# Airline Operating Cost Reduction through Enhanced Engine Health Analytics

by

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Submitted to the Department of Aeronautics and Astronautics and the Sloan School of Management in partial fulfillment of the requirements for the degrees of

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**Abstract**

Engine Health Management (EHM) is a comprehensive maintenance service offered by engine manufacturer Pratt & Whitney (PW) to its airline customers. In its current form, engine performance is monitored through recorded physical metrics, such as gas temperature, pressure, and altitude, taken as single snapshots at various phases of flight. The advent of the Enhanced Flight Data Acquisition, Storage and Transmission (eFAST™) system, which allows for near-continuous recording of engine metrics, provides Full-Flight Data Analytics (FFDA) that may proactively alert and recommend maintenance activity to airlines. Adopting eFAST™ may help avoid Adverse Operational Events (AOE) caused by unexpected engine failures and the associated cost burdens. With respect to operating cost, airlines standardly report Cost Per Available Seat Mile (CASM) and Cost Per Block Hour (CBH). EHM services that prevent operational disruptions can help airlines reduce these unit-cost metrics, whose scrutiny by industry analysts affect investment guidance, stock performance, and overall business outlook.

In this study, the value of FFDA services to airlines is investigated on the International Aero Engines V2500, a mature engine with customers' operational histories well-documented. Using a Poisson distribution to model the occurrence of six operational disruption types—Inflight Shutdown, Aircraft-On-Ground, Aborted Takeoff, Air Turn-Back, Ground Turn-Back, and Delay/Cancellation—the cost savings potential is quantified as a function of events avoided by a hypothetical FFDA service. Airline Form 41 financial data from the Bureau of Transportation Statistics is then used to estimate the magnitude of savings on CASM and CBH retroactively for 2012-16. Results show that unit cost reductions of 0.5% to 1.5% are possible through engine event avoidance, representing savings up to $104M annually, but outcomes are highly dependent on assumptions about cost of operational disruptions for each individual carrier. Overall, a baseline model and procedure is developed for valuating FFDA and associated EHM services. Further collaboration between airlines and Pratt & Whitney on data availability and accuracy will help refine this model, which is the first to bridge publicly available airline costs with engine history data, helping stakeholders transition to an eFAST™ ecosystem that promises greater operational efficiency and safety.

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# Chapter 1

# Introduction

## 1.1 Commercial Engines and Aftermarket Services

Engine Health Management (EHM) is a comprehensive aftermarket service offered by jet engine manufacturers to airlines to monitor, troubleshoot, and maintain the fidelity of the engine's long-term functionality. American manufacturer Pratt & Whitney (PW) has long offered EHM through individual data snapshots on engine temperatures, pressure, altitude, oil debris, and other physical properties transmitted through ACARS (Aircraft Communications Addressing and Reporting System). Advancements in data storage and transmission technology have enabled PW to introduce Full-Flight Data Analytics (FFDA), a more comprehensive EHM service utilizing near-continuous data point capture of even more engine performance properties. FFDA is expected to enable faster, more accurate predictive capabilities with respect to the metrics of interest. Specifically, the prospect of full-flight "fault detection"—instantaneously observing and reacting to an impending engine failure—holds promise for better safety and reduced maintenance burden for airlines.

## 1.2 Airline Cost Economics

For airlines, enhanced EHM services offer the opportunity to improve maintenance scheduling and reduce direct operating costs. Predictive services can help avoid major engine overhauls or reduce the work scope of engine events by alerting airlines to likely faults and failures, and recommending repairs or replacements in a proactive manner. In turn, airlines can expect reduced unplanned engine removals (UERs), aircraft-on-ground (AOG) events, and other service disruptions that have direct maintenance costs as well as further expenses due to extra crew pay, passenger re-accommodations, airport penalties, and other burdens resulting from operational disruption. These cost components all factor into airlines' unit cost metrics, most commonly the Cost Per Available Seat Mile (CASM) and Cost Per Block Hour (CBH). The airlines' profitability, perceived shareholder value, stock market performance, and investment outlook are all directly tied to CASM and other related cost metrics. Therefore, implementation of enhanced EHM services to control engine operating costs holds promise for reduced CASM for the airline industry.

## 1.3 Research Premise and Objectives

The present study aims to define the value of EHM services for the US domestic airline industry through the lens of unit cost reduction. First, background on the history of engine health monitoring and management services is reviewed. Next, a data sample of airline operating costs, publicly available through the Department of Transportation's Bureau of Transportation Statistics, will be evaluated for components related to engine maintenance. Using PW's historic data on the International Aero Engines (IAE) V2500 engine, Poisson probability models of various engine faults are calculated and presented to understand the current incidence of engine events. A model for unit cost reduction is formulated through sensitivity analysis of incremental prevention of engine fault incidence. Finally, the calculated cost benefits are analyzed and discussed as an approximation for EHM value to the industry at-large, with PW's nascent eFAST™ service as a product model. Commentary on further FFDA growth, big data development and usage, and cybersecurity implications conclude the thesis.

# Chapter 2

# Background and Current Literature

## 2.1 Pratt & Whitney and the Jet Engine

### 2.1.1 History of Pratt & Whitney

Pratt & Whitney, a subsidiary of United Technologies Corporation (UTC), has produced commercial and military aircraft engines since the early twentieth century. The original Pratt & Whitney Company of Hartford, CT was a manufacturer of measuring instruments. In 1925, it provided funding, factory space, and its namesake to Frederick Rentschler's aircraft engine business, which became the Pratt & Whitney Aircraft Company [1]. Throughout the twentieth century, Pratt & Whitney played a pivotal role in the emerging aerospace industry as part of the United Aircraft and Transport Corporation, which was eventually split by the U.S. government for anti-trust purposes and renamed United Technologies Corporation. As part of UTC, Pratt & Whitney (PW) pioneered both commercial and military aero-engines that powered propeller and jet aircraft, including prominent commercial models such as the Bombardier Q400, the Airbus A320 family, the Boeing 747, and the Airbus A380. Today, PW engines make up about 25% of in-service commercial aircraft across the globe [2].

### 2.1.2 The Gas Turbine Engine

Since 1951, PW has focused on producing jet engines after moving its major propeller products to Pratt & Whitney Canada. In the years since, PW turbofan engines have been at the forefront of major breakthroughs in the commercial airline industry. Gas turbines have powered the majority of commercial aircraft since the so-called "jet age" of the 1960s. The prototypical gas turbine engine, shown in Figure 1, generates propulsion for an aircraft through two airflows. First, air taken in through the fan and then forced through combustion with fuel and exhausted through its back nozzle. The core of the engine is separated into a "cold section" and "hot section," corresponding to the internal temperature of the components and the gas that passes through. Second, a larger volume of air bypasses the engine's core, along its inner nacelle (engine casing) and then exits through back nozzle.

