STOCHASTIC FORECASTING METHODS WHEN KEY VARIABLES ARE POLITICALLY DETERMINED: FUEL PRICES FOR AIR TRAFFIC AND FERRY FORECASTING

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Introduction

Forecasting airport and ferry passenger traffic can be problematic when one of the exogenous variables is politically determined, rather than determined by the market. In particular, fuel costs, which typically make up the largest non-labour cost for airlines, are influenced by geopolitical and policy developments rather than fundamental market dynamics. Because of their impact on airline and ferry operating expenses, fuel costs are an important supply-side consideration for projections of future passenger traffic. The unpredictability, volatility and uncertainty surrounding the future price of a politically-dependent and policy-motivated variable such as fuel prices makes it difficult to provide medium and long-term projections of passenger traffic. This paper will examine the use of stochastic forecasting techniques using Monte Carlo simulation methods to develop traffic forecasts where oil and fuel prices can vary widely and unpredictably. The Monte Carlo modelling process also allows for the inclusion of risk factors to quantify and model that uncertainty. An illustrative forecasting example is developed to demonstrate the stochastic forecasting process and quantify an illustrative selection of risk factors pertaining to oil price volatility. The results show that the stochastic forecasting approach provides meaningful information regarding the range of impacts uncertain and volatile factors to traffic development may have and provides additional insight into the risk associated with future shock events and uncertainty.

Background

Crude oil and aviation jet fuel prices are subject to significant volatility and fluctuations, making them challenging to predict and forecast (Spitz & Berardino, 2010). This difficulty in forecasting under uncertainty leads to challenges for airlines, ferry operators, and airports in planning for future demand when a key input to both airline/ferry cost and passenger demand is volatile and uncertain. Air carriers are particularly sensitive to fluctuations and increases in fuel prices, especially as fuel costs are typically the largest non-labour cost airlines incur in their operations (Wensveen, 2015). This section will briefly discuss the geopolitical nature of oil prices and the impact volatility has on air traffic.

Over the past four decades, a number of major evolutions in the price of oil have been driven by geopolitical or policy actions, as depicted in the chart below. External events, ranging from military activity and intervention in oil-producing regions in the Middle East, to the actions of OPEC to constrain production and global supply have precipitated often significant swings in the price of oil. Historical oil prices also have a clear linkage to economic growth, both in terms of consumption (i.e. demand) patterns and supply policies (U.S. Energy Information Association, 2019). The impact of these political and economic drivers in shocking the price of oil may be transient and short-lived – as was seen in the early 1990s and the major spike and drop in prices in 2008/09 – or persist for a prolonged period – such as the slow return of prices following the Iran-Iraq war or the long run up in prices in the early 2000s. These geopolitical and policy events "exacerbate the effects of inelastic supply and demand on global energy markets" leading to significant price volatility even though the longer-term determinants of the market are less affected (Pascaul & Zambetakis, 2010, p. 11). The ability of these external actions to contribute to

