Demand Forecasting for Aircraft Engine Aftermarket

By

Kien K. Ho

Bachelor of Science in Electrical Engineering, Cornell University 1999

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Signature of Author

Department of Civil and Environmental Engineering
MIT Sloan School of Management

Certified by

David Simchi-Levi
Professor of Civil and Environmental Engineering and Engineering Systems
Thesis Supervisor

Certified by

Roy Welsch
Professor of Statistics & Management Science, Dir CCREMS
Thesis Supervisor

Accepted by

Daniele Veneziano
Chairman, Departmental Committee for Graduate Students

Accepted by

Debbie Berechman
Executive Director of MBA Program, MIT Sloan School of Management
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By

Kien Ho

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ABSTRACT

In 2006, Pratt and Whitney launched the Global Material Solutions business model aiming to supply spare parts to non-OEM engines with minimum 95% on-time delivery and fill-rate. Lacking essential technical knowledge of the target engines, predictability and associated confidence of the parts demands are very limited.

This thesis focuses on exploring alternative and innovative approaches to providing more accurate demand forecasts based on limited information. Approaches including application of fundamental sampling theorems, random walk simulations based on Markov Chain simplification, and sensitivity analysis on incremental scrap rates were introduced. A software tool, based on the sensitivity analysis was introduced for all gas path parts. The methodology could potentially be applicable to industries other than Aerospace.

Thesis Supervisor: David Simchi-Levi
Title: Professor of Civil and Environmental Engineering and Engineering Systems

Thesis Supervisor: Roy Welsch
Title: Professor of Statistics & Management Science, Dir CCREMS
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Lastly, I thank the almighty for adding the LFM experience to my life. You are always my guidance.
Biographical Note

Kien Ho graduated from Cornell University, Ithaca, NY in May, 1999 with a Bachelor of Science degree in Electrical Engineering. Kien worked in the high technology industry, including Sun Microsystems, Oracle Corporation at the Silicon Valley, and his own startup company prior to MIT.
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1. Introduction

I had the privilege to work with Pratt & Whitney\(^1\), a United Technologies Corporation company for six months. Pratt is one of the top three leaders designing, manufacturing and servicing aircraft engines, industrial gas turbines and space propulsion systems. This thesis project focused on tackling demand forecasting challenges associated with Pratt’s newly-launched program, Global Material Solutions (GMS), a unique business model in the aerospace engine-making industry. This thesis reports the analysis and findings regarding the aerospace industry as a whole. It also describes Pratt as one of the major players in the marketplace and the specific challenges and methodologies adopted for the GMS program. Lastly, this thesis offers observations and suggestions for Pratt’s organizational processes.

Chapter 2 analyzes the dynamics of the industry as well as Pratt’s position within the industry. The value chain and industry competitiveness analysis will be provided along with Pratt’s products and services. Chapter 3 examines the details of the Global Material Solutions program. Legacy decisions and ongoing industry reactions to GMS from both customers and rivals will be elaborated. Because of the tight interdependent relationship between business challenges and forecasting difficulties, the interplay between the two will be discussed. Chapter 4 covers, within the context of GMS, the basics of aircraft engines parts and services which may not be apparent to readers who have a background in an industry other than aerospace.

\(^1\) Pratt & Whitney and Pratt are used interchangeably in this thesis.
Chapter 5 focuses on the forecasting challenges encountered by GMS and evaluates the pros and cons of methodologies available, Pratt's internal processes, and methods previously utilized in other LFM\(^2\) projects. One of the related projects is the "Forecasting and Strategic Inventory Placement for Gas Turbine Engine Aftermarket Spares" project completed in 2006\(^3\).

Chapter 6 introduces new forecasting approaches designed to address some of the unique challenges identified for GMS. These include Markov Chain analysis, Markov Chain Monte Carlo simulation, and a sensitivity analysis specifically designed for the parts business for the GMS. Chapter 7 elaborates the results of validation approaches adopted. The verifications include a retrospective forecast on past periods using the method and side-by-side comparisons to forecasts projected by independent research in the industry. Chapter 8 describes the architecture of a software tool that automates the forecast methodology developed in this project.

Though many of the challenges identified in this project reside in the forecasting side, I will also provide an organizational analysis under strategic, cultural, and political views.

\(^2\) Leader for Manufacturing Program at MIT

\(^3\) Conducted by Joshua T. Simmons, LFM 2007
2. Industry

The aerospace industry is segmented into two categories: the military agencies and the commercial airlines. While the military customers put highest priority on security and technical customization, commercial customers, e.g., the airline operators, are very sensitive to open market conditions such as price fluctuations and availability of parts.

At the time of this project, many airline operators were at the early phase of growing out of the “distressed” difficulties triggered by the 911 incident. Thus, financials and cash flows were often discussed when it came to buying new engines and servicing existing engines. Due to the financial distress that most of the airlines are experiencing, customers’ buying decisions on repairing and overhauling an engine is heavily driven by short term cash flows. For example, a distressed airline would prefer replacing a broken part with a used part in the aftermarket instead of purchasing a new part replacement, even though the life expectancy per dollar invested in the new parts is significantly longer than that of a used part.