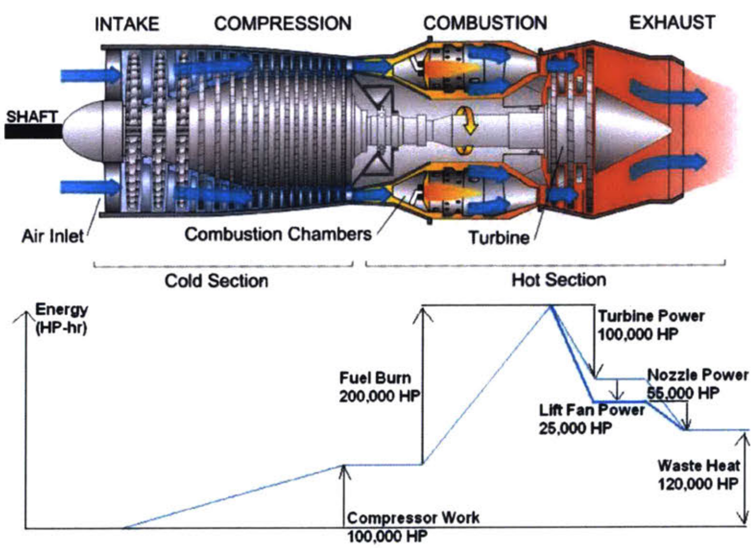


Figure 1. Typical modules of an aero engine, along with spatial energy profile. Source: Wikimedia Commons (Open Source)

### 2.1.3 The V2500 Turbofan Engine

International Aero Engines (IAE), a manufacturing joint venture of which Pratt & Whitney is now the majority stakeholder, introduced the V2500 engine to revenue air service in 1989 [3], powering Airbus Industrie's A320 family of single-aisle aircraft. It has since grown to be one of the most successful gas turbine engines in aviation history, reaching over 5000 deliveries in 2012, and continues to be produced for the three variants of this popular Airbus family of aircraft. Across the global airline industry, the A320 family numbers over 7000 of in-service aircraft, representing about half of the single-aisle, mid-range market [4]. Of these, about 3250 are powered by IAE V2500 engines [5]. The V2500 competes directly with CFM International's CFM-56 engine, the other power plant option for airlines operating the A320 family. Figure 2 below provides a cross-section of the IAE V2500 engine.

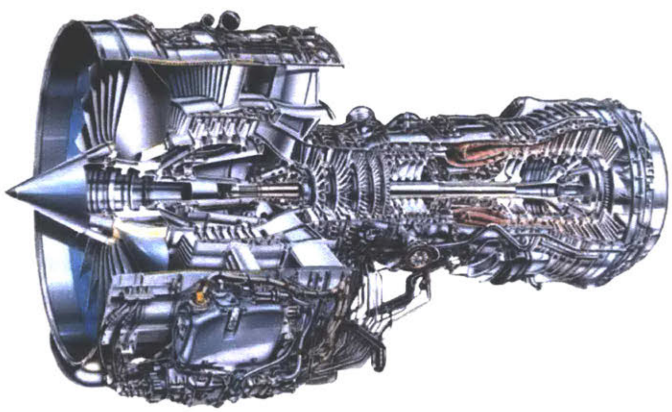



Figure 2. Cross section of the IAE V2500 engine. Source: Pratt & Whitney public website

## 2.2 Engine Performance, Health, Monitoring, and Management

### 2.2.1 Definition of Engine Health

Gas turbine engines consist of hot and cold rotating parts operating in high-altitude environments that physically deteriorate over repeated use. The life of an engine is dictated by its ability to power airframes consistently and safely across varying atmospheric conditions.

Because understanding of the physics of jet engine propulsion is mature and has been refined throughout their engineering history, the components determining engine performance and engine life are well-understood. As such, the state of any commercially produced engine can be systematically monitored via sensors that report on the physical properties of propulsion and flight. Data collected from sensors can be compared against known physical limits defined from the product's initial design and engineering. Thus, standard operating limits for the various sections, parts, and components determine whether or not an engine can safely operate a flight mission. This systematic understanding of engine properties has fueled the practice of engine health monitoring, and more broadly, engine health management.

### 2.2.2 Engine Health Monitoring and Engine Health Management

Engine Health Monitoring is the practice of ensuring that engines operate within bounds. The known physical limits of each module and component are built in during the engineering and design phase, ensuring that upper and lower bounds for operation are clearly defined. As mentioned, properties such as temperature, air pressure, and altitude are metrics that can be monitored by sensors to understand the engine's physical state during flight. These metrics measure engine performance at the time of data capture, but the collection of data for a single engine can be analyzed over its history to show patterns and trends. Over time, the metrics of interest for engine health are bound by their control limits, such that a standard profile of behavior is known. This standard profile provides the baseline against which all engines can be compared to identify either (1) synchronicity with a known pattern, indicating normal "wear and tear" over time, or (2) deviation from the known baseline, indicating the potential for unexpected faults or failures. The analysis of physical metrics against known baselines forms the foundation of Engine Health Monitoring [6]. This practice is akin to monitoring the vital signs for human health, ensuring measurable properties such as body temperature, blood pressure, and pulse are within the known limits of standard health. Extending the analogy, Engine Health Monitoring would be akin to maintaining a patient's health record over time, watching for patterns in the vital signs and ensuring that trends and drifts are within normal bounds.

Engine Health Monitoring forms the basis of Engine Health Management (EHM), a broader classification that encompasses the suite of aftermarket services offered by the original equipment manufacturer (OEM). Amongst OEMs, the "aftermarket" refers to the various products and services offered to their customers to maintain equipment performance, such as spares, repairs, replacements, and maintenance labor [7]. In the aviation industry, airplane engine OEMs incorporate aftermarket services in initial contract negotiations for engine orders. At PW, EHM is offered as a comprehensive aftermarket service that includes not only Engine Health Monitoring, but also the associated products and labor needed for maintaining engine performance, such as spare parts supply, repair shops, data analysis, and recordkeeping via database storage of historic engine metrics.

