next 20 years.

Keywords
Forecasting, Brownian motion, Geometric Brownian motion, Aviation

Disciplines
Operational Research

Comments
This proceeding is published as Zhang, Minxiang, Cameron A. MacKenzie, Caroline Krejci, John Jackman, Guiping Hu, Charles Y. Hu, Gabriel A. Burnett, and Adam A. Graunke. "Probabilistic methods for long-term demand forecasting for aviation production planning." In *Proceedings of the 2017 IISE Annual Conference and Expo*. May 20-23, 2017. Pittsburgh, Pennsylvania. Posted with permission.

Authors
Minxiang Zhang, Cameron A. MacKenzie, Caroline Krejci, John K. Jackman, Guiping Hu, Charles Y. Hu, Gabriel A. Burnett, and Adam A. Graunke

This conference proceeding is available at Iowa State University Digital Repository: https://lib.dr.iastate.edu/imse_conf/176

Proceedings of the 2017 Industrial and Systems Engineering Conference
K. Coperich, E. Cudney, H. Nembhard, eds.

Probabilistic methods for long-term demand forecasting for aviation production planning

Minxiang Zhang, Cameron A. MacKenzie, Caroline Krejci, John Jackman, Guiping Hu
Industrial & Manufacturing Systems Engineering, Iowa State University
Ames, IA, USA

Charles Y. Hu, Gabriel A. Burnett, Adam A. Graunke
Boeing Research & Technology
Seattle, WA, USA

Abstract

The aviation industry represents a complex system with low-volume high-value manufacturing, long lead times, large capital investments, and highly variable demand. Making important decisions with intensive capital investments requires accurate forecasting of future demand. However, this can be challenging because of significant variability in future scenarios. The use of probabilistic methods such as Brownian motion in forecasting has been well studied especially in the financial industry. Applying these probabilistic methods to forecast demand in the aerospace industry can be problematic because of the independence assumptions and no consideration of production system in these models. We used two forecasting models based on stochastic processes to forecast demand for commercial aircraft models. A modified Brownian motion model was developed to account for dependency between observations. Geometric Brownian motion at different starting points was used to accurately account for increasing variation. The modified Brownian motion and the geometric Brownian motion models were used to forecast demand for aircraft production in the next 20 years.

Keywords

Forecasting, Brownian motion, Geometric Brownian motion, Aviation

1. Introduction

As globalization increases, so does air travel, which in turn increases the demand for new aircraft. In this environment, Boeing is analyzing its capacity to manufacture commercial aircraft to satisfy future demand. Given the substantial investment required to increase capacity, this analysis is predicated on a forecast model for demand for new aircraft for the next 20 years. There is no “best” method for long-term demand forecasting [1]. The goal of this research is to develop a way to measure risk and uncertainty for future demand, so that it could provide adequate information for a decision maker in enterprise strategic planning.

Forecasting future demand given historical data often applies traditional time series models (e.g., Autoregressive Integrated Moving Average). Demand in the aviation industry is influenced by numerous factors such as macroeconomics, fuel price, globalization, and competitiveness. Historical demand for airplanes exhibits large variability. It may not be possible to accurately predict demand without establishing a multivariate causal model which requires enormous effort. Compared to traditional forecasting, probabilistic methods explicitly incorporate uncertainty and therefore show a range of plausible scenarios. For a production planning problem with high capital investment, probabilistic information for future states is more meaningful than a deterministic forecast of demand. This paper favors probabilistic models to quantify the uncertainty in future demand.

This paper focuses on Boeing’s future painting capacity planning for new airplanes and to determine whether additional painting capacity is needed. Forecasting demand is necessary to develop a reasonable production planning model. This paper uses probabilistic methods for long-term demand forecasting that is based on historical data of annual airplane orders and develops innovative methods to apply these models to forecasting aircraft demand. First, a Brownian motion model is developed to account for dependency between annual orders. Brownian motion assumes independence, but this paper proposes a unique method to dynamically adjust the forecast based on observed correlation. We borrow from the autoregressive model to introduce correlation into Brownian motion. This approach is helpful when the historical data show a strong correlation. This model is applied to forecasting demand for Boeing's 737. Second, this paper constructs a model for geometric Brownian motion (GBM) in which the starting point is shifted to forecast demand for Boeing's 777. We demonstrate how these models account for both the trend (mean shift) and variation in annual demand.

