

International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Visit: www.ijirset.com

Vol. 8, Issue 3, March 2019

Problem Solving on Decision Making and Forecasting in Ambiguity: A Survey

Hitender Thakur¹, Prabhdeep Singh Bajwa²

P.G. Student, Department of Mechanical Engineering, L.R.I.E.T, Solan, Himachal Pradesh, India¹

Assistant Professor, Department of Mechanical Engineering, L.R.I.E.T, Solan, Himachal Pradesh, India²

ABSTRACT: The aviation industry represents a compound organization with low-volume high-value manufacturing, long lead times, large capital investments, and highly variable demand. Formulating vital conclusions with rigorous capital investments requires precise forecasting of future demand. However, this can be perplexing because of major changeability in future developments. The tenacity of this research is to improve an approach on making long-term production planning decision with suitable demand forecasting model and decision-making theory.

The first study is concentrated on demand forecasting. Probabilistic models are assessed based on the model traditions and statistics test with historical data. Two forecasting models established on stochastic processes are used to forecast demand for commercial aircraft models. A modified Brownian motion model is developed to account for dependency between observations. Geometric Brownian motion at different starting points is used to accurately account for increasing variation. A comparison of the modified Brownian motion and Autoregressive Integrated Moving Average model is discussed.

The second study associated several prevalent decision-making methods: Expected Utility, Robust Decision Making and Information Gap. The comparison is conducted in the situation of deep uncertainty when probability distributions are difficult to ascertain. The purpose of this comparison is to explore under what circumstances and assumptions each method results in different recommended alternatives and what these results mean making good decisions with significant uncertainty in the long-term future.

KEYWORDS: Aviation, forecasting, moving average, Brownian, decision-making.

I. INTRODUCTION

As the production rate of airliners increases dramatically following the nadir in 2009, major airplane manufactures such as Boeing and Airbus are benefiting from the extraordinary selling record. Figure 1.1 shows the historical direction for global commercial airliners (Boeing, 2015; Airbus, 2015). In 2014, universal orders were exceed 3,300 which is six times of orders in 2009. As the emerging of new market and positive outlook of worldwide macroeconomics, the demand is likely to keep increasing in future. However, if the production rate approaches an upper limit, Boeing and other aircraft manufactures will encounter a tough capacity planning decision: whether they should expand their capacity? And if they should, how to sort a long-term capacity planning strategy? It is a distinctive long- term capacity planning problem under high uncertainty. For such a compound problem, making decisions based on gut feelings is certainly not a worthy choice as it would make company in huge risk. A wary production planning can help a decision maker grab this complex strategic problem.

International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Visit: www.ijirset.com

Vol. 8, Issue 3, March 2019

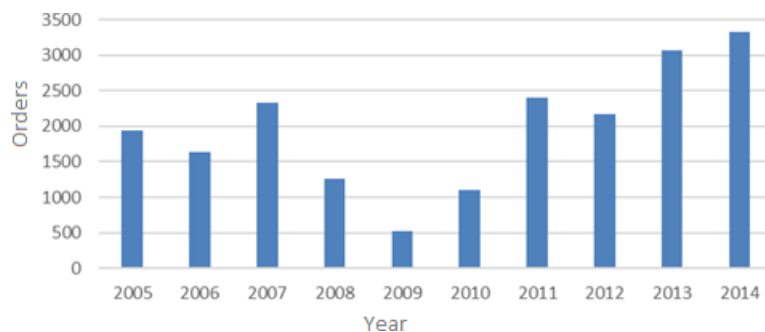


Figure (a) Historical order of global commercial airliners

The figure depicts long-term capacity planning under the presence of ambiguity is a big challenge for many establishments. Because of the large uncertainties convoluted, most traditional short-term or medium-term capacity planning techniques are not applicable. Thus it is essential to find new ways of dealing with this difficult problem. There are various literatures deliberated capacity planning problems in various industries. Higgins described how simulation model could be used for capacity planning under un- certainty in food industry [16]. The solicitation of simulation for capacity planning is also found in biomedicine which is used to sustenance decision making[13]. Several articles have discussed the capacity planning problem in industrial and manufacturing field. Eppendevolved a practical model using Mixed Integer Linear Programming to resolve a capacity planning problem for General Motors [11]. Nazzal proposed a comprehensive capital investment decision framework by integrating simulation, statistics, and financial models to support decision making [10].