### 2.2.3 Fleet Management Programs

EHM can involve even more comprehensive services, such as Fleet Management Programs (FMP), whereby the airline and the engine OEM enter into a business relationship colloquially called "power-by-the-hour" [8]. Coined by a manufacturer later purchased by Rolls Royce, the term refers to an arrangement in which the OEM charges the airline a set cost per flight hour delivered by an engine, and assumes maintenance and repair responsibilities based on contract agreement. Such a relationship allows the airline to know its engine-related operating costs with greater certainty, and shifts much of the burden of spare part storage, maintenance staff, and other direct maintenance responsibilities to its OEM supplier. Small or new carriers often engage in power-by-the-hour agreements given the capital-intensive requirements for establishing maintenance facilities. FMP relationships fall at the more extreme end of engine cost management for an airline. Along the spectrum of EHM services, airlines have the freedom to selectively engage with the engine OEM. A carrier may, for example, limit its relationship to basic monitoring and alerting services, and perform maintenance in-house or contract that work out to a third party provider. Ultimately, the EHM relationship can vary widely from carrier to carrier, and is customized according to the contractual relationship with the OEM. The methodology covered in this study makes no assumption about the exact business terms on which a given EHM agreement is defined, as the cost of such agreements is generally individualized and confidential.

### **2.2.4** Diagnostics and Prognostics

EHM is, at its heart, a service of diagnostics and prognostics. The former, diagnostics, as its name suggests, is a study of empirical observations to *diagnose* a problem after it has occurred. Retrospective in nature, diagnostics has generally formed the bulk of EHM services given the need to troubleshoot, investigate, and resolve issues. While engines themselves are very well understood, the exact reason for engine faults or events requires extensive information to ascertain. Dearth and overabundance of information are both issues that complicate the task of finding one or more causes to a given engine incident [9]. Nevertheless, through continuous trial and error, the foundational understanding of engine physics, constraints on possible phenomena, and process of elimination, EHM diagnostic methods have become an advanced practice.

Prognostics, on the other hand, requires an understanding of past incidents, past solutions, and sufficient levels of data and repeated trials that provide enough confidence to the predictor of an event. Given the uncertainty inherently tied to an event that has yet to occur, lack or dearth of data generally stymies progress on prognostic methods in EHM. Regardless, OEMs continue to have a strong incentive to improve and enhance prognostic capabilities for several reasons, only some of which will be defined here. First, the trajectory for sensor-based monitoring is always toward more information, not less, given continued advances in data capture, storage, and processing abilities. Second, with the advent of so-called "next generation" products in the aviation sector, whereby reduction in noise, fuel consumption, and emissions drive engine design, accurate prognostic methods help to reduce events that contribute to these adverse byproducts of gas turbine engines. Finally, in a highly competitive market with only a few players, advances that improve operational efficiency for airline customers provide any engine OEM a strong business advantage.

## 2.3 Snapshot Versus Full-Flight Data

### 2.3.1 Snapshot Data: ACMF, ACARS, ADEM

Commercial aircraft today use the Aircraft Communications Addressing and Reporting System (ACARS) to communicate with ground control [10]. The ACARS system is also the platform on which engine data is transmitted. At PW, the ACARS-produced "ACMF Report" is the snapshot data file from which current generation EHM services are rendered. Because of bandwidth limitations, engine data transmitted by ACARS is limited to a single data point captured at the so-called transient steady state for three phases of flight: takeoff, cruise, and landing [11]. ACMF reports allow identification of data trends over the life of the engine, such as gas exhaust temperature, which creates a profile of likely deterioration over the flight cycles that the engine has completed.

The ACMF method of reporting has allowed PW to develop a service called Advanced Diagnostics and Engine Management (ADEM), which, as its name suggests, is a diagnostics-focused type of EHM service. ADEM is a productionized platform—that is, a standard product offering—available to airline customers that purchase the service for their own maintenance needs. Through ADEM, fleet managers at the operating airlines can access the full set of data captured in ACMF, create reports on a Graphical User Interface (GUI), and identify data patterns and trends. ADEM is a mature product that has been offered by PW for decades, forming the basis of its engine health monitoring apparatus and providing 24/7 field support for existing, in-service engines.

### 2.3.2 Full-Flight Data

ADEM performs diagnostic services well, given its long maturation period and repeated use by both airline customers as well as by PW's engine monitoring team. Despite its efficiency, ADEM's prognostic abilities are limited by the amount of data fed by ACMF. Specifically, because only snapshot data of the physical metrics is captured at the designated flight phases, users are blind to any data point appearing in-between captures. Figure 3 illustrates this concern. On the left, the current snapshot method shows trending of a generic metric, with each data point representing a single flight. In contrast, any one of the single flights can be monitored throughout its full flight cycle as in the right panel, with single data points now corresponding to individual moments. Data can go uncaptured if the metric of interest fluctuates within the same flight phase, such as during the cruise phase illustrated in the figure.