2. Background on Brownian Motion and Geometric Brownian Motion

Airplane demand can be viewed as a stochastic process since future demand in each year is uncertain and can be represented by a random variable. In the context of modeling demand, a Brownian motion model with drift assumes that annual demand follows a normal distribution with mean $\mu t + e$ and variance $t\sigma^2$, where μ is the mean shift in demand, t is the number of years since the current year, e is the current demand, and σ^2 is the variance of demand at time $t = 1$. Hence, the model implies that the uncertainty (variance) increases each year. Brownian motion assumes that demand in each year is independent of the other years and that demand in each year follows a normal distribution. If the annual demand for airplanes follows a Brownian motion process, the demand at time t is:

$$X(t) = \sigma B(t) + \mu t + e \tag{1}$$

where $B(t) \sim N(0, t)$ is a standard Brownian motion (i.e., it is normally distributed with a mean 0 and variance t).

GBM is a stochastic process that is used when we believe that the percentage changes in demand are independent and identically distributed [2]. GBM is commonly used to predict stock prices and oil prices. The annual demand in year t according to a GBM is $Y(t) = \exp(X(t))$ where $X(t)$ is calculated as in Equation (1). The GBM requires a normality assumption, but in this case the logarithm of ratio, $\frac{Y(t+1)}{Y(t)}$, should follow a normal distribution [3]. The normality assumption can be checked via a standard probability plot or quantile-quantile (Q-Q) plot. The GBM also assumes independence of log ratio. The independence assumption can be tested by whether there is association between the variables. If only linear association is considered, it could be checked by measuring the autocorrelation function (ACF) of demand ratio, $\frac{Y(t+1)}{Y(t)}$, which should be not significant for lag > 0. The maximum likelihood estimation (MLE) method can be used to estimate model parameters such as the mean (i.e., drift) and standard deviation for Brownian motion or GBM based on historical data.

3. Modified Brownian Motion for the 737

The annual orders for the 737 airplane model were obtained from Boeing's website[4]. Figure 1 shows annual orders for the 737 from 1965 to 2015, and Figure 2 depicts the difference in orders between two adjacent years. These figures show an increasing trend in orders. The increasing differences between adjacent demands suggest that the variance in annual orders increases with time. It matches the assumption of Brownian motion with positive drift.

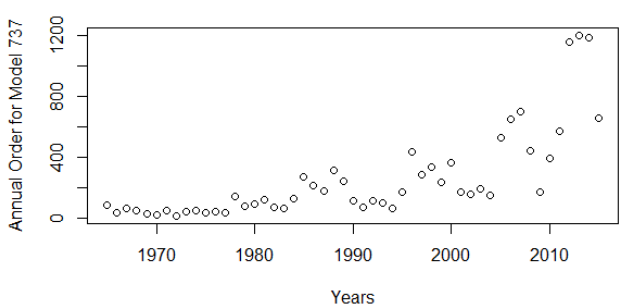

Figure 1: Annual orders for the 737

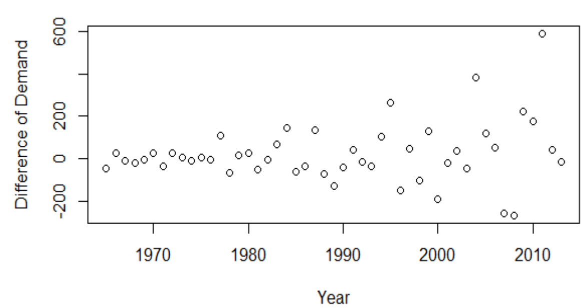

Figure 2: Difference in orders between adjacent years for the 737

A plot of the ACF and partial autocorrelation function (PACF) are used to examine linear dependence in the data. The ACF has a slow decay and depicts that the annual order data is dependent. Therefore, it violates the independence assumption required for Brownian motion, and simple Brownian motion is not a good model for this data.