But much of this earlier research has concentrated on deterministic problems or short or medium-term planning. When handling uncertainty in capacity planning, multi-stage stochastic programming is a popular method [8], [2], [12]. To understand the risks of capacity planning, Bonfill considered three risk factors (financial risk, downside risk, and worst-case revenue) in a two-stage stochastic programming model [1]. Incorporating game theory, utility theory, financial hedging, and operational hedging can provide a financial model for a capacity planning problem [17]. However, understanding how to represent the risk and making worthy decision of long-term capacity planning problems that can be applied to real world problems in aviation industry generally remains an unanswered question.

A collaboration research is initialed in order to overcome this challenge. The goal of the collaboration research is to develop a flexible and practical airplane painting capacity planning tool for Boeing. It is designed to provide Boeing with sufficient information to support decision making for long-term capacity planning strategy. It consists four parts: Demand forecasting, calculated modeling, simulation modeling, and decision making. This thesis shows fractional work (demand forecasting and decision making) within the collaboration research.

The tenacity of this thesis is to show several approaches for long-term production planning problem. A good decision making procedure about whether to increase capacity should require a trustworthy demand forecasting which provides sufficient information on plausible situations rather than single prediction. In the first study, different types of demand forecasting methods have been applied and evaluated based on the historical orders of the 737, 777 and other airplane types. A modified Brownian motion model to account for dependency between observations is purposed. We relate this new probabilistic model with Autoregressive Integrated Moving Average model. In the second study, a tactic level production planning model is established. Under the framework of prior model, three decision making methods (Expected Utility, Robust Decision Making and Information Gap) are executed and smeared to the model. The results acquired from those decision-making theories are matched. Finally, we make suggestions and conclude the finding of this research.

International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Visit: www.ijirset.com

Vol. 8, Issue 3, March 2019

II. RELATED WORK

1. Background on Brownian Motion and Geometric Brownian Motion

Brownian motion is a widespread probabilistic model in forecasting. Brownian motion assumes that demand in one year is autonomous of demand in the other years. A Brownian motion model with drift assumes that annual demand tracks a normal distribution with mean $\mu t + b$ and variance $\sigma^2 t$, where μ is the mean shift in demand, t is the number of years after the current year, b is the current demand, and σ^2 is the variance of demand at time $t = 1$. Uncertainty (or variance) surges each year in this model. If the yearly demand for airplanes trails a Brownian motion process, the demand at time t is:

$$X(t) = \sigma B(t) + \mu t + b \quad (1)$$

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

GBM is a stochastic method in which the annual percentage variations in demand are independent and identically distributed. GBM is universally used to predict stock prices and oil prices [18]. The annual demand in a GBM is

$Y(t) = \exp(X(t))$ where the logarithm of ratio $Y(t+1)$ follows a normal distribution $N(\mu + b, \sigma^2)$ [20].

A standard probability plot or quantile-quantile (Q-Q) plot can be used to confirm the normality conventions of both Brownian motion and GBM. A Q-Q plot shows the residuals of the perceived data minus the mean versus the quantiles of the normal (Gaussian) distribution. For the GBM, if $Y(t+1)$ is log-normal distributed, the points on both plots should approximate a straight line. A Shapiro-Wilk test can be directed to further authenticate the assumption of normality. If the p -value from Shapiro-Wilk test is less than 0.05, it is rational to reject the null hypothesis: the original data follow a normal distribution. Brownian motion undertakes independence between observations, and GBM undertakes independence of the log ratio.

The linear independence assumption can be tested by the autocorrelation function (ACF), which calculates the correlation between demand of different years. The difference in the years is the lag. For the GBM to be valid, the correlation between demand ratios $Y(t+1)$ and $Y(t+1+k)$ should be not significant $Y(t) Y(t+k)$ where $k > 0$ represents the lag. The maximum likelihood estimation (MLE) method can be used to evaluate model parameters such as mean (i.e., drift) and standard deviation for Brownian motion or GBM centered on historical data.