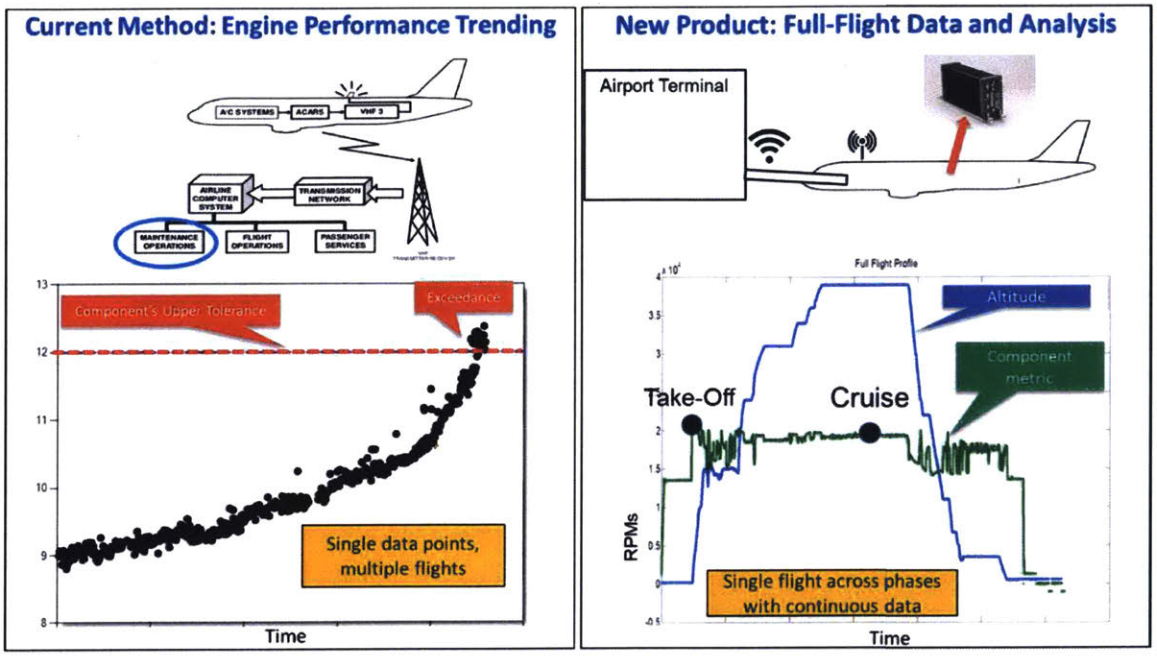


Figure 3. Comparison of current snapshot data collection method (left), and full-flight data capture (right). In the current snapshot method, single points correspond to individual flights. With full-flight data, a continuous profile of one or more metric is possible. Note that graphs and axes are hypothetical and meant for illustrative purposes only. Source: Author's research, with data obscured for confidentiality.

Full-flight data capture is the newest development in engine data technology, and has been enabled by improved speed and capacity of data acquisition, storage, and transmission. Beyond typical ADEM services, which will continue for the foreseeable future, PW is now turning its attention to creating an ADEM-like system that will offer even more data availability. This full-flight data availability is an investment PW believes will allow it to expand prognostic abilities. Furthermore, there is desire to make use of artificial intelligence and machine learning methods to create an "Internet-of-Things" product, such as a mobile application, that puts data and control together more efficiently for the engine operator [12]. Much like a health-focused "wearable" alerts the user to the number of steps taken and calories burned, a mobile application could be developed for airline fleet managers to track and be alerted to impending engine maintenance needs.

### 2.3.3 The eFAST™ System

PW began its quest for full-flight data acquisition with its Pratt & Whitney Canada (PWC) division, which launched the Flight Data Acquisition, Storage, and Transmission (FAST) system, to serve Cessna and Bombardier aircraft running on the PW100 family of turboprop engines [13]. The FAST system was based on PW's first hardware product for full-flight data capture, and has become a productionized option for PWC customers. FAST is used on turboprop missions that are lower in capacity, stage length, and altitude, and was enhanced in 2015 to accommodate full-flight capabilities for narrow-body jets [14]. This enhanced FAST (eFAST™) system was developed to serve PW's Geared Turbofan (GTF) family of high-bypass ratio engines, as well as their predecessor, the V2500. With eFAST™, PW aimed to capture greater depth and breadth of data by near-continuous capture, from power-up to power-down, of a plethora of additional engine performance metrics beyond those of the FAST system.

The eFAST™ product was developed in conjunction with the GTF, and formed part of a suite of so-called next generation products predicated on fuel efficiency, noise and emissions reductions, and range extension. The small to mid-size (150-180 seats) narrow-body market, now dominated by the two most popular commercial aircraft families in the industry, the Airbus A320 and the Boeing 737, was the focus of the GTF. Today, the GTF is the sole engine option for the Bombardier CSeries family, Embraer E2 family, and Mitsubishi Regional Jet; additionally, it is an option for the Airbus A320 family's New Engine Option (NEO) and the Irkut MC-21.

Importantly, the eFAST™ hardware was first introduced in the build-of-material (BOM) for Bombardier's CSeries, and thus delivered to each airline customer by default [14]. This first foray as a Health Monitoring Unit (HMU) installed aboard a commercially-operated PW turbofan aircraft inspired the transfer of the eFAST™ hardware onto PW's most popular engine in service, the V2500, as a business case emerged for establishing FFDA for the existing fleet of Airbus A320 family Current Engine Option (CEO) aircraft, the moniker given to all A320 variants running on the V2500. The eFAST™ hardware box, which is connected to the avionics bay of the aircraft, is shown below in Figure 4.

Figure 4. The eFAST™ hardware in its current form, which connects to the avionics bay of the aircraft.

### 2.3.4 V2500 Engine Faults and Adverse Operational Events

The V2500 is a mature engine that has not received an HMU device for full-flight data capture, but at the time of writing, PW has received the supplemental type certificate to incorporate eFAST™ onto Airbus A320 family aircraft [15]. The prevailing ACMF reports transmitted through ACARS has established a mature, single-snapshot level of Engine Health Management that, while effective for diagnoses of faults that have already occurred, has limited prognostic capability in its current form. In its current mature state, the V2500 experiences engine faults that induce adverse operational events (AOE), which PW categorizes by their disruption to the customer. The AOEs of interest in this study are outlined below.

- Aircraft-On-Ground (AOG): the unplanned grounding of an aircraft from commercial revenue service due to an engine fault, often caused by an unplanned engine removal
- In-Flight Shutdown (IFSD): a fault that results in a full loss of engine functionality while at cruising altitude, often induced by the engine's sensors as a precautionary measure against more severe damage
- Air Turn-Back (ATB): otherwise known as a diversion, an event whereby the flight crew either chooses or is advised to make a landing at an airport other than its intended destination
- Aborted Takeoff (ABTO): a planned takeoff is stopped before reaching takeoff decision speed, either before or during the takeoff run, due to engine sensor notification or any visual indication to the flight deck that the takeoff cannot be completed safely
- Delay and/or Cancellation (DC): the delay or cancellation of a scheduled commercial flight due to any suspected or actual engine fault, which may be experienced in conjunction with mechanical checks or any of the above events
- Ground Turn-Back (GTB): an engine fault is noted on the flight controls' electronic centralized aircraft monitor (ECAM) either during engine startup or aircraft taxi out. Maintenance check or repair occurs at the gate.

PW's existing health monitoring employees record all AOE and non-AOE incidents related to engine performance. This valuable database of engine events has created a searchable toolkit from which past data, trends, and associations can be deciphered. The utility of this database will be covered further in Chapter 3.

### 2.3.5 The eFAST™ Engine Health Management Business Proposition

The existing record of AOEs mentioned above form an extensive database that represents the status quo of V2500 engine health over two decades. If the status quo represents the current health and safety record of the engine, then a future state can be defined in which the full-flight data advancements improve on all of the AOE metrics for engines going forward. The advent of eFAST™ presents such an opportunity to usher in an EHM product that, in its nascent stages, can simply be benchmarked on its improvement to the status quo. Stated differently, one could use the current AOE rates as a baseline, and then show that the value of full-flight data analytics is realized through reduction of event incidence rate. Models for aircraft and engine life cycle cost for airline operators has been studied extensively, generally in analyses of *total* expected cost of a given aircraft or engine type based on its known performance parameters and maintenance cycles, with assumptions made on labor, fuel, and crew costs [16]. The present study will not make statements about theoretical life cycle costs, but rather will make estimates on likely cost reductions against the status quo of AOEs for V2500 operators. That is, the potential for AOE reductions is used as a heuristic for unlocking the possible cost savings enabled by a full-flight data analytics paradigm for EHM services.