Since the traditional Brownian motion method is unsatisfactory for the 737, we develop a unique approach to forecast annual orders for the 737. Because the annual orders exhibit autocorrelation, we incorporated dependence into the

Brownian motion. The correlation between two adjacent years is defined as ρ. If N_1 and N_2 are random variables from a standard normal distribution, we define N_{cor} to be a random variable where

$$N_{cor} = \rho N_1 + \sqrt{1-\rho^2} N_2. \quad (2)$$

It can be shown that N_{cor} also follows a normal distribution and has a correlation of ρ with N_1. If $X(t) = \sigma\sqrt{t}N_1 + \mu t + e$ and $X(t+1) = \sigma\sqrt{t+1}N_{cor} + \mu(t+1) + e$, then the correlation between $X(t)$ and $X(t+1)$ equals ρ. Thus, we can use the idea of Brownian motion but induce correlation between annual years.

The historical data of annual orders for the 737 was used to calculate the standard deviation (σ=173.8) and the correlation ($\rho = 0.71$). The ACF suggests using a period of 12 years to calculate the baseline or current demand. We calculated the corresponding correlation (w_k), which is the correlation between annual orders separated by k years. The baseline $e = 334$ was computed as a weighted average of the historical data:

$$e = \sum_{t=1}^{12}[X(-t) * w_t] \quad (3)$$

where $X(-t)$ represents the annual orders t years prior to the baseline. We estimated the drift for the Brownian motion by assuming a linear increasing trend for the 737. However, only data after 1989 was used for two reasons. First, it usually takes a while before the market adopts a new product. Second, by observing the time-ordered plot, 1965 to 1988 served as a transition period for the 737. The estimated drift was $\mu = 31.7$ by using regression analysis of the data from 1989 to 2015. The data from the past three years were removed before estimating the standard deviation, as we consider them to be extreme cases. If we had incorporated them into the calculation, the standard deviation would be 294.8, and the baseline would be 403. These numbers produced a very wide 90% probability interval that in most cases ranges from 0 to more than 3000 orders. It seems very unlikely that there would be more than 3000 737s ordered in a single year. Thus, we ignore the data from the last three years for the estimation of standard deviation and baseline demand. Table 1 shows the parameters for this modified model.

Table 1: Modified Brownian motion parameters for the 737

Model	**Time scale**	**Brownian motion parameters**			
		Drift	Sigma	Baseline	Correlation
737	Year	31.7	173.8	334.3	0.71

We used a Monte Carlo simulation to simulate this modified Brownian motion model and ran 100,000 replications over a 20-year period. The median (red circles) and a 90% prediction interval (blue circles) are shown in Figure 3. These values were obtained from the output of the simulation by finding the values at the 0.5, 0.05, and 0.95 quantiles.

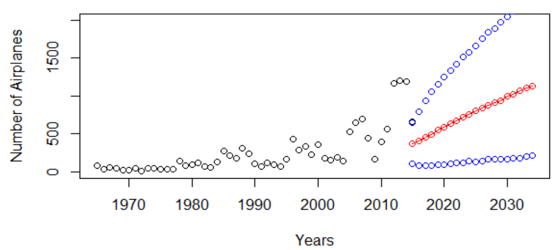

Figure 3: Twenty-year demand forecast for the 737

For comparison, Boeing's 20-year outlook [5] for a single-aisle airplane demand in the next 20 years is 26,730 airplanes. Assuming that Boeing captures 50% of the market, the demand for the 737 airplane is 13,365 planes. Based on our modified Brownian motion model, the forecast median demand for the 737 is 15,370 planes.

4. Geometric Brownian Motion Model for the 777

Similar to the 737, the annual historical orders for the 777 airplane model were obtained from Boeing's website[4]. Figure 3 shows the annual orders for the 777 for years 1990 to 2015. Figure 4 displays the difference in annual orders between each of the adjacent years. The annual orders for the 777 exhibit an upward trend and increasing variance over time. Figures 5 and 6 depict the ACF and PACF of ratio of annual order for the 777.