2. Modified Brownian Motion and GBM

As will be conferred in the application section, the historical demand for airplanes does not always monitor the independence postulation. We develop a unique method to estimate demand based on Brownian motion when the demand observations are dependent. The correlation between two adjacent years is defined as ρ . If N_1 and N_2 are random variables from a standard normal distribution with correlation ρ , 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 presented that N_{cor} also trails a normal distribution and has a correlation of ρ with N_1 . At time t , if the demand are $X(t) = \rho \sqrt{t} N_1 + \mu t + b$ and $X(t+1) = \rho \sqrt{t+1} N_2 + \mu(t+1) + b$, then the correlation between $X(t)$ and $X(t+1)$ equals ρ . Thus, we can use the idea of Brownian motion but persuade correlation between annual demands in following years. A distinct challenge to using the GBM to forecast demand is the surge in variance. In the Brownian motion model, the normal variance surges by a factor of $t+1$ each year. In the GBM model, the normal deviation (or variance) rises by approximate a factor of $e^{\mu} \sigma$. Such a huge variance with the GBM may end result in an unrealistically large level of uncertainty. We propose a modified GBM based on the lag variable k . The lag $k = 1$ in the customary GBM, which means that the ratio between two adjacent years $R(1) = Y(k+1)$ follows a lognormal distribution with mean μ and variance σ^2 . In the alternative method, lag $k = t$. For each year t , $R(t) = Y(t)$ has a lognormal distribution with mean μt and variance $\sigma^2 t$. A forming challenge is to determine the time $t = 0$ at which the GBM instigates. If $t = 0$ is set too far back in the past, the difference in the forecasted demand will be enormous. If $t =$

International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Visit: www.ijirset.com

Vol. 8, Issue 3, March 2019

0 is set as the last perceived demand point in the historical data, the variance in the forecasted demand will be comparatively small, which indicates more certainty than is probably warranted for the future.

3. Autoregressive Integrated Moving Average

Autoregressive Moving Average is one of the conventional forecasting models [7]. Unlike Brownian motion, which entails independent observations, ARMA executes well when time-series data exhibits strong dependence. Autoregressive Integrated Moving Average model extends the ARMA model by adding more parameters to handle the non-stationarity (trend and seasonality) in the data.

Typically, there are two popular approaches to deal with heteroscedasticity in time-series data, which indicates that variance increases with time [6]. The first option is to develop a specific variance stabilizing transformation. According to Ziegel, a variance-stabilizing alteration is a data transformation that is "precisely chosen either to simplify contemplations in graphical tentative data analysis or to allow the application of simple regression-based or analysis of variance methods" [22]. The second option is the Box-Cox transformation. One-parameter Box-Cox transformation is defined as the following:

$$S(\lambda) = \begin{cases} f - \lambda / \log(X) & \text{if } \lambda \neq 0 \\ f & \text{if } \lambda = 0 \end{cases} \quad (3)$$

Where $S(\lambda)$ is the altered data and λ is the alteration parameter. As the discussion mentioned the risk of using logarithmic transformation blindly to heteroscedastic time series, Box-Cox transformation was applied to test the hypothesis of using logarithmic transformation [9].

Autoregressive Integrated Moving Average model can be conveyed as the subsequent:

$$\phi(B)(1 - B)dSt = \theta(B)Zt \quad (4)$$

Where St is time successions, $\{Z(t)\} \sim W N(0, \sigma^2)$. $W N$ is white noise. B is backward shift operator which is defined as $St-j = BjSt, j = 0, \pm 1, \dots$. $\phi(B)$ and $\theta(B)$ are AR and MA polynomials correspondingly.

$$\phi(B) = 1 + \phi_1B - \dots - \phi_pB^p \quad (5)$$

$$\theta(B) = 1 + \theta_1B + \dots + \theta_qB^q \quad (6)$$

So, there are three parameters in ARIMA(p, d, q) process. Typically, we want to find a ARIMA process with non-negative p, d and q estimated by MLE which has lowest Akaike information criterion (AIC).