## 2.4 Airline Economics and Metrics

### 2.4.1 History of the Airline Industry in the US

The US airline industry was de-regulated in 1978 following decades of profitability supported by government controls over airline routes and pricing, which established high barriers for new entrants. This radical change in the airline business ushered in a plethora of upstart carriers that have come and gone in a fiercely competitive landscape [17]. The events of September 11, 2001 marked a turning point for the industry as demand for air travel plummeted in the immediate aftermath, and carriers were forced to reckon with oversupply of seats, labor costs in a highly unionized environment, and increasing fuel costs. At the same time, the emerging strength of low-cost carriers (LCC), with their cost-conscious business models and disruptive, low fares, added downward pressure on revenue at the network legacy carriers [18]. Leading up to the Great Recession of the late 2000s, the industry had already begun a series of mergers and acquisitions that resulted in significant consolidation of players in the US market. The decade from 2000 to 2010 saw most US carriers going through bankruptcy proceedings, allowing significant restructuring of business models, labor contracts, and security operations. The introduction of so-called ancillary amenity and service fees came about as airlines sought to increase revenue channels and "unbundle" the standard level of services of a flight ticket to match those of the LCCs; henceforth complimentary inflight meals became buy-on-board meals, and the standard two complimentary checked bags became fee-based checked baggage [19]. These industry-wide changes paved the way for continued improvement in operating costs, and converged with advancements in revenue maximization methods through internet distribution, revenue management, and ancillary fee management. The fortuitous, record-low fuel costs in the mid-2010s helped usher in an era of unprecedented profitability for the smaller number of US-based carriers remaining. The so-called era of "capacity discipline," which in practice meant the strategic reduction by multiple carriers of seats on unprofitable routes, became and continues to be an industry trend [20].

### 2.4.2 Motivation for Airlines to Adopt Engine Health Services

Historically a low profit margin industry, airlines have continued to chase cost savings through better fleet scheduling and operations. A shift in fleet utilization for mid- to long-range domestic flights away from wide-bodies to narrow-body, twin-engine equipment types has demonstrated the value of engine efficiency. The development of GTF-powered aircraft, as described above, is a major contribution to this industry trend. Enhanced services such as full-flight EHM complement the "next generation" products by offering greater visibility into engine performance and maintenance, and can also be adapted for legacy products such as the IAE V2500. OEMs have pushed for more aftermarket products and services beneficial to their businesses. For the airlines, the promise of greater visibility on maintenance provides yet another cost-cutting vehicle by way of detecting, preventing, or otherwise proactively mitigating unplanned service disruptions. Figure 5 below shows the various components of an engine data transmission paradigm, with particular detail on the alert and monitoring cycle that ties the operations between the OEM and an airline.

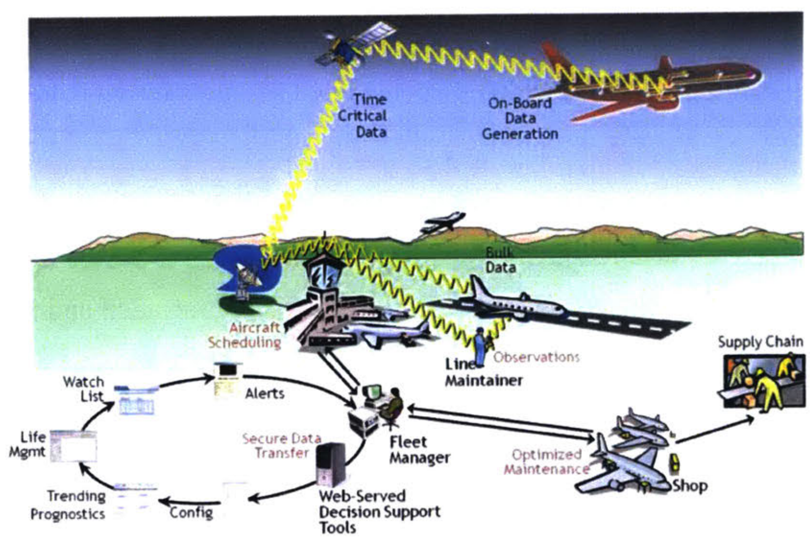


Figure 5. Engine data transmission paradigm, from aircraft to ground station, diagnostics and prognostics cycle, and maintenance optimization for aircraft. Source: Volponi 2014 [9]

Importantly, Figure 5 depicts the entire process of data capture, transmission, storage, processing, analysis, and delivery as a continuous cycle that involves several stakeholders across air transportation operations. This visualization sets the stage for characterizing an eFAST™ "ecosystem" that depends on the collaboration of the various players to ensure data integrity, accuracy, and security.

### **2.4.3** Different Definitions of Cost

Airline costs are typically measured on the unit level, most often by Cost Per Available Seat Mile (CASM) or Cost Per Available Seat Kilometer (CASK). Other unit cost metrics include Cost Per Scheduled Block Hour (scheduled gate-to-gate hours) and cost per actual block hour (actual gate-to-gate hours). The aim of these cost metrics is to measure the airline's cost efficiency, given its supply of seat-miles, scheduled flying, or actual flying—that is, on a single unit basis, what does it cost the airline to operate? There is also a distinction between operating cost, operating cost excluding fuel, and total cost [21], [22]. Generally, these categories do not align perfectly with the traditional notion of fixed and variable costs. Instead, airline costs tend to be categorized by functional purpose. The nuanced ways of calculating *costs* are covered below [23], while particularities on *unit* costs are shown in the next section:

- Flight Operating Cost, Direct Operating Cost, or Aircraft Operating Cost refers to pilot pay, fuel cost, maintenance and overhaul, and allocated capital cost (depreciation and amortization). Stated more simply, these are costs that have to do with the flying of an aircraft. Approximately 50% of total costs for an airline can be attributed to Aircraft Operating Cost.

- Ground Operating Costs include airport-related fees and services: ground handling, landing fees, passenger processing fees, and reservation centers/travel agencies/distribution system fees. These comprise 17-20% of total costs.
- System Operating Costs are the remaining "general overhead" costs not directly associated with transporting passengers. These include passenger services (on-board meals, amenities, and flight attendant pay), and marketing. Also included are "transport-related costs," a category the encompasses a mainline carrier's fees paid to a regional partner for regional flights. System Operating Costs comprise the remaining 30-40% of total costs.