Pratt and Whitney is positioned at the center of the aerospace engine and engine parts manufacturing industry. Engine makers, partnering with airplane manufacturers, e.g., Boeing, supply Original Manufactured Equipment (OEM) engines to airline operators. Very often, engine parts need to be repaired or replaced during the maintenance cycles. Not surprisingly, engine makers would typically repair and overhaul their respective OEM engines under long term maintenance contracts with customers.
Suppliers to the OEMs of aircraft engines consist of two categories: raw material suppliers and third party engine and parts servicing companies. Because of the limited supply of precious metals, such as titanium, raw materials suppliers have tremendous power to set price. With very few raw materials suppliers for the precious metals, demand lead time is long. Third party engine servicing centers do not make engines. Instead, these companies focus on inspecting and servicing aircraft engines. Their positions are analogous to a generic auto shop in the auto industry. These shops usually service aircraft engines with a lower price than the OEMs charge. While a small portion of the parts often needs to be repaired in the servicing center, a major component of service is to replace parts in an engine. At this point, the servicing center needs to procure replacement parts from the OEMs or in the parts aftermarket.

Because of the intensive capital expenditure needed to set up manufacturing and servicing facilities, it is very unattractive and difficult for a new entrant to enter this industry. Competition, however, is fierce. Because of the capital intensive nature of the business, the aircraft engine making and servicing industry is highly concentrated with a small number of OEMs. The competitive dynamics can be best described as a combination of competition and collaboration. On one hand, it is critical for a player to gain as much market share as possible through technology leapfrogging and business model innovation. On the other hand, considering stringent requirements imposed by governmental agencies and the push to standardize parts and services in the industry, players also collaborate on design and sharing best practices through joint ventures and creation of alliances. The International Aero Engines (IAE) and Engine Alliance (EA) are such organizations in which players including Pratt, GE, and Rolls-Royce are active members. Deep technology details and innovation concepts are
frequently discussed and shared via these venues. Therefore, players of the industry are generally aware of the technology trends in the industry.
3. Global Material Solutions (GMS)

In 2006, Pratt launched the Global Material Solutions program to service and supply parts to OEM engines not made by Pratt. The program targets CFM56 series engines, the proprietary engine designed and made by GE. These engines are exclusive engines used on the popular Boeing 737 aircraft. The GMS business model is considered a disruptive method breaking into the traditional engine making and servicing models in the industry.

3.1. Incumbent Business Model

Viewing engine programs in financial terms, one could summarize the business as an exchange between high initial investment and stable cash flow in perpetuity. Traditionally, engine makers would incur heavy capital investment to design, test, and manufacture new OEM engines. To attract customer’s adoption, engine makers typically sell engines at prices lower than the total upfront investment cost. Proprietary design and rich engineering knowledge of the OEM engines, however, enables OEM makers to promote themselves as the experts to service their engines and have the latitude to charge a premium for the servicing contracts. This results in a high margin in the scrap part supplying business with these contracts. Even with this advantage, an engine program would not break even until 3-5 years after the first engine is sold to a customer.

3.2. Pratt’s Disruption

Pratt’s GMS is a clever way to disrupt the existing business model. Pratt was once the leading player in the industry with its rich engineering capability. Historically, Pratt is famous for its complex and advanced engine design. However, as GE came up with simple engines, such as
the CFM56 engine series, customers started to appreciate the simplification and low
maintenance cost of adopting simple engines. Therefore, GE’s CFM56 engines became the
exclusive engines on wing of the industry’s best selling airplane, the Boeing 737. This caused
Pratt to lose its leading position and have excess manufacturing and engineering capacity in its
facilities. By focusing on supplying parts to OEM engines, Pratt’s GMS program capitalizes on
several advantages given its unique positioning in the industry:

First, GMS allows Pratt to avoid the high investment required to re-enter the market. This
created significant advantage for Pratt to compete on price for simple parts in the CFM56
engines.

Secondary, by breaking into GE’s territory, GMS effectively utilizes its excess engineering and
manufacturing capacity and mitigates the potential complication and large cost associated with
managing a labor union relationship.

Third, with the focus on engine parts, GMS could initially leverage its in-house rich
engineering talent to study the CFM56 engines and gradually move up to serve higher value
components of the engine.

Fourth, with a relatively smaller OEM engine market share, Pratt’s GMS program is less
vulnerable to GE’s retaliation by launching a similar program. In other words, it will cost Pratt
less to capture a reasonable size of GE’s market than for GE to win a significant portion of
Pratt’s customer base.
3.3. Challenges

Benefits of GMS come with a few business challenges, including several fundamental forecasting difficulties. In order to win business, Pratt will need to enter the market at a lower price point, and with high availability and quality. If Pratt could not supply quality replacement parts at the time needed, customers would revert back to GE’s OEM parts. Thus, it is imperative that Pratt hits at least 95% fill-rate of demand in the market it tries to enter.

Because of long lead-time of material supply and high cost of the raw material, a small volatility in the demand would force Pratt to maintain a high level of inventory to meet the demand.

Because of the proprietary design of the CFM56 engines, Pratt’s engineering and servicing knowledge of the engines are very limited. One would anticipate that the forecasting error of the GMS program will be massive.

Lastly, with the cyclical nature of the business, a new engine program, such as GMS, usually has one time to adequately plan appropriate production and inventory levels. If Pratt over predicts demand, the high inventory level will be a large cost on its balance sheet. If Pratt under predicts demand, it will miss the market opportunity and leave room for customers to doubt its capability to compete in the market, which in term jeopardizes its long term market competitive advantage.
4. Aircraft Engine

Before discussing the proposed methods to solve the business challenges, it is important to provide an overview of the individual parts contained in US gas turbine engines. These engines, which are approved by the Federal Aviation Administration, include two major part classifications: Life-Limited Parts and Gas Path Parts. These parts are subject to stringent inspection and must be replaced based on usage or wear-and-tear conditions. Both of these classifications are discussed below.