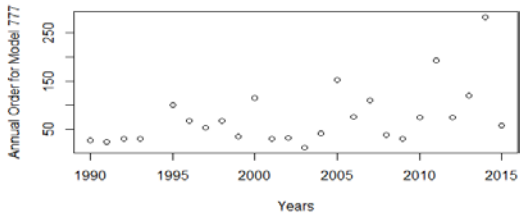

Figure 3: Annual orders for the 777

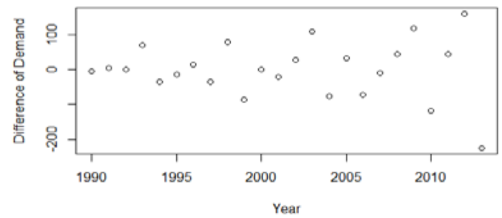

Figure 4: Difference in orders between adjacent years for the 777

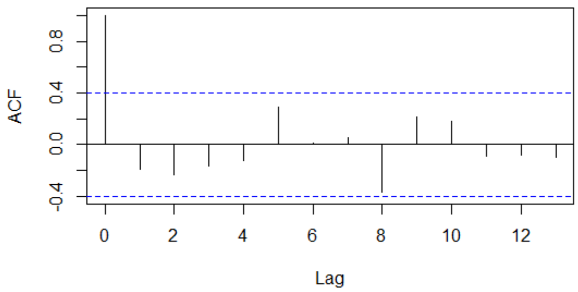

Figure 5: Autocorrelation of Ratio of Annual Orders for the 777

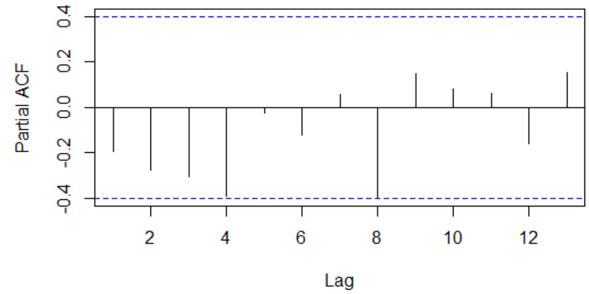

Figure 6: Partial Autocorrelation of Ratio of Annual Orders for the 777

The ACF and PACF plots for the 777 demonstrate that the ratio of orders is linearly independent. This suggests that the GBM could be an appropriate model if the normality assumption is valid.

4.1. Traditional Geometric Brownian Motion Method

First, we created a normal Q-Q plot without a log transformation for the 777 to check the normality assumption for Brownian motion. The result showed that the data for the annual orders for the 777 did not satisfy the normality assumption. We used a similar approach to check the normality assumption under the GBM framework. After taking the log transformation of the original data, the normality plots for the 777 are shown in Figures 7 and 8. We did the Shapiro-Wilk test on log transformed data with p-value 0.7, so we failed to reject the null hypothesis: the original data follow a lognormal distribution. Hence, it appears that the annual orders for the 777 satisfy the GBM normality assumption, and the GBM can be used to forecast annual orders for the 777.