### 2.4.4 Basic Airline Metric Equations

As described above, CASM is the main unit metric for comparing costs. The unit in this metric is the Available Seat Mile (ASM). The ASMs of any given flight, route, or network is the scheduled seat capacity planned by the airline. For a given origin and destination (O&D), ASM is calculated as one seat flown one mile, hence its equation,

$$Available\ Seat\ Miles = Total\ Seats * O\&D\ Distance \tag{1}$$

This equation holds for an individual flight, the sum of many individual flights, the sum of flights in one airline's network, or even the sum of all flights in the industry, provided that seats are multiplied by their corresponding O&D distance before summation. It is itself a unit metric of supply in the industry, with extra weight given in direct proportion to the distance flown by a given seat. Generally, on a single flight level, ASM is calculated as

$$ASM\ of single\ flight = Seats\ on\ Aircraft * O\&D\ Distance\ in\ Miles \tag{2}$$

As described above, the cost component of CASM can be defined in various ways, depending on the intended purpose for analysis. At the highest level, an airline will report its total network CASM as the sum of all costs realized, including all three categories described in the previous section: Aircraft Operating Cost, Ground Operating Cost, and System Operating Cost. Since Aircraft Operating Costs include even the amortization of capital, an airline's total CASM is a succinct, single metric that accounts for the entire airline's operations. Therefore, the general equation for CASM is

$$CASM = \frac{Total\ Costs}{Available\ Seat\ Miles} = \frac{Aircraft, Ground, and\ System\ Operating\ Costs}{Total\ Seats * Miles\ Flown} \tag{3}$$

CASM takes this general equation form, but reported CASM can vary based on the elements of the numerator intentionally included or, conversely, excluded. As one of the most volatile components of operating cost, fuel is often excluded in order to calculate an "ex-fuel" CASM independent of the fluctuations in oil price. Ex-fuel CASM is useful for comparing "internal" unit cost performance, that is, how the airline is performing on factors in its control, such as labor, overhead, distribution, and marketing expenses. For reporting purposes, airlines may also choose to report only their mainline operations—that is, flights operated only under its two-letter International Air Transport Association (IATA) code, rather than that of any regional subsidiary or regional partner operating on a seat-lease basis. This latter arrangement, seen most often in short-haul, low-capacity flights to smaller spokes from an airline's hub, are regarded as seats "sold and marketed" by the mainline carrier, but "operated by" a fleet and crew that are not considered to be directly owned or employed by the airline itself. Regional carriers, including

SkyWest, Mesa Airlines, and ExpressJet, often operate regional flights for more than one mainline carrier. In CASM calculations, an airline or any reporting entity may choose to exclude all regional seat-lease agreements, subtracting out the contract cost for these operations and their associated ASMs [23].

With respect to units, CASM is customarily reported as cents per ASM. Typical system CASM in the domestic US industry has ranged from low single digits to high teens, with CASM generally decreasing as the carrier's average stage length increases [24]. CASM is replaced by Cost Per Available Seat Kilometer (CASK) for airlines using the metric system. Raw numbers for CASM and CASK are different owing to the inherent numerical difference between a mile and a kilometer, but the metric serves the same purpose, and all relative comparisons hold true under CASM or CASK.

CASM is an industry-wide metric that captures the attention of financiers, consultants, and academics for its simplicity of aggregation. Figure 6 below shows mainline CASM for ten major US carriers from 2007 to 2016.

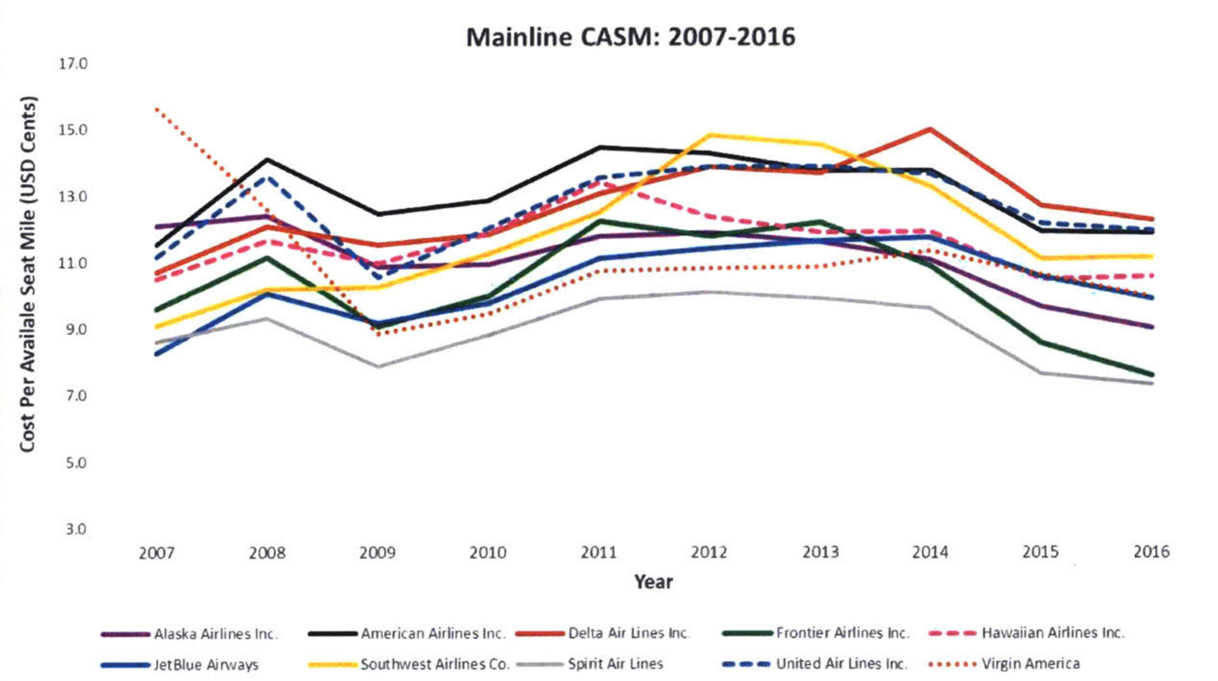


**Figure 6. Domestic mainline CASM from 2007 to 2016. Data Source: US Department of Transportation and Bureau of Transportation Statistics.**

In the decade shown in Figure 6, CASM dipped in 2009 following the 2008 financial crisis, but appeared to pick up again quickly from 2010 to 2014, years in which oil prices continued on an upward trajectory. From 2014 onward, the oil industry faced historically low prices, coinciding with a period of low CASM and high profitability for the airline industry [25].