4.1. Life-Limited Parts (LLPs)

Life-Limited Parts (LLPs) are parts in an aircraft engine that must be replaced after a measured number of usages in order to prevent fatigue failures which can eventually lead to a break-down of the entire aircraft if the engines stop rotating in air.

Preventive maintenance schedules for LLPs are determined by the OEMs. Such schedules define the useful life of the engine parts in terms of the number of cycles, defined as the number of take-off’s and landings, allowed before replacement is required. Another specification includes determining the acceptable number of operating hours of a part before it requires replacement. Between the above two measures, the number of cycles measure is usually the limiting factor.
The cycle limitation is determined based on the stress experienced by the part during the highest thrust periods of operation, takeoffs and landings\(^4\).

### 4.2. Gas Path Parts

Gas Path Parts are parts that deteriorate at certain rates but pose little risk of causing catastrophic failure to the engine or the aircraft. However, poor performance of these parts does affect the overall performance of the engine. The best example is a turbine blade in a gas turbine engine. A blade failure is rarely caused by material fatigue or fracture. Instead, the blade suffers material loss from various operating conditions, such as excessive heat and sandy regions. Such material loss will cause engine performance to decrease. For instance, it will take an engine with a deteriorated blade more work to generate the same thrust as compared to one with a new blade. For this reason, operators have the incentive to keep the condition of the Gas Path Parts optimal. Typically, Gas Path Parts are replaced before safety is a concern.

The rate of deterioration, referred as scrap rate\(^5\), is the key to forecasting the demand for Gas Path Parts replacements. OEMs usually measure these rates very accurately based on their proprietary design, long servicing history, and calibration. The GMS program, which lacks the necessary service history and engine knowledge, faces tremendous challenges in estimating the scrap rates. In its limited number of years servicing the engines, experts in GMS had used the scrap rate from the previous year to calibrate the rate expected in the current year. This practice

\(^4\) Source: Forecasting and Strategic Inventory Placement for Gas Turbine Engine Aftermarket Spares, Joshua T. Simmons, June 2007

\(^5\) Ratio of replacement unit amount to original unit of amount in an engine
implicitly assumes that the scrap rate is constant. However, the limited data set collected from Pratt’s engine servicing centers indicates that scrap rate fluctuates widely with time.

A noteworthy consideration is that the timing of the Gas Path Parts replacement is partially driven by the timing of the LLPs inspections. Because engines will visit service shops at a set time or cycle interval defined by the OEMs, the service facilities will utilize the shop visits as check points to inspect the condition of Gas Path Parts. Repairs and replacements of these parts are typically performed at the scene.

### 4.3. Repairs and Overhaul

While the LLPs are replaced at set schedules, the Gas Path Parts in the same engine degrade at various rates. Typically, an engine goes through a series of shop visits in which each part is manually inspected and tested against FAA regulations. In some cases, parts will have to be replaced by either new replacement parts or by aftermarket parts. By industry observation, the original set of parts in an engine will scrap incrementally as the engine goes through a series of shop visits and is expected to have a completely new set of parts after a certain number of shop visits.

Take a set of turbine blades as an example. Let’s say that we have 72 blades in the original set and that a part would not survive more than four shop visits. As described in Figure 1 below, parts will go through series of discrete stages named as SV\(n\), with \(n\) indicating the sequence of

---

6 An engine visits a repair and overhaul shop when it reaches to predefined cycle limited or meets certain condition
shop visit stages. When a part arrives at SV1, a portion of the parts will scrap, hence, moving back to SV1 state. The rest of the parts will survive SV1 and move onto SV2. At SV2, a similar process happens, a portion of parts that reach SV2 will scrap, moving back to SV1 state, and the rest survives and moves the SV3. The process repeats until the remaining parts arrive at SV4. At SV4, all parts are expected to scrap.

Conventional wisdom based on linear extrapolation would hypothesize that a quarter of the blades are scraped after each shop visit. In reality, however, more blades scrap at the earlier shop visits. As observed in engines similar to the CFM56 engines, more than a third of the blades will scrap at the first shop visit. Moreover, as the majority of the blades typically have a lifespan of two to three shop visits, replacement of the blades is concentrated in the first three shop visits.

![Figure 1: Parts Scrapping Process](image-url)
5. Forecasting Challenges and Methodologies

The forecasting challenges for the GMS program are best depicted in Figure 2. OEMs operate comfortably in a region with long observation and service history, an intimate knowledge of their own engines from day one. These two advantages grant OEMs unparalleled ability to predict scrap rates at the most accurate level possible. On the other hand, GMS resides in the opposite side of the map with limited service history and little engine knowledge. On the surface, the lack of data almost precludes GMS from predicting the demand within a reasonable range.

![Forecasting Challenge Perception Map](image)

**Figure 2: Forecasting Challenge Perception Map**

5.1. Data Available

Observations are primarily collected from a Pratt engine servicing facility with four years of servicing history. Because of the newly launched program, only 100 data points were collected.
A significant portion of these data points was unusable due to human input errors and duplicated entries. Therefore, the amount of usable data points is less than 2% of the data points available in a typical OEM program.

5.2. Incumbent Forecasting Methodology

Demand forecasting is a critical function, especially for business and production planning at Pratt and Whitney. Because of the long lead times of product spare parts and the short lead times expected by customers, Pratt constantly needs to carry a sizeable safety stock of inventory to ride with the volatility and forecasting errors of actual demand.