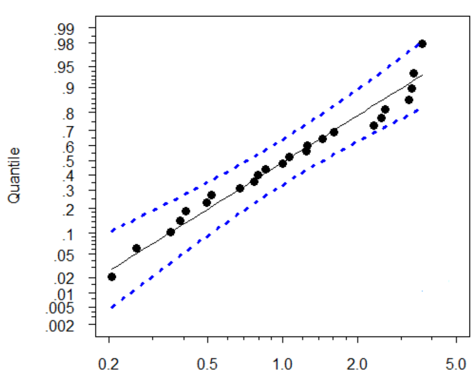

Figure 7: Lognormal probability plot for the GBM normality check for the 777

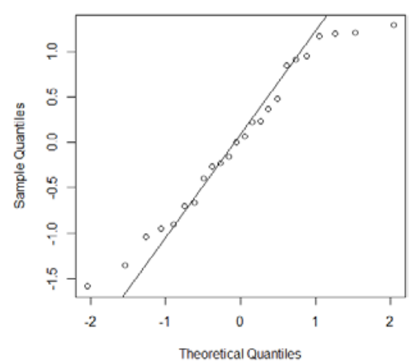

Figure 8: Normal Q-Q plot for the GBM normality check for the 777

We computed $R(t)$ from historical annual orders $Y(t)$, where $R(k) = \frac{Y(t+k)}{Y(t)}$, t is the year starting from 0, and the lag $k = 1$. A lognormal distribution was fit for $R(k)$. The estimated mean $\hat{\mu}$ is the drift for GBM and the estimated variance $\widehat{\sigma^2}$ is the variance for GBM. Based on the estimated mean $\hat{\mu}$, $Z(t) = \log[Y(t)] - \hat{\mu}t$. $Z(t)$ has a normal distribution with mean e and variance $\sigma^2 t$, where e is the initial point (i.e., baseline orders). Table 2 shows all estimated parameters that are used in GBM for the 777.

Table 2: GBM parameters (traditional method) for the 777

Model	Time Scale	Drift	Sigma	Baseline
777	Year	0.030	0.847	3.635

We used Monte Carlo simulation to generate 10,000 random forecasts for a 20-year period. The median forecast values for each year (red circles) and the associated 90% probability interval (blue circles) were obtained from the simulation and are shown in Figures 9. Because of the log transformation, the 90% probability intervals for the 777 are too wide to be shown on the graph. The upper bound for the 777 after three years is larger than 500 planes and increases to more than 10,000 planes in years 2025 and beyond. These numbers are unrealistic.

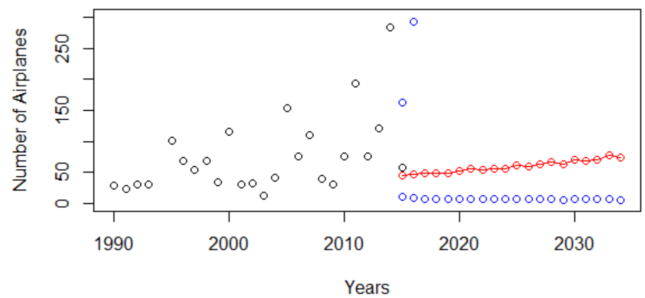

Figure 9: Twenty-Year Demand Forecast for the 777 (Traditional GBM Method)

4.2. Alternative Geometric Brownian Motion Method

Since the uncertainty is very large using the traditional GBM model, an alternative method was proposed. In the traditional method, the lag k is set to 1, which means that we are interested in the difference between two adjacent years, and $R(1) = \frac{Y(k+1)}{Y(k)}$ has a lognormal distribution with mean μ and variance σ^2. In the alternative method, lag k equals t. For each year t, $R(t) = \frac{Y(t)}{Y(0)}$ has a lognormal distribution with mean μt and variance $\sigma^2 t$. The MLE method is used to obtain the most likely μ and σ from the sum of log-likelihood function of lognormal distribution with $R(t)$. Table 3 shows all GBM parameters that were estimated using the alternative method.

Table 3: GBM parameters (alternative method) for the 777

Model	Time Scale	Drift	Sigma	Baseline
777	Year	0.0563	0.1913	3.635

The median forecast values (red circles), the 90% probability interval (blue circles), and the historical data (black circles) are shown in Figure 10. Note that the initial probability interval is very small which may not capture the uncertainty well. This is because the alternative method provides a best fit to historical data (by beginning at $t = 0$) under the GBM framework. The estimated sigma is much smaller than the estimation from the traditional method since the alternative method incorporates the influence of time in variance estimation.

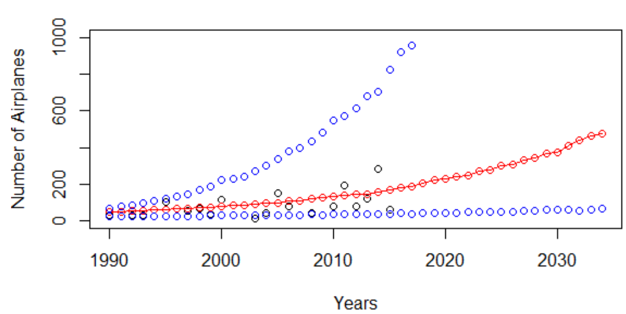

Figure 10: Fitted GBM for the 777 (Alternative Method)

We can move the initial point backwards and forwards along the time axis. For example, Figure 11 shows what the estimation would be if we choose year 2000 as a restart point for the 777, and Figure 12 shows the estimations for the 777 if the model starts at year 2015. However, it is important to mention that even when we start the estimation in the middle of the timeline, the GBM parameters are the same as in Table 3.