III. DISCUSSION

Making good risk-based decisions is especially hard for situations with deep uncertainty that extend over time. Production planning problems may be especially prone to difficult uncertainties (such as demand, operations and supply chain) and yet firms need to plan for several years or decades into the future. Traditional decision-making theories such as subjective expected utility may be challenging to implement if probability distributions are difficult to ascertain. This paper compares different decision-making methods for a complex problem under the presence of long-term uncertainty. The decision-making methods are expected efficacy, strong decision making, and information gap. The purpose of this comparison is to explore under what circumstances and assumptions each method results in different recommended alternatives and what these results mean making good decisions with significant uncertainty in the long-term future.

International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Visit: www.ijirset.com

Vol. 8, Issue 3, March 2019

1. Capacity Planning Model with Uncertain Demand

An airplane manufacturer wants to plan when and if it should construct new hangars to paint airplanes. It can plan to construct hangars on an annual basis, and $I(t)$ is defined as the number of new hangars at time t , where t is an integer representing years. In this model, we only ponder building new hangars and not eradicating hangars, so $I(t) \geq 0, \forall t$.

The demand of airplanes for the manufacturer in year t can be written $D(t)$, and we assume the manufacturer cannot influence demand. Based on prior analysis of aviation industry, we undertake that demand follows Brownian motion with trend. Mathematically, demand is $D(t) \sim Nor(\mu_D, \sigma^2 t)$, where $\mu_D = \mu_{D0} + \mu_{D1}t$, μ_{D0} is the mean of demand at $t = 0$, μ_{D1} is the annual trend coefficient, and σ^2 is the variance in demand at $t = 1$. We undertake the manufacturer's production of airplanes in time t equals the demand at time t .

2. Decision-making Methods

In this section, we discuss the framework for the three decision-making methods: EU, RDM, and Info-gap.

2.1. Expected Utility

In this case, we undertake a single decision shows a risk-averse or risk-neutral risk attitude. Given the large uncertainty in this problem, a risk-averse decision is very realistic. Exponential utility function is used to compute the utility of profit. The general form of exponential utility function is:

$$U(g) = a_1 - b_1 \exp(-g/r)$$

where $r > 0$ is the risk tolerance; a_1 and b_1 define the scale of utility function; $g = G(T, s) - E[G(T, s_0)]$ which is the additional profit over T years given strategy s after removing the baseline expected profit. The baseline profit $E[G(T, s_0)]$ is the expected profit over T years given strategy s_0 (no additional hangars). If the decision maker is indifferent between obtaining the expected baseline profit and a p probability of gaining an additional m million dollars and $1 - p$ probability of losing m million dollars, then the decision maker's risk forbearance r can be calculated.

The parameters a_1 and b_1 can be ascertained by defining two values for utility, such as $u(0) = 0$ and $u(\$m \text{ million}) = 1$, and solving for a_1 and b_1 . The decision maker should choose the approach that maximizes his or her estimated utility. Once the projected utility is obtained, the certainty equivalent (CE) which is the inverse of utility function and is in units of dollars could be computed for comparison and judgment:

$$CE = U^{-1}(E[U(g)])$$

2.2 Robust Decision Making

RDM includes various uncertainty into the model to backing decision making. Uncertainty is represented as "a set of multiple, plausible future states of the world" [14]. For example, the state x can be construed as the parameters μ_{D1} , σ_D in demand model. RDM undertakes three sets: strategy set S , a plausible future state set X , and a probability distribution set Θ . The projected regret of strategy $s \in S$ contingent on distribution $\theta_i(x) \in \Theta$ is given by Lempert [18].

The parameter can be interpreted as the level of confidence in the probability distribution $\theta_{best}(x)$. According to RDM, the decision maker should select the strategy s that minimizes V_s given value of z . For example, if decision maker has 100% confidence on that $\theta_{best}(x)$ is the exact representation of truth, then $z = 1$ and the result turns out to be the same as expected utility. Because the expected regret of one strategy is the difference between its expected utility and the maximum expected utility over all strategies. Conversely, if $z = 0$, the decision maker believes there is high uncertainty in the probability distribution over the future state X and should prepare for worst case. Preparing for the worst-case corresponds to the well-known mini-max decision rule.