### 2.4.5 CASM in its Various Forms

As mentioned in the previous section, CASM can take one of various nuanced forms depending on the intended purpose of discussion, whether that is a carrier's CFO, a Wall Street analyst, or an industry publication. Some of the more common types of CASM are outlined below:

- CASM Ex-Fuel: One of the most commonly reported forms other than total CASM, ex-fuel CASM excludes fuel expenses to keep cost components to those internal to, or otherwise controllable by, the airline itself.
- CASM Excluding Special Items: In some cases, airlines report a CASM that excludes "special items" such as one-time costs of, say, a merger partner or acquisition [26].
- CASM Ex-Transport-Related Costs: As explained above, the costs of a seat purchase contract to regional airline(s) by a mainline carrier is categorized as "transport-related costs," a component of the aforementioned System Operating Costs. Exclusion of the transport-related costs leaves a CASM that is "mainline only," that is, reflects only the performance of revenue service flown by a carrier's distinctive two-letter IATA code.
- Total CASM: Generally, without explicitly stated exclusions, CASM is understood to be Total CASM, incorporating the total costs incurred by the airline for the given period of time being reported (usually quarterly or full year results for the airline's entire network). Because Total CASM includes transport-related costs, fair comparison across carriers requires that one keep in mind the inclusion of outsourced, regional flying.

Given the complexity of spreading fixed costs over an airline's entire network of operations, it is often difficult to calculate the true CASM or other unit cost of a single route or flight. The traditional hub-and-spoke model, moreover, makes it nearly impossible to calculate a true CASM for a flight given the plethora of connecting itineraries that spread the "true cost" of a trip across multiple flight legs [23]. CASM comparisons are also complicated by the numerical fact that unit costs do not scale up linearly with the distance flown. In practice, since costs for each departure-arrival cycle are generally fixed, simple arithmetic shows that the longer the flight, the lower its CASM, as those costs are spread out over more seat-miles. Conversely, short stage length flights see higher CASM than network average, since the fixed costs incurred are spread over fewer seat-miles. As airlines differ significantly in their route networks and hub geography, a direct comparison of total network CASM over all routes may misrepresent an airline's productivity relative to its peers. Inherently, an airline that operates more long-haul flights will appear to perform better on CASM. Because of this imbalance, airlines will also calculate a stage-length adjusted metric for CASM in order to make a viable comparison that controls for the effect of flown distance [27].

### **2.4.6** The Maintenance Component of Airline Costs

Maintenance has been shown to constitute up to 13% of an airline's total operating cost [28]. Although fuel and labor remain the largest components of airline operating costs, the focus on cost-cutting measures as the industry continuously chases the lowest cost carrier means that any opportunity to reduce the CASM numerator is part of the financial discussion. The AOEs mentioned above all disrupt operations and contribute to unexpected expenses. The *unexpected* aspect of these disruptions is only partially covered in the present study, given data availability.

Although maintenance costs refer generally to mechanical system repairs and upkeep, an irregular operation (IROP) induced by an engine fault can have implications on costs in various aspects of the business, such as additional labor cost for staffing airport or flight crews, re-accommodation costs for affected customers, extra fuel required for route diversions, among others. The main focus of this study is on the direct maintenance costs as reported by two carriers of interest, so it should be noted that estimates presented here are conservative estimates of cost savings, given the lack of data on airline IROP costs (particularly at the individual airline level).

Comprehensive studies of actual CASM effects would require collaboration across all stakeholders of AOEs. For the time being, this study seeks to bridge two disparate metrics of cost, one from the OEM and the other from airlines, to understand how incidence of engine events can be translated to unit cost metrics, which are important for airline investment, profitability, and performance outlook.

### 2.4.7 Maintenance Regulations

All commercial carriers must abide by Federal Aviation Administration (FAA) regulations regarding maintenance. In particular, there are scheduled maintenance events that must occur after certain thresholds of flight cycles or hours, elapsed time since the previous check, or elapsed time since entry-into-service. In industry parlance, these are denoted the "A," "B," "C," and "D" checks, labeled in order of increasing complexity, person-hours of labor, and cost [29], [30]. These are briefly detailed below:

- "A" Check: Performed every 65 flight cycles, for routine, light maintenance and engine inspections; completed overnight without disruption to aircraft availability.
- "B" Check: Similar to A Check, but with more comprehensive tasks; generally occurs every 300-600 flight hours.
- "C" Check: Determined by flight hours, flight cycles, and months in service, and as such occurs every 1-2 years; generally involves check of a majority of an aircraft's components; takes aircraft out of service, from a few days to a couple weeks.
- "D" Check: Considered a heavy maintenance visit, this comprehensive check involves essentially a complete disassembly of an aircraft for complete evaluation of its

components and parts; this check may take up to a month to complete, at a large maintenance facility.

The work scope of these checks may also depend on the equipment type, the recommendations from manufacturers, and the degree of fleet utilization. These scheduled checks, though required by the FAA for comprehensive safety protocol, do present both a time and cost burden on operators. In particular, they create a set of constraints in the so-called fleet assignment problem in operations research literature, wherein the optimal aircraft, crew, and route assignment for an airline's given fleet is solved to maximize utilization and minimize operating costs [31], [32]. One advantage of the routine, scheduled nature of these checks is that they can be predicted with certainty as to their time of occurrence. The challenge of unexpected engine faults and failures, leading to the AOEs mentioned above, is that maintenance schedules need to be reassessed, since even one aircraft taken out of service leads to downstream disruptions to the entire schedule. The work of this present study, therefore, can help to explain the contribution of probabilistic modeling of unexpected engine events in the context of this fleet assignment problem. With EHM services provided by full-flight data analytics, the impact of the AOE on scheduled maintenance can, at the least, minimize unexpected disruptions and/or provide a heuristic for better understanding of aircraft maintenance schedules.

### **2.4.8** CASM and Maintenance Optimization

The advent of more sophisticated schedule optimization solutions has helped to improve the operational efficiency of airline operations, including crew scheduling and maintenance scheduling [33], [34]. Generally, such optimization problems have the objective of minimizing cost for the operation of interest. Although CASM and unit costs are not explicitly stated as objectives, an optimization solution that minimizes costs would logically extend to optimizing CASM and unit costs. Given the current separation between internal engine data and external airline cost data, the hope for this study is to develop a better understanding of the relationship between engine monitoring, maintenance services, and realized costs—all of which will help define the value of full-flight data analytics for the customer. More broadly, further work of this type can help inform and refine future formulations of the ever-growing complexity of air transportation operations research.