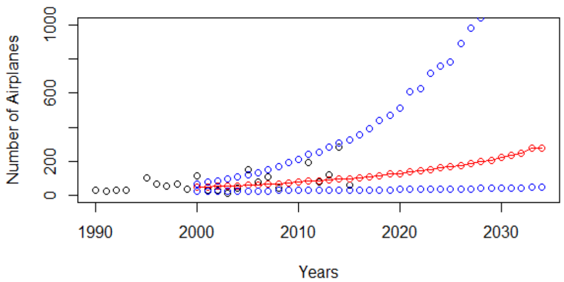

Figure 11: Fitted GBM starting at year 2000 for the 777 (alternative method)

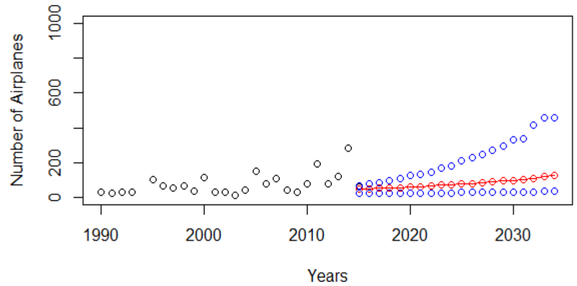

Figure 12: Fitted GBM starting at year 2015 for the 777 (alternative method)

By comparison, according to Boeing's 20-year outlook [5], the global medium wide-body airplane demand in the next 20 years is 3,520 airplanes. Assuming that Boeing captures 50% of the market, the demand for the 777 is 1,760 planes. Based on our modified GBM model (Figure 11), the forecast median demand for the 777 is 1,188 planes.

5. Conclusion

This research explores different methods for forecasting long-term demand based on historical data for Boeing's airplanes. We have used Brownian motion and GBM models and have shown how these models need to be adjusted to fit the nature of the historical data. The median forecasted demand compares favorably to the 20-year Boeing demand forecast. Both the Brownian motion model for the 737 and the GBM model for the 777 have significant uncertainty in the forecasts 15-20 years in the future. Although some reduction of uncertainty may be possible, we believe that accurately forecasting demand such a long time into the future will have a lot of uncertainty, and relying on models without such uncertainty could exhibit overconfidence in our knowledge of the future.

These demand forecasts serve as an input into a larger systems model that evaluates Boeing's current production capacity for airplanes. Given a demand realization based on the probabilistic models for the 737, 777, and other airplane models not discussed in this paper, a production planning model optimally schedules the painting of new airplane orders. The schedule determines how Boeing can most efficiently utilize its current painting capacity. Based on running this model with several demand realizations, we can calculate the probability that Boeing's current painting capacity will be exceeded in any given year. The demand forecasts will be used by the systems model to assess if and when Boeing should expand its capacity for painting airplanes. Future research can compare these probabilistic models to other forecasting models including an autoregressive integrated moving average and a demand model based upon other factors such as gross domestic product.

Acknowledgements

The research is supported by research funds from the Boeing Analytics Research Scholars.

References

[1] J. S. Armstrong, "Evaluating Forecasting Methods," in *Principles of Forecasting: A Handbook for Researchers and Practitioners*, J. S. Armstrong, Ed., ed Boston, MA: Springer US, 2001, pp. 443-472.
[2] S. Ross, *Introduction to Probability Models*. Boston: Academic Press, 2014.
[3] R. R. Marathe and S. M. Ryan, "On the validity of the geometric Brownian motion assumption," *The Engineering Economist*, vol. 50, pp. 159-192, 2005.
[4] Boeing. (2015). *Boeing Commercial*. Available: http://www.boeing.com/commercial/
[5] Boeing.com, "Boeing Current Market Outlook," Nov. 2015 2015.