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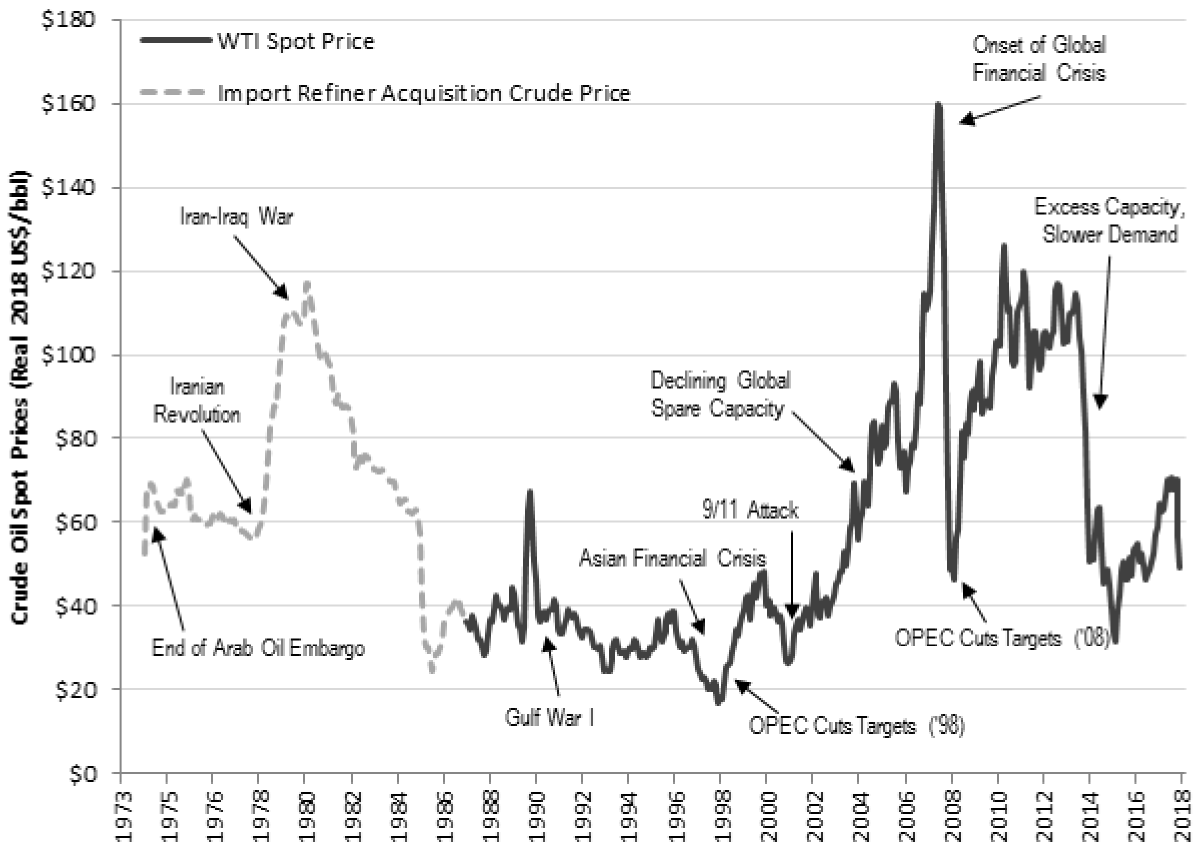
and directly cause significant price swings then leads to difficulty in predicting future price levels and any forecast or analysis that relies on oil and energy prices.

Historical Crude Oil Prices and Key Shocks to Price Levels (Real 2018 US$/barrel)



In forecast modelling, fuel prices – either directly or using crude oil prices as a proxy – are a cost consideration for both passengers and airlines (Carson et al, 2010, p 9). As a supply side consideration, fuel prices impact the operating costs for airlines and ferry operators. From a demand perspective, the increased operating costs typically result in higher fares and/or fuel surcharges. Morrell and Swan (2006, p. 722) note that airlines typically carry out three strategies to manage their risk to volatile fuel prices: increase fuel efficiency, either operationally or through fleet changes; pass through price increases to customers in the form of fares or surcharges; and, engage in fuel hedging. Carriers may also engage in downsizing or schedule reductions to manage the impact of volatile fuel prices as Spitz and Berardino (2010) demonstrate, but that schedule reductions or reallocations may also be linked to declines in economic growth or recessions which may also instigate carriers to reduce capacity to match reduced economic demand. The combination of these strategies provides mitigation against volatility, but would rely on the ability to predict future price levels to act accordingly.

Rationale for the Stochastic Risk-Based Forecasting Methodology

The rationale for employing a stochastic forecasting methodology is twofold. Firstly, the method recognizes that there is uncertainty about the future from a myriad of factors and quantifies what is relevant and feasible for the forecast at hand. It recognizes that the timing or appearance or risk events is unknown and is difficult to capture in a single, static scenario. It employs analytical methods to recognize and quantify risk and models the multitude of different ways these uncertainties may lead to different outcomes using Monte Carlo simulation techniques. (Kincaid et al, 2012)

Secondly, the methodology produces a range of results, for each year, which can be aggregated and results interpreted as probabilities of outcomes. This provides users of a forecast a deep insight into critical strategic questions such as: how likely is it in 5/10/20 years that a facility will exceed its current capacity, or with is the probability in each future year that traffic will exceed some minimum value to meet financial obligations? By being able to quantify the likelihood, or not, of future levels of traffic occurring planners and decision makers can make more informed decisions about the future than with a forecast which only posits a selection of scenarios with no probability attached to any outcome.