At Pratt, the spare parts demand forecast process is a top-down approach which involves forecasting the number of expected shop visits and estimating the expected scrap rate for each of the parts. A 12-month demand forecast is described in the formula below:

\[
\text{Demand Forecast} = \text{Expected # of shop visits} \times \text{standard expected scrap rate}
\]

A key assumption for the shop visit forecast is that engines must return to the repair facilities after a predefined cycle limit. With an observation that the shop visit numbers across all operators tend to converge to an average number, Pratt applies an expected number of shop visits by taking into account the average age of the fleet\(^7\). The first drawback of this simplistic approach is the failure to predict the actual timing and the overall distribution of the shop visits.

\(^{7}\) Age of fleet refers to average accumulative cycle time incurred on all active engines. It is usually measured in term of shop visit stage. For example, the age of fleet can be said to be between second and third shop visits.
With a high mix of engine age\(^8\) in a fleet, every engine would have its unique service schedule. The exact timing of its shop visit schedule directly impacts the demand volatility observed by the engine repair facility.

The second drawback of the approach is the oversimplification of scrap rate. Although at a macro level, the total scrap rate tends to converge to an average, the industry has long hypothesized that scrap rates are very much dependent on the age of the engine. This is a critical consideration for GMS as the program is expected to add new customers incrementally. Thus, a global scrap rate may not be accurate enough to facilitate business and production planning. Pratt has an internal engineering organization dedicated to study scrap rates for all parts being serviced. Even though it provides valuable insight into Pratt’s OEM engines, the organization faces the challenge of limited data availability for GMS.

In addition to the top-down approach, Pratt utilizes classical and advanced trending analytic tools available in ERP and MRP software packages, such as SAP, to conduct short-term production planning. Fundamental calculation of safety stock, reordering points and quantities are provided as references to the production planners for specific parts. The planners will apply their business judgments, taking market condition and industry trends into account, to fine tune appropriate inventory levels.

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\(^8\) Similar to Age of fleet, as measured in term of shop visit stage
5.3. Life-Limited Parts

As described in the section above, the key challenge for accurately forecasting the demand for LLPs is estimating the timing of the shop visit arrivals. A previous LFM project\(^9\) tackled this challenge and developed a methodology for processing customer inputs and specific engine conditions. Using the methodology described in this previous project, Pratt was able to predict the timings of LLP replacements within a reasonable range.

5.4. Gas Path Parts

Unlike their LLP counterparts, the Gas Path Parts pose multifaceted forecasting challenges. First, parts eventually come to 100% scrap at unknown rates. Figure 3, depicts this challenge graphically. Based on industry knowledge\(^10\), parts eventually scrap 100% after 4-5 shop visits. However, the speed at which the scrap rates mature varies depending on the airlines’ operating condition, geographical factors, and other unquantifiable elements. As shown in Figure 3, although one might be able to calibrate an average scrap projection (the middle line), the variation of the mature rate is still unknown without an extensive servicing history of the CFM56 engines that GMS intends to service.

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\(^9\) Conducted by Joshua T. Simmons, LFM 2007
\(^10\) Source: Maintenance and Engineering
Second, as mentioned in section 4.2, scrap rates of the Gas Path Parts vary depending on the shop visit stage. Figure 4 depicts sample incremental scrap rates\textsuperscript{11} at various shop visits observed. Each of these scrap rates measured would have a forecasting error. Without access to the insider engineering design information, the scrap rates of the Gas Path Parts, which are crucial to forecasting the demand, cannot be determined. Scrap rates also vary depending on the cumulative age of the parts. Typically, parts that survive more accumulative cycles have higher scrap rates than the parts with fewer cycles. As such, having an “average” scrap rate to proxy all stages is bound to provide inaccurate forecasts. Moreover, when the forecasting errors of each shop visit rates are summed up into a global forecast, greater forecasting error will be introduced.

\textsuperscript{11} Scrap rate at specific part age.
Third, due to the geographic and operating condition bias, the limited set of service data available at Pratt & Whitney’s engine centers is not representative of the characteristics of the fleet that GMS targets to serve.
6. Alternative Methodologies

Given the limited set of data and knowledge available, it is apparent that traditional forecasting methods, including trending analysis based on history and specific engineering studies, cannot accurately estimate scrap rates in the short term. What's left is a fundamental statistical and probabilistic analysis based on existing data.

With classical sampling methods, we are able to retrieve basic statistical behaviors of the data observed. These characteristics will be used as references throughout the analysis. Moreover, we can analyze the probability of scrapping parts at a deeper level. Referring to the scrapping process in Figure 1, we see that the scrapping process is a complex probability map. We can simplify such a map into a sequential map using Markov Chain simplification. Lastly, given the limited set of observations and possible high variation of the estimate, we need to understand the estimation errors. Using simulation and sensitivity analysis, we will be able to answer the question of "how wrong we could be in our estimation?"

6.1. Fundamental Statistical Analysis

According the Central Limit Theorem, as sample size increases, the sampling distribution of sample means approaches that of a normal distribution with a mean the same as the population and a standard deviation equal to the standard deviation of the population divided by the square root of the sample size. Remember that we have about 100 scrap rates observed. We can utilize the limited data in two applications. The first application is to calibrate standard errors within the 100 data points by selecting various sampling sizes. The second application is to project the
general average scrap rate assuming that the whole 100 data points arrived at random (i.e. Sampling size = 100).