International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Visit: www.ijirset.com

Vol. 8, Issue 3, March 2019

2.3 Information Gap

Both EU and RDM assume that uncertainty can be measured with probabilities, the uncertainty in Info-gap model is treated as a family of nested sets[4]. In RDM, we use state x (recall it includes the parameters μ_D , σ_D in the demand model) in set X to represent uncertainty.

Unlike RDM, which tries to measure a fixed uncertainty set with a branch of plausible probability distributions, the Info-gap model has a dynamic uncertainty set Φ and does not assume any probability distribution over that uncertainty set. The dynamic uncertainty set Φ is defined by a variable α . Given a fixed α , the set $\Phi(\alpha, x^{\wedge})$ states a degree of variability around x^{\wedge} which is interpreted as the most likely state. The parameter α is called the “horizon of uncertainty” and explains the variability of x [4]. The greater the value of α , the larger the size of set $\Phi(\alpha, x^{\wedge})$ and the higher variation. If $\alpha = 0$, there is no improbability in the model. Several types of uncertainty models $\Phi(\alpha, x^{\wedge})$ exist, and a fraction error model is one of the most common [15].

IV. CONCLUSION

This research discusses demand forecasting and decision making for the purpose of long-term production planning. Although the analysis and discussions are tailed to aviation industry, the methodology could extend to other industries in industrial and manufacturing field.

Several demand forecasting methods were studied and applied to Boeing’s airliners (737, 777). We clarifies the assumptions of Brownian motion, geometric Brownian motion and ARIMA model. A modified Brownian motion model is purposed to address the correlation in historical orders of the 737. A comparison between purposed model and ARIMA is piloted. We conclude that ARIMA is appropriate when high lag correlation is detected in data and accurate estimated prediction is desired. Purposed Brownian motion model has more conservative projected prediction and shows wide range of possible forthcoming states. These information could be highly valuable when a long-term strategy decision needs to be made based on the forecasting. The application of GBM on forecasting of the 777 is also included. We shows that the traditional GBM fitting method does not work well under the present of high variability from small dataset. We demonstrate a new approach to fit GBM for the entire dataset. The starting position of fitted model could be adjusted according to variability of historical data. The advantage of this method is that it provides a flexible way for a decision maker to interpret the variability of data which could be highly dependent on domain knowledge. Same methods are applied to forecast other types of airliners (747, 767 and 787) which does not show on the paper.

A capacity planning which dedicates to investment decision is developed. As both non-linearity and uncertainty present in the model, simulation based method is used to find the solution. Three different decision making methods (Expected Utility, Robust Decision Making, and Information Gap) are introduced and applied. We find the optimal strategy suggested by each method and test the sensitivity of model given different inputs. As expectation, expected utility method is highly sensitive to the input probability distribution. RDM and Info-gap which are planned for deep uncertainty, execute fairly stable and consistent outcomes. Detailed analysis and interpretation of result is conducted for each method. We find that the interpretation of z parameter in RDM is not exactly as the claim made by Lempert [18]. The actual effect of z primarily depends on problem which yields different minimum and maximum regret matrix. These three methods yield different suggested strategies under same setting. Compared to expected utility, the strategies made by RDM and Info-gap are more robust. In addition, RDM with extreme risk aversion and Info-gap have similar outcomes for this problem. We conclude the advantages and limitations of these decision making methods and specify the situations when they are applicable.

By combining demand forecasting and decision making together, we purpose an over- all framework on long-term capacity planning. The research provides a quick overview of capacity planning problem by choosing proper models.

It helps decision maker to understand the risk of decision with existing univariate data without putting enormous amount of effort on collecting multivariate data and developing complex causal model. Therefore, the study is a good starting point for the initial estimation of risk in long-term capacity planning problem. In future research, more important data such as macroeconomics, fuel price could be collected. With the support of additional information, a

International Journal of Innovative Research in Science, Engineering and Technology

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Visit: www.ijirset.com

Vol. 8, Issue 3, March 2019

Careful designed multivariate model is likely to reduce the uncertainty further and yields high quality capacity planning strategy.