These two motivations are especially relevant to projecting future price levels of a volatile and geopolitically motivated variable like crude oil prices. As a single scenario is unlikely to capture the actual future development of oil prices, the stochastic, risk-based forecasting methodology provides an approach to appropriately forecast both the volatile variable(s) and the traffic forecast that it relies on.

Illustrative Forecasting Example

To demonstrate an application of this process we will develop a representative forecasting model and subject it to the risk-based stochastic forecasting approach. For this example, assume that a forecast of passenger traffic is being developed for a single airport. The forecast is of total passengers and is based on annual Enplaned-Deplaned (E/D) passengers. A reduced-form econometric model[i] is specified to estimate the determinants of air travel with respected to incomes and oil prices. The illustrative model is specified as a log-log model.

$$\ln(pax_t) = \beta_0 + \beta_1 \ln(GDP_t) + \beta_2 \ln(OilPrice_t) + \epsilon_t$$

Where pax_t is the airport's total annual E/D passenger volume, GDP_t is real gross domestic product, and $OilPrice_t$ is the annual average spot price of WTI crude oil in real 2018 US$/barrel.

Therefore, β_1 is income elasticity of air travel, and β_2 is the passenger traffic elasticity with respect to real oil prices, and ε_t is the model's error term.

Assume that the model has been estimated such that the following parameters were estimated: β_1 = 1.5 and β_2= -0.20. The hypothetical income elasticity (β_1) is of a value consistent with meta studies conducted by Gillen et all (2007)and Gallet and Doucouliagos (2014), empirical analysis such the study conducted by Inter*VISTAS* Consulting for IATA (2007), and practical experience from forecasting consulting engagements. The assumed oil price elasticity at -0.20 is based on practical forecasting experience and implies that passenger traffic is negatively affected by increasing oil and thus fuel prices. The negative sign is supported by the impact of higher fuel costs to airlines through a demand price mechanism and a capacity supply mechanism which should, *ceteris paribus*, lead to lower levels of passenger traffic.[ii]

Baseline projections of future oil prices were sourced from the U.S. Energy Information Association (EIA)'s *Annual Energy Outlook 2019* using the reference scenario. In real 2018 US Dollars, annual average prices of WTI crude oil per barrel are projected to increase from $68/bbl in 2018 to $100/bbl by 2038. While the EIA notes that "future oil prices are highly uncertain and are subject to international market conditions" (EIA, 2019, p. 32) they do not assign a probability to either their reference (i.e., central) case forecast or any of the alternative scenarios. The EIA's range of alternative scenario posits real crude oil prices ranging between $46/bbl in the Low Oil Price scenario, to $186/bbl in the High Oil Price scenario. The *Annual Energy Outlook 2019 Case Descriptions* indicates that the potential range of forecast oil price outcomes based largely on reduced demand in the Low Price scenario, while lack of supply driven by lack of investment in production is the primary driver of the High Price scenario. Like the Reference case scenario, there is no information provided on how likely or unlikely it would be for either scenario to be realized.

GDP data for the example model is Canadian GDP. A composite projection of real Canadian GDP was developed using long-term forecasts of real GDP from Oxford Economics and the Organization for Economic Cooperation and Development (OECD), and is projected to average 1.7% per annum in real growth over the coming 20 years.

Conducting the Risk Simulation

ACRP Report 76: Addressing Uncertainty about Future Airport Activity Levels in Airport Decision Making (2012) and *Probabilistic Forecasts for Aviation Traffic at FAA's Commercial Terminals: Suggested Methodology and Example* (2007) provide the theoretical and analytical basis from which this work derives. This paper will provide a brief overview of the risk analysis method using Monte Carlo simulation sufficient to provide a background for the illustrative forecasting example and the use of risk simulation techniques applied to traffic forecasting. Readers interested in the theoretical and analytical framework of the Monte Carlo simulation model and statistical modelling should refer to these reports.

At the heart of the risk-based forecast model is a Monte Carlo simulation. Rather than relying on static and unvarying assumptions regarding inputs to a model, the Monte Carlo technique allows inputs to the model to be specified as probability distributions. Using computerized techniques, the model is run many times, with each simulation and each period of the simulation drawing new sets of random numbers to determine results from the model's input probability distributions and thus new outcomes are created in each simulation of the model. By aggregating the results of hundreds or thousands of iterations of the model, a range of outcomes can be established and probabilities of various outcomes can be compiled. In contrast to traditional forecasting techniques, which typically post a central case supplemented with alternative scenarios, the Monte Carlo simulation methodology can quantify and assign probabilities about the range of potential outcomes of the future in a way that traditional for casting technique cannot.