Figure 5 shows the standard errors with various sampling size out of the 100 data points as the general population. We can see that the standard error as percentage to the actual average scrap rate decreases as sample size increases. For example, with a standard error of 5.2%, we can be confident that the estimated average scrap rate falls into a 20.8% window centered by the actual average scrap rate 95% of the time. When we treat the 100 data point as random sampling from the general population, the standard error is expected to shrink to 2-3%. This statistics is quite encouraging as we achieve a relatively high confidence on the estimation using a limited set of data.

![Figure 5: Standard Errors Observed from Sample Data](image)
6.2. Markov Chain

Referring back to the scrapping process showed in Figure 1, we note that the process seems to fit the properties of Markov Chain Process, a finite number of discrete state stochastic processes. A proper Markov Chain simplification can transform complex probability map into a sequential probability map. This sequential probability map contains the key scrapping probabilities that we need to derive the scrap rates for GMS Gas Path Parts.

6.2.1. Example

A classic example of a Markov Chain is Light bulb Replacement. Imagine a sign entirely made of 1000 light bulbs. The owner of the sign, is interested in forecasting the number of bulbs needed to be replaced in a monthly basis and the financial budget associated with the maintenance. Based on studies, we know the probabilities of a bulb going dark the next month depend on the ages of the bulbs. The probabilities can be summarized in form matrix below:

\[
P = \begin{bmatrix}
0.5 & 0.5 & 0 & 0 & 0 & \text{New} \\
0.2 & 0 & 0.8 & 0 & 0 & 1\text{-mo.} \\
0.25 & 0 & 0 & 0.75 & 0 & 2\text{-mo.} \\
0.333 & 0 & 0 & 0 & 0.667 & 3\text{-mo.} \\
1 & 0 & 0 & 0 & 0 & 4\text{-mo.}
\end{bmatrix}
\]

Each row of the matrix describes what might occur for a bulb of a particular age. For example, the row labeled New indicates that if a new bulb is inserted in a socket during one of the monthly maintenance inspections, the probability that it will fail during the month and be replaced with a new bulb at the next inspection is 0.5. The probability that it will not fail and survive to an age of one month is also 0.5. This poor quality seems to be rather extreme, but we exaggerate for
illustration. The remaining rows indicate similar data for other ages. In every case the bulb is replaced with a new one or ages by one month. In the example, we assume the bulb is always replaced after it is four months old.

The names “New”, “1-mo”, “2-mo”, etc. are the states of the system. At a monthly inspection the bulb must be in one of these states. The matrix is called the transition matrix because it shows the probability of transition from each state to every other state. We call this a Markov process when the transition probabilities depend only on the current state of the system. The figure appearing at the beginning of this article is called the State Transition Diagram and represents the same information as the transition matrix.

### 6.2.2. Markov Chain Properties

A random process is a Markov Chain Process if

$$P(X_{n+1} = j | X_n = i, X_n \neq 0).$$

This means the probability of a discrete state is only dependent on its previous state. In the case of GMS Gas Path Parts, a part can only arrive at the second shop visit by surviving the first shop visit. A state in a Markov Chain is recurrent if there is non-zero probability of leaving the state. All shop visit states described in Figure 1 are recurrent. Probabilities going from one state to the next state are called transitional probabilities, usually denoted by $P_{ij}$ (read as the probability of going from the $i$th state to the $j$th state). A square matrix is used to indicate all transition probabilities. Such a matrix is called the transition matrix.
To be qualified for Markov Chain simplification, a Markov chain needs to possess the properties of irreducibility, aperiodicity, and ergodicity. The scrap process of the Gas Path Parts fulfills such requirements.

6.2.2.1. Irreducibility

A Markov chain is irreducible if, starting from any one of the states, it is possible to get to any other state (not necessarily in one jump). If there are any absorbing states, the chain is not irreducible. Shop visits described in Figure 1 possess this property.

6.2.2.2. Aperiodicity

In a Markov chain, a state $i$ has a period $k$ if any return to state $i$ must occur in multiples of $k$ time steps. For example, if it is only possible to return to state $i$ in an even number of steps, then $i$ is periodic with period 2. Thus, the period of a state is defined as

$$k = \gcd\{n : \Pr(X_n = i|X_0 = i) > 0\}$$

(where "gcd" is the greatest common divisor). Note that even though a state has period $k$, it may not be possible to reach the state in $k$ steps.

If $k = 1$, then the state is said to be aperiodic; otherwise ($k>1$), the state is said to be periodic with period $k$. In the case of the shop visit chain described in Figure 1, it is inconceivable to have $k>1$. If there exists a $k$ which is greater than 1 (e.g., 2), then all odd states (e.g., shop visit 1, 3, etc) would not be reachable. Thus, we know that the chain in Figure 1 is aperiodic.
6.2.3. **Ergodicity**

A state $i$ is said to be ergodic if it is aperiodic and positive recurrent. If all states in a Markov chain are ergodic, then the chain is said to be ergodic. All shop visits stated in Figure 1 conform to this property.