REFERENCES

- [1] A. B. Bonfill, Miguel; Espua, Antonio; Puigjaner, Luis, "Risk Management in the Scheduling of Batch Plants under Uncertain Market Demand," *Industrial & Engineering Chemistry Research*, vol. 43, pp. 741-750, 2004/02/01 2004.
- [2] Ahmed, S. K., AlanJ; Parija, Gyana. (2003). A Multi-Stage Stochastic Integer Programming Approach for Capacity Expansion under Uncertainty. *Journal of Global Optimization*, 26(1), 3-24.
- [3] Airbus Commercial. Available: <http://www.airbus.com/company/market/orders-deliveries/>, 2015
- [4] Ben-Haim, Y., Demertzis, Maria. (2015). Decision Making in Times of Knightian Uncertainty: An Info-Gap Perspective. *Economics: The Open-Access, Open Assessment E-Journal*, 9(2015-42).
- [5] Boeing Commercial. Available: <http://www.boeing.com/commercial/>, 2015
- [6] Box, G. E. P., and D. R. Cox. An Analysis of Transformations. *Journal of the Royal Statistical Society. Series B (Methodological)*, vol. 26, no. 2, 1964, pp. 211-252
- [7] Brockwell, Peter J., and Richard A. Davis. *Introduction to time series and forecasting*. Springer, 2016
- [8] Chen, Z.-L. L., Shanling; Tirupati, Devanath. (2002). A scenario-based stochastic programming approach for technology and capacity planning. *Computers & Operations Research*, 29(7), 781-806.
- [9] Chatfield, C., and D. L. Prothero. "Box-Jenkins seasonal forecasting: problems in a case-study." *Journal of the Royal Statistical Society. Series A (General)* (1973): 295-336.
- [10] D. M. Nazzal, Mansooreh; Anderson, Dave, "A simulation-based evaluation of the cost of cycle time reduction in Agere Systems wafer fabrication facility a case study," *International Journal of Production Economics*, vol. 100, pp. 300-313, 4// 2006.
- [11] G. D. M. Eppen, R. Kipp; Schrage, Linus, "OR Practice A Scenario Approach to Capacity Planning," *Operations Research*, vol. 37, pp. 517-527, 1989/08/01 1989.
- [12] Geng, N. J., Zhibin; Chen, Feng. (2009). Stochastic programming based capacity planning for semiconductor wafer fab with uncertain demand and capacity. *European Journal of Operational Research*, 198(3), 899-908.
- [13] Groothuis, S., Van Merode, G., & Hasman, A. (2001). Simulation as decision tool for capacity planning. *Computer methods and programs in biomedicine*, 66(2), 139-151.
- [14] Hall, J. W., Lempert, R. J., Keller, K., Hackbarth, A., Mijere, C., & McInerney, D. J. (2012). Robust Climate Policies Under Uncertainty: A Comparison of Robust Decision Making and Info-Gap Methods. *Risk analysis*, 32(10), 1657-1672.
- [15] Hayes, K. R., Barry, S. C., Hosack, G. R., & Peters, G. W. (2013). Severe uncertainty and info-gap decision theory. *Methods in Ecology and Evolution*, 4(7), 601-611.
- [16] Higgins, A., & Davies, I. (2005). A simulation model for capacity planning in sugarcane transport. *Computers and Electronics in Agriculture*, 47(2), 85-102.
- [17] J. A. V. Miegheem, "Commissioned Paper: Capacity Management, Investment, and Hedging: Review and Recent Developments," *Manufacturing & Service Operations Management*, vol. 5, pp. 269-302, 2003.
- [18] Lempert, R. J., & Collins, M. T. (2007). Managing the risk of uncertain threshold responses: comparison of robust, optimum, and precautionary approaches. *Risk analysis*, 27(4), 1009-1026.
- [19] Postali, F. A. S., & Picchetti, P. (2006). Geometric Brownian Motion and structural breaks in oil prices: A quantitative analysis. *Energy Economics*, 28(4), 506-522.
- [20] R. Marathe and S. M. Ryan, "On the validity of the geometric Brownian motion assumption," *The Engineering Economist*, vol. 50, pp. 159-192, 2005.
- [21] Takewaki, I., & Ben-Haim, Y. (2005). Info-gap robust design with load and model uncertainties. *Journal of Sound and Vibration*, 288(3), 551-570.
- [22] Ziegel, E. R. (2003). *The Cambridge Dictionary of Statistics*. Technometrics, 45(2), 183.