The risk simulation of the traffic forecast is conducted in two complementary phases:

1. Annual variation of input variables to the traffic forecast model, and;
2. Risk factors quantifying exogenous shocks to the development of traffic and of input variables to the forecast model.

The two key input variables to the illustrative model, crude oil prices and GDP, are simulated in such a way to vary their year over year growth according to statistical distributions designed to model their expected future behaviour and uncertainty. This variation occurs in each year of the forecast, across each simulation run using repeated samples of each variable's probability distribution. The probability distribution for both oil prices and GDP takes the variable's baseline forecast as a mean or modal value in each year, and then randomizes the annual growth based on the specification of the distribution. For example, in year 10 of the forecast assume some input variables has an expected annual growth of 2% and could range between 0.5% and 3.0%, or -1.5% to +1.0% variation from the expected value. An appropriate probability distribution for the simulation would then be specified such that the mean or most likely value of the probability distribution is set at 2% with a minimum and maximum value at 0.5% and 3.0%, respectively.[iii] For each iteration of the simulation, a random sample is drawn from the probability distribution to determine the value to be used in the given year for the given variable. As the baseline projection or expected range of potential impacts change over time, the probability distribution for each year can be modified to reflect the changing assumptions and risk quantification over the time horizon of the forecast. This process occurs for each time period for each variable in the simulation model and each iteration of the simulation.

A variety of statistical distributions may be used in conducting simulation risk analysis. For this example forecast model, the PERT distribution was chosen to model the annual variation in growth of input variables. The PERT distribution is a special form of the beta distribution, which allows modellers a flexibility to set distribution parameters to model the desired phenomenon including: skewing the distribution,[iv] setting the kurtosis of the distribution (i.e., how concentrated the distribution is about is mean), and bounding the distribution to a defined maximum and minimum (Kincaid et al, 2012, p. 52).

The parameters of the probability distributions for simulating future annual variation in oil prices and GDP were developed from analysis of historical variation of those variables. These initial distribution parameters were reviewed and modified with professional judgement to best simulate the range of future outcomes.

The second stage of risk quantification in the forecast simulation is the risk factors. Each factor captures some potential event or shock to the evolution of traffic or model input variables which can be identified and quantified, but an exact timing of when an event will occur (if at all) or at what magnitude the impact will have on the model remains unknown. For the purposes of this example model, a small selection of risk factors have been developed by analyzing historical events, research from subject matter experts, and professional judgement. As the focus of this research is to investigate simulation of oil and fuel prices on transportation forecasts, the list of risk factors is weighted to that theme. A more complete forecast or risk analysis may include dozens of risk factors covering a wide range of potential events – with both positive and negative potential impacts.

The illustrative forecast model employs the following risk factors:

Risk Factor	Annual Probability of Occurrence	Expected Impact	Range of Impact	Duration of Impact
Transient Spike in Oil Prices	6.7% per annum	+25 % Increase in Oil Prices	+10% to +50% increase in prices	1-2 Years
Transient Drop in Oil Prices	6.7% per annum	-25 % Decrease in Oil Prices	-10% to -45% decrease in prices	1-2 Years
Constraints on Global/Regional Supply	5.4% per annum	+25% Increase in Oil Prices	+15% to +15% increase in prices	3-6 Years
Conflict in Oil Producing Region	3.0% per annum	+20% Increase in Oil Prices	+15% to +100% increase in prices	2-5 Years
New Technology: Extraction or Production Gains	1.1% per annum	-10 % Decrease in Oil Prices	-5% to -30% decrease in prices	10 Years
Persistent Low Prices: High Supply/Low Demand	1.1% per annum	-35% Decrease in Oil Prices	-10% to -50% decrease in prices	Persistent Impact