6.2.2.4. **Steady-state analysis**

After we show that the shop visit sequence depicted in Figure 1 conforms to all properties of a finite state Markov chain, we can use steady-state analysis to derive a sequential probability map. In a finite Markov Chain, the transition matrix, similar to that in the light bulb example, represents the probability distribution across all the states. Because the Markov chain is time-homogeneous, one can keep making transitions by raising the power of the transition matrix. For example, at the $k$-step transition probability, the probability distribution will be in form of $P^k$, where $P$ denotes the transition matrix. When $k$ goes to infinity, the Markov Chain is said to reach steady-state, in which case the stationary distribution, a sequential probability map, is derived, so that

$$\pi = \pi P.$$  

Equation 1: Verification at steady-state

Where $\pi$ is the stationary distribution.

Therefore, using steady-state analysis, we can simplify the complex scrapping process in Figure 1 into a sequential map as denoted in figure 6. Using this map, we can look-up and apply shop-visit-dependent scrap rates to the demand forecast.
6.2.2.4.1. Calculation and Verification

Similar to the transition matrix in the light bulb example, we can translate the raw probability map into a transition matrix. Figure 7 shows the mechanism for such a translation for a hypothetical shop visit chain.

Through multiple iterations of matrix multiplication, we can arrive at the stationary distribution vector. We can verify the result by plugging the stationary distribution and transition matrix back into Equation 1. As shown in Equation 2, we arrive at the stationary distribution vector after joining the vector with the transition matrix.
Equation 2: Verification at Steady-state for GMS Parts

6.3. Markov Chain Monte Carlo Simulation

Because a Markov Chain is transitory, we can start at an arbitrary vector and conduct random walks around the sample points to find the best vector that fits the verification equation. We call such a random walk algorithm a Markov Chain Monte Carlo (MCMC) Simulation.

As illustrated in Figure 8, to find the best-fit vector in $X$, we start with random points and compare it to the value of $X P(x)$. As the number of samples increase to infinity (steady-state), we are likely to find a vector that closely matches the two values.

Figure 8: Random Walk
Utilizing the same transition matrix shown in Figure 7, the MCMC simulation arrives at a steady-state solution, which is shown in Figure 9. The result matches with the industry knowledge that, typically, a part would not survive beyond the fourth shop visit. In fact, the result shows that more than 95% of the blades in this case scrap before the fourth shop visit.

<table>
<thead>
<tr>
<th># of steps</th>
<th>SV1</th>
<th>SV2</th>
<th>SV3</th>
<th>SV4</th>
<th>SV5</th>
<th>SV6</th>
<th>SV7</th>
<th>SV8</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>0.3400</td>
<td>0.2800</td>
<td>0.1900</td>
<td>0.1300</td>
<td>0.0500</td>
<td>0.0100</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>500</td>
<td>0.3940</td>
<td>0.2860</td>
<td>0.1840</td>
<td>0.0860</td>
<td>0.0400</td>
<td>0.0100</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>1000</td>
<td>0.4230</td>
<td>0.2810</td>
<td>0.1880</td>
<td>0.0880</td>
<td>0.0340</td>
<td>0.0050</td>
<td>0.0010</td>
<td>0.0000</td>
</tr>
<tr>
<td>1500</td>
<td>0.4160</td>
<td>0.2867</td>
<td>0.1660</td>
<td>0.0880</td>
<td>0.0280</td>
<td>0.0127</td>
<td>0.0027</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Steady State: 0.416065867 0.2829248 0.1667549 0.0848774 0.033951 0.0101853 0.0020371 0.0002037

95% of blades scrap by SV4 in reality

Figure 9: MCMC Result

6.4. Sensitivity Analysis on Incremental Scrap Rates

One of the alternative ways to estimate potential forecasting errors is to simulate and replicate the dynamics of the part scrapping processes, including the effects of new replacement parts.

6.4.1. Scrap Dynamics

The scrap dynamics of Gas Path Parts, illustrated in Figure 10, are as follows: Let’s say a set of 72 blades starts brand new. At the first shop visit, 37 of the original 72 blades survive and move on to shop visit 2. The rest of the 35 blades are replaced with new blades added into the engine. Note that the 37 blades that survive at this point are considered to have an age of shop visit 1. At the second shop visit, 19 of the 37 blades at the age of shop visit 1 survive and move on to shop visit 3. At the same time, 18 of the 35 new blades introduced in shop visit 2 survive and have the age of shop visit 1. The rest of the 35 blades are replaced with new blades added into the engine.
This same process replicates itself with more and more age stages. Thus, the cumulative scrap rates observed by GMS, which are the rates to be used in its demand forecasting, at various stages are:

<table>
<thead>
<tr>
<th>Scrap Qty</th>
<th>SV1</th>
<th>SV2</th>
<th>SV3</th>
<th>SV 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scrap Rate</td>
<td>35%</td>
<td>49%</td>
<td>49%</td>
<td>40%</td>
</tr>
</tbody>
</table>

Table 1: Derived Accumulative scrap Rates

As indicated in Figure 4, incremental scrap rates vary depending on the ages of the parts when they visit a repair facility. Moreover, the incremental scrap rates dictate the scrap quantity at various part ages. In the example shown in Figure 11, the incremental scrap rate at the age of shop visit 1 is 51.4% (37/72 and 18/35), and the incremental scrap rate at the age of shop visit 2
is 51.3% (19/37). As these incremental scrap rates change, it is expected that the cumulative scrap rates would change. The question is how much the cumulative scrap rates vary.