Each of the risk factors have been designed to simulate an uncertain event that may, or may not, occur in the future. An annual probability of occurrence is specified, to indicate how likely an event is to occur in any individual year. The probability distribution for each risk factor is defined by its expected impact and potential range of impacts, interpreted as the minimum and maximum bounds of the distribution. All risk factors are modelled using a PERT distribution. Lastly, risk factors are programmed with a duration of impact, that is how long is required for the initial impact to dissipate.[v] The risk factors for oil prices have been developed by the author through analysis of historical shock events on crude oil prices and reviews of industry sources. The list of risk factors modelled here is not intended to be exhaustive but illustrative of the type of shock factors that could be modelled with a focus on exogenous events which would likely be precipitated by difficult to predict geopolitical or technological events.[vi]

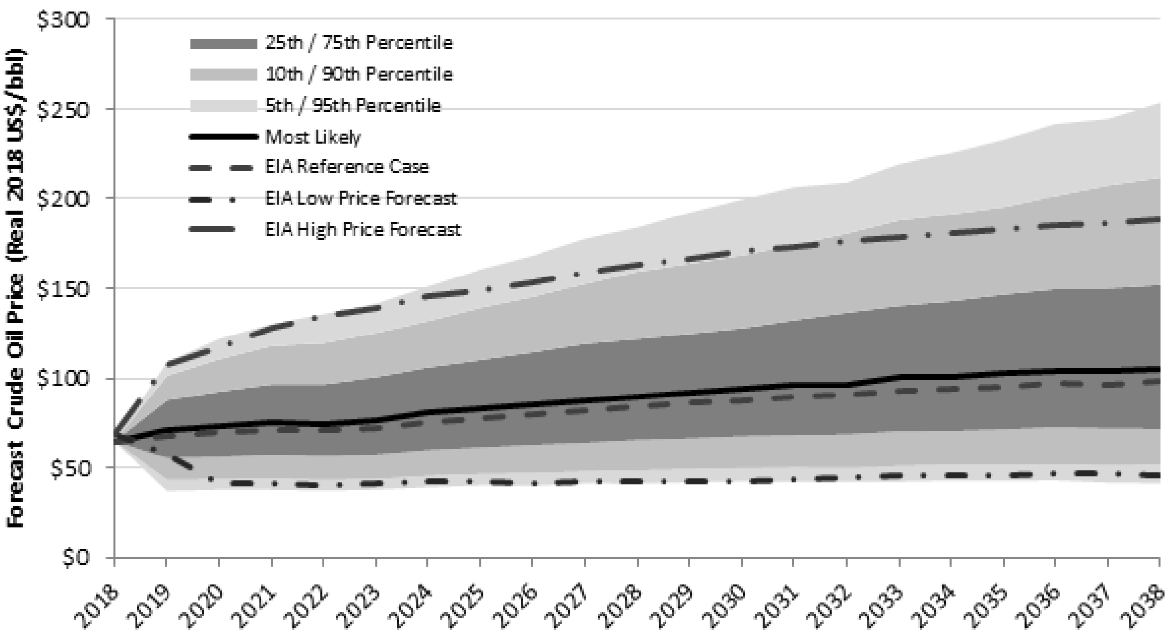
Forecast Simulation Results

For the illustrative example, we assume that the airport has a passenger volume of 5 million passengers in the most recent full year. The forecast is developed for a 20 year period, a typical time horizon for long-term traffic forecasts for planning purposes. Stochastic forecast results are presented as probability ranges (based on percentiles of the aggregated simulation data), with bands identifying the 5th, 10th, 25th, 75th, 90th, and 95th percentiles. A central, Most Likely, result is derived from the median or 50th percentile result of the simulations. The Most Likely result is presented as a central case as the probability of simulated forecast results being either above or below that level is equal. The forecast is the result of 10,000 iterations of the Monte Carlo simulation.

Base case econometric projections were developed as a comparison to the stochastic forecasting results and to provide a reference to a typical forecast output. Two alternative econometric-model only scenarios were developed using alternative scenario forecasts of crude oil prices published by the EIA. The two scenarios chosen were a Low Oil Price and High Oil Price scenario (US EIA, 2019).

The following plot depicts the stochastic forecast range of crude oil prices over the 20 year forecast period based on the uncertainty in annual variation in growth of oil prices as well as the six risk factors covering exogenous shocks to price levels. Between the 5th and 95th percentile outcomes, oil prices in this illustrative simulation are projected to range between \$42/bbl and \$254/bbl in 20 years' time. That is, there is a 90% probability that oil prices will be within that range, and only a 10% probability that oil prices will be either above or below those price points (only 5% in either direction). The Most Likely, or 50th percentile, outcome projects a price of \$105/bbl at year 20, only slightly higher than the \$98/bbl projected in the base case EIA Reference Case forecast. While the set of risk factors for oil prices are balanced between price increasing and price decreasing factors, those factors which would lead to price increases are rated as more likely to occur and have higher potential impacts.

Stochastic Forecast of Crude Oil Prices with Base Case and Alternative Scenarios

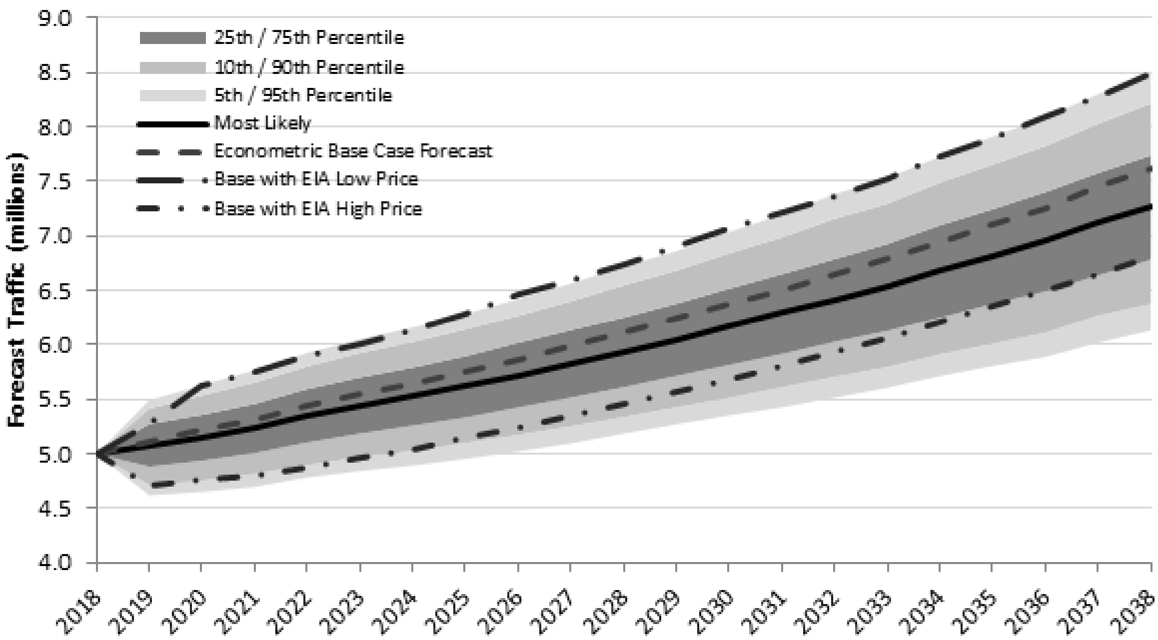


Additionally, the plot above includes lines showing the alternative price forecast scenarios developed by the US EIA. While the EIA forecasts do not specify a probability of any of their scenarios occurring, the illustrative forecast suggests that the EIA's High Oil Price scenario price level falls between a 75 and 90 percent probability of occurring. While the list or risk factors pertaining to oil prices is not exhaustive, it does provide useful information on how such volatile variables may evolve over time.

The following plot presents the stochastic traffic forecast results and a comparison with the econometric base case scenario (using the EIA's Reference Scenario oil price forecast), as well as alternative static scenarios using the Low Oil Price and High Oil Price scenarios from the US EIA. Recall that the forecast model only takes two inputs – oil prices and GDP, both which have stochastic projections of their growth and levels – but only oil prices have specific risk factors to represent external shock risks.

The stochastic forecast range between the 5th and 95th percentile of traffic is projected to be between 6.1 and 9.0 million annual passengers, with a Most Likely forecast of 7.3 million. Compared to the econometric base case forecast using a static projection of oil prices, the stochastic forecast's Most Likely result projects traffic to be -4.7% lower than the econometric base case. This is due to the stochastic simulation of oil prices projecting a higher Most Likely price level than the EIA Reference Case, the greater potential for above Reference Case oil prices, and the potential for oil forecasts to reach price levels above the EIA High Oil Price scenario levels.

Stochastic Forecast of Airport Traffic with Base Case and Alternative Scenarios



Note reduced vertical axis scale for illustrative purposes.