### 6.4.2. Sensitivity Analysis

The challenges of limited knowledge and service history compromise the understanding of the incremental scrap rates for GMS. However, conventional industry knowledge enables us to make reasonable assumptions and conduct a meaningful sensitivity analysis on the incremental scrap rates. It is industry-wide knowledge that a new part could not physically survive four shop visits. This means that the original set of parts will reach 100% scrap by the fourth shop visit. We can then that the sum of the incremental scrap rates for the first three shop visits is 100%. Moreover, without new replacement parts entering the engine at the shop visit 1, the incremental scrap rate at shop visit 1 is the same as the cumulative scrap rate observed by GMS. Given the fundamental statistical analysis described in section 6.1, the confidence level of the estimated accumulative scrap rate at shop visit 1 is reasonably high. The rest of the incremental scrap rates at shop visits 2 and 3 sum to a constant value because they complement each other. Therefore, the sensitivity analysis becomes a process of toggling only one variable, the incremental scrap rate, at shop visit 2.

By fitting incremental scrap rates to observed cumulative scrap rates, we determined the base case of incremental scrap rate at the second shop visit. By considering a wide range of scrap rates (plus and minus two standard deviations), we discovered an interesting phenomenon. As shown in Figure 11, accumulative scrap rates apparently converge to a stable rate in the long term despite the wide range of values selected for incremental scrap rates at the second and third shop visits. A consistently low standard deviation, ranging from 1%-4%, supports this observation.
Therefore, to answer the original question asked earlier, our estimation would only have 8% error at the worst case 95% of the time. This striking metric is reassuring given the narrow estimation error, GMS should be able lower its safety stock while still maintaining high confidence that it can fulfill a 95% fill-rate and on-time delivery. This should result in significant saving in inventory and production planning for GMS.
7. Bottom-up Forecasting and Validation

With a better understanding of the key absolute scrap rates, we are ready to use a bottom-up approach to estimate the demand for Gas Path Parts in a three-step process.

First, we forecast arrival times for all shop visits. Based on the LLPs characteristics, we know that engines will visit a repair facility when they reach a certain cycle limit. From public data, we have detailed engine conditions, including accumulative engine cycles, flying hours, and expected utilization rates. This information is sufficient to determine the current age of an engine and the speed with which an engine will approach its next shop visit. Thus, a projection of shop visit timings for all flying engines is established.

Second, for a specific part, we can project the scrap quantity at its next shop visit by looking up the absolute scrap rate, which is dependent on the current age of the part.

Lastly, the market demand is simply the summation of all expected scrap quantity for all engines.

7.1. Validation

To verify that the forecasting method discussed in Section 6 generated plausible results, we conducted a backtest in the most recent 12 month period for an operator that Pratt served. Three year's worth of data was fed into the Markov Chain and Sensitivity Analysis models to produce forecasts in the latter 12 months. We found that the forecasting error of the 12 month average demand to be less than 7%.
8. Automated Tool

To support the large number of parts serviced in the GMS program, a software package was needed to automate and standardize the forecasting methods proposed. At the time of this document, Pratt is in process of developing a dashboard tool with two primary functions (Figure 12). The first function is to automatically conduct sensitivity analysis for all parts and integrate the analysis with Pratt’s mainstream forecasting process. The second function is to provide a top-down view of forecasting estimates for all parts.

![GMS Global Forecast Dashboard](image)

Figure 12: GMS Global Forecast Dashboard
9. Observations and Recommendations

Through the process of tackling the forecasting challenges at GMS and Pratt, this study utilized extensive collaboration with cross-program and cross-functional groups. This project provided significant exposure to Pratt’s organizational processes and GMS’ business model. Observations and recommendations on Pratt’s organizational processes, the GMS business model, and future projects to solve future forecasting challenges are provided herein, and should be treated as independent views.

9.1. Organizational Processes

Strategically, Pratt organizes its workforce into a large matrix organization consisting of functional groups and a line of business groups. The goal of such a design is to achieve specialization for all functions and business groups so that resources can be centralized to support multiple businesses simultaneously. With the acknowledgement of this goal, I found that the flexibility and resource pooling are achieved at the expense of inevitable communication overhead.

In this project, I worked at the cross point among a material management organization, business teams, engineering studying organization, engine servicing centers, and other functional teams. The material management organization holds a centralized team of professionals specializing in forecasting and inventory planning. It helps prioritize functional needs and efficiently shares functional knowledge across all businesses. For instance, the forecasting method generated in this project will be applied to other similar programs to GMS as deemed fit. On the other hand, the business teams house experts in specific groups, either programs or products. Teams in GMS,
for instance, are the most knowledgeable individuals who can answer questions about the
CFM56 engines within Pratt. In addition, business teams own the profits and losses of a specific
program, and have the ability to pull in resources as needed. Note that the resources pulled
usually report to their own management command chain in their specializations. Therefore, an
individual running a project at the ground level would need to coordinate communication across
many functional teams in order to move the project forward. With this arrangement,
communication overhead is significant. Moreover, due to independent prioritization processes
and misaligned incentives across all of these teams, individual resources have a tendency to
delay the process.

Pratt has a strong engineering culture. Employees at all levels respect engineering knowledge
and expertise in a specific function or product. An executive mentioned that it is rare to see an
individual without any academic discipline in engineering rises up in the ranks. Seasoned
engineers who are individual contributors also receive high visibility.