The illustrative stochastic forecast of traffic with a risk analysis on oil prices highlights two major themes:

- Volatility of key inputs to airport and ferry traffic such as oil and fuel prices can have a substantive impact on the level of traffic realized in the future and that forecasts should take this uncertainty into account.
- The stochastic forecasting methodology provides forecast users with a quantification of how likely traffic outcomes are and provides useful information on the range of traffic that may unfold in the future as well as how major impact events or volatile drivers of traffic may impact future traffic levels.

Both of these themes are useful to users of a traffic forecast, be they transportation facility owner/operators, airlines and ferry operators, planners, financial analysts and researchers. The application of stochastic forecasting methods is particularly relevant to input variables and events which are volatile and unpredictable due to being driven more by geopolitical action, policy, or shock events than fundamental economic theory. The methodology allows for forecasters to capture and quantify 'out of model' effects without being limited to one or more forecast scenarios with static assumptions.

Conclusion

Fuel costs are an important input into the current and future operations of airlines and ferry operators. Taking into account the impact of fuel prices on forecasts of traffic for airports and ferries is an important supply-side consideration for forecasting models. However, when important inputs such as fuel and oil prices are volatile and their prices are determined not only by fundamental supply and demand relationships in the market but also exogenous geopolitical, regulatory, and policy shock factors it can be difficult to accurately project price levels as inputs to a traffic forecast.

This paper has used a stochastic forecasting methodology to create an illustrative forecast of crude oil prices as an input to a stochastic forecast of traffic using a Monte Carlo simulation methodology. The stochastic forecast of oil prices includes a series of illustrative risk factors covering a number of geopolitical, policy, and regulatory shock events that are difficult to predict but could have substantive impacts on future oil price levels, and thus forecast traffic levels. The stochastic simulation of forecast oil prices produces a wider range of potential price level results than external low and high price forecasts and additionally provides probabilities for the price level outcomes. Employing the stochastic, risk-based forecast of oil prices into a traffic forecasting model produced a traffic forecast which results in a Most Likely, or central, forecast that is below the pure econometric projection without the risk analysis. The moderately lower level of traffic projected in the stochastic forecasting model results from the forecast volatility and, on average, higher than base case price of oil.

The illustrative stochastic forecast of traffic with a risk analysis on oil prices has brought forward two key themes for the practice of traffic forecasting. Firstly, volatility of key inputs to airport and ferry traffic such as oil and fuel prices can have a substantive impact on the level of traffic realized in the future. Secondly, the stochastic forecasting methodology provides forecast users with a quantification of how likely traffic outcomes will be and provides useful information on the range of traffic that may be realized in the future. As the traffic forecast model accounts for the volatility and unpredictability of its input variables and risks to future traffic levels, a stochastic risk-based forecast provides users with greater insight into how traffic may evolve, and the risks associated with those projections, to make more informed planning and business decisions.

References

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[i] Reduced form models are common practice in traffic forecasting as a means to remove the complexity of estimating structural models with endogenous variables. While not always explicitly identified as such, a number of aviation activity forecasting manuals and guidelines suggest reduced form econometric model specifications. See: Spitz and Golaszewski (2010), and ICAO's *Manual on Air Traffic Forecasting* (2006) for examples, while Carson, Cenesizoglu and Parker (2010) explicitly noted the reduced form specification.

[ii] Higher fuel prices leading to one or both of: higher fares leading to a reduction in demand from travellers, and/or a decrease in the supply (i.e., capacity) of air services.

[iii] The minimum and maximum of the distribution may either be bounded limits (such as in a uniform, triangular, or beta distribution), or may be practical limits corresponding to a cut-off probability value of an unbounded distribution (Normal, or Gompertz, as examples) depending on the needs of the phenomenon to be modelled.

[iv] The skewness of the PERT distribution allows for modelling of risks where the expected distribution of impacts is not symmetrical. In practice this is particularly powerful to model risks in which there may be low probabilities of extreme (i.e., meaningfully different from the average or most likely impact) impacts which the forecaster wishes to model.

[v] For example, a risk factor with a duration of two years would simulate the impact fully in the year it activates, and in the two following years an equal proportion of the impacted effect would be added/removed.

[vi] *ACRP Report 76* provides a discussion on methods to identify and quantify risk factors to be used in the stochastic forecasting model.