Knowledge and expertise are thought to be accumulated through long serving tenures. While the
typical average tenures in the organization I worked in was about 7 years, many of the team
members had worked in Pratt more than 10 years and never had worked outside of the company
throughout their careers. The tendency to reward long tenure and deep engineering knowledge,
contrasted with the typical shop-and-switch culture in many other industries, serves as a major
factor that deters young talent from considering joining Pratt and the Aerospace industry. One of
the challenges that the industry players face, including Pratt, is finding enough young talent to
backfill the retiring workforce who hold precious knowledge about the products and programs.
The matrix organizational design also poses the risk of political battles among groups. With the natural diverse incentives across functional groups, individuals belonging to different groups would hold different perspectives on the same program. Political power plays tend to arise when two or more organizations see a program as a vehicle to expand their personal and organizational influence. This results in resource contention and lack of cooperation among cross groups.

As discussed before, the original goal of resource pooling and knowledge sharing through the matrix organization is admirable and should continue to be the goal. The challenge is the missing gap between the vision set by the top executives and actual implementation on the floor. One of the possible ways to cope with the strategic, cultural and political issues discussed is to empower young and rising talent at the ground and middle level of the organization. Often these individuals already possess the right attitude and desire to lead changes from which Pratt as a whole would benefit. Working at the ground and mid level in the command chain, these employees have tremendous exposures to, and can make direct impact across functional groups. Equipped with proper guidance and granted adequate authority, these young leaders would do the right things on the floor and stay in constant connection with senior management in cross functional engagements. In addition, these effective leaders should be able to cut down unnecessary communication overhead by exercising the right judgment and authority.

9.2. GMS as a Business Model

GMS is arguably an innovative business model within this industry. It leverages all of Pratt's internal capabilities, including engineering talent, excess manufacturing capacity, and unique market position to break into competitor's profit making region. GMS had to take on the risk of
high uncertainty on initial demand, which results in high inventory to achieve a desirable fill-rate. This risk, however, is thought to be well calculated and appears to be balanced by the ramification of having excess unionized workforce and manufacturing capacity with decreasing market share.

However, from the perspective of a customer, GMS could do more to solve an airline operator’s pain and achieve faster customer adoption. It is assumed that the spare parts supplied by GMS would be less expensive and hold equivalent, if not superior, quality as compared to the OEM parts. But this may not be enough to convince an operator to convert to GMS. The biggest concern from the airlines is the impact to their existing engine warranties and service agreements should they choose to switch. In fact, CFM International, a 50/50 joint company of Snecma and General Electric, subtly hinted that they would “support people who use PMA parts (GMS parts) in a different way than we support customers that use OEM parts.”

The second factor that poses more risks to GMS is that customers can always go back to procure OEM parts. Unavailability of parts will cause delay of an engine’s schedule to return to service, which in turn may cause airlines to fly fewer flights. As soon as the GMS parts are not available, or show signs of low availability, customers would likely switch back to OEM parts permanently to minimize impact to their business loss.

A potentially viable model to solve these two issues is to incentivize customers to convert all of their service contracts to GMS at once. Since Pratt is able to leverage the same engineering

12 Source: Air Transport World Media Group, February 2007
capacity to supply spare parts, there is no significant barrier for Pratt to take over the repair and
overhaul business for the customer as well. With this model, Pratt will ease customer’s worry of
voiding existing warranty and service agreements by standing behind all services needed for
customers to fly engines. On the other hand, this allows Pratt to collect a wealth of knowledge
about airline engine operating behavior and achieve economies of scale in serving similar
products.

GMS could go further by offering to maintain a customized quality level of parts for each airline.
Keeping track of the ages of the parts, and procuring and installing the parts in the aftermarket, is
a nontrivial task. Such a task, however, is not part of the airlines’ core competency, which is
transporting customers by air with reasonable price and excellent service. With this GMS
service, airlines can be focused more on their core business. By providing such service, GMS
will achieve a higher level of economies of scale that would potentially improve Pratt’s
competitive advantage.

9.3. Future Related Projects

The forecasting methods explored in this project serve only as a beginning to the alternative
forecasting regime, which is relatively new to Pratt. Further validation, monitoring,
standardization, and integration are needed to institutionalize these methods into Pratt’s
mainstream forecasting process.

In addition to the backtest conducted in this project, Pratt should apply the new forecasting tool
to their OEM engines. Owning deep knowledge and having serviced their OEM engines for a
long history, Pratt can use their OEM as the next safe opportunity to test and fine tune the methodology proposed.

The sensitivity analysis on incremental scrap rates were conducted based on a limited set of assumptions. Further relaxing these assumptions will give Pratt the opportunity to adjust and augment the models to fit broader business needs. One example is that the model assumes a certain cycle time interval between shop visits. In practice, such intervals might or might not be followed by an operator’s repair policies. Further simulation could be conducted to gauge the potential impact to the forecast demand due to this consumer behavior.
10. Conclusion

GMS, as an innovative and disruptive business model, introduced challenging requirements to its demand forecasting functional organization. Based on the nature of data available, the alternative forecasting methodology introduced in this project was adequate to address the difficult issues. A backtest demonstrated the robustness of the forecasting method and tools developed with an increased level of forecasting accuracy. The set of methodologies and related software tools are good additions for Pratt to enhance its internal forecasting capability and fine tune features as similar programs mature. Lastly, with the generic nature of concepts discovered from this project, it could be expected to see the same concepts being applied to solve similar challenges in other industries relevant to business and technology forecasting.
11. Appendix

Global Fleet Age

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<th>SV</th>
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</tr>
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<tr>
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</tr>
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</tr>
<tr>
<td>SV6</td>
<td>0</td>
</tr>
<tr>
<td>SV7</td>
<td>0</td>
</tr>
</tbody>
</table>

Legend:
- SV
- # of Engines
- w. Average