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# Chapter 3

# Methodology and Procedures

## 3.1 V2500 Fault Detection Database

### 3.1.1 Data Recording

Internal to Pratt and Whitney's (PW) existing EHM services for the V2500 engines is a repository of the data transmitted in ACMF reports through the Aircraft Communications Addressing and Reporting System (ACARS). These reports are fed into the Advanced Diagnostics and Engine Management (ADEM) portal, which serves as the user interface for the plethora of data captured from every V2500 in commercial service throughout the world. In addition to the raw data—the actual gas temperatures, pressures, oil debris counts—the data of interest for this present study are the engine event reports generated each time an operational disruption occurs due to an adverse engine event, or an impending adverse event. Events can be triggered by flight crew observation or by monitoring staff working around the clock at multiple facilities worldwide.

In the case of an engine event, the field support personnel from PW can survey signals from the engine or components whose physical metrics led to alerts, and can order a borescope procedure to be done, whereby a narrow tube with light and camera is inserted into the engine and is used to probe for signs of damage or deterioration. This procedure is not unlike a colonoscopy that would be done on a human patient. Results from line inspection and any borescoping are recorded into an incidence report, which also indicates what type(s) of AOE were caused as a result of the engine issue. Each event may trigger more than one AOE; in many cases, one type of AOE is logically linked to another. For example, an aborted takeoff is almost certainly going to trigger a delay or cancellation, depending on the severity of the engine fault.

In addition to records of damage, repair orders, spare orders, and other maintenance action, the engine's operational record is also available. These include flight hours and flight cycles experienced by each engine. Therefore, for any given AOE recorded, the incidence rate can be expressed as the occurrence per number of flight hours or flight cycles. This rate of incidence is important for the present study, as the premise of full-flight fault detection is to reduce as many of these unexpected AOEs as possible. In other words, the aim of diagnostics and prognostics at PW is to prevent or scale down the severity of any such AOEs, and the rate of incidence is a key performance metric that indicates the success or failure of the monitoring, alerting, and prevention tactics of EHM services.

### 3.1.2 Sample Size Determination

While the V2500 is widely used throughout the global airline industry, it is often not the only power plant chosen for a given carrier's fleet of A320 family aircraft. In fact, most major network legacy carriers in the US and Europe operate a mix of V2500 and CFM-56 engines on their Airbus fleet. As a result, the incidence rates analyzed were reduced to two North American carriers that operate the V2500 engine exclusively on their Airbus narrow-body fleet. Moreover, the two carriers chosen also share characteristics that make them useful subjects of study:

- Both operate a mix of long-haul and short-haul routes throughout North America.
- While aircraft age varies between the carriers, both have active orders for more PW engines for upcoming Airbus deliveries and maintain a relatively young fleet.

- The carriers compete on many overlapping routes, creating an incentive for either carrier to be astute to cost of operations for competitive concerns.
- Both carriers skew similarly toward a leisure-heavy route network.
- Both carriers are legally required to report operating expense information to the Department of Transportation, which makes the data publicly available.

In addition to the market and strategic similarities, there carriers both have long-term EHM agreements with PW through which their engines are monitored and managed. These arrangements allowed for many years' worth of data to be available for analysis.

### 3.1.3 Data Collection

Incidence reports were obtained for the two carriers of interest for the five years between 2012 to 2016, inclusive. This time period has the advantage of having largely emerged from the Great Recession of 2008-09. The full body of data for the two carriers include categorical data such as date of event, engine serial number, tail number of the corresponding aircraft, event location, and the flight phase at which the event occurred, Meanwhile, quantitative data include total flight hours, total flight cycles, and a count of the total Adverse Operational Events (AOE): Aircraft-on-Ground (AOG), Inflight Shutdown (IFSD), Air Turn-Back (ATB), Aborted Takeoff (ABTO), and Delay/Cancellation (DC). Table 1 summarizes the categorical and quantitative data available in the engine history.

Table 1. Data represented in engine incidence reports, available through engine history records.

| V2500 Incidence Report Data | |
|---|---|
| *Categorical* | *Quantitative* |
| Event Date | Flight Hours |
| Engine Serial Number | Flight Cycles |
| Aircraft Tail Number | Count of Adverse Operational Events |
| Event Location | |
| Flight Phase | |
| Basic/Non-Basic Label | |
| *Other* | |
| Reason for Trigger | |
| Support Personnel's Notes | |
| Unique Event Identifier | |

## 3.2 Characterization of Data Set

### 3.2.1 The Poisson Distribution

In examining the available data set, it was determined that the incidence of engine faults is best approximated using the Poisson distribution, which describes the occurrence of discrete events that arrive with a constant rate across a finite interval of time or space [35]. Each individual event of a given Poisson-type process arrives independently of any prior or future individual event. Many everyday events can be described by a Poisson distribution, such as the calls made to a customer service center on one day, attendees to a museum, or vehicles passing a toll booth. More weighty applications of Poisson can be found in the claims filed to an insurance company in a set period [36], number of corporation defaults in a period [37], and industrial accidents and suicides in a period [38]. Perhaps most importantly for the present study, occurrence of adverse events can often be modeled after a Poisson distribution, including occurrence of earthquakes [39], cancer cell growth [40], and memory chip failures [41].

In particular, a discrete compound Poisson distribution is appropriate for modeling the behavior of the V2500 engine faults explored in this study. Several characteristics of the adverse engine events and the data set lend themselves well to a Poisson analysis:

- Engine faults are discrete, individual events.
- The total number of each AOE category is known for a set period of time: the total flight hours, or the total flight cycles experienced by the engine.
- At this mature state of the V2500 engine, manufacturing and design defects are assumed to have been addressed sufficiently such that faults occur independently of one another.
- The compound nature of this Poisson process is represented by the multiple AOEs that can be manifested due to engine fault: each AOE has its own incidence rate per interval of time, flight hours, or flight cycles.

Given a Poisson characterization for V2500 engine faults, the rate of an AOE can be defined by

$$\lambda, \textit{the incidence rate in one year's worth of flight hours} \tag{4}$$

The formulation of the entire Poisson probability distribution continues as follows:

$$\textit{An individual AOE is binomial, that is, it either occurs or it does not} \tag{5}$$

$$\textit{For each AOE type, one occurrence is independent of a past or future occurrence} \tag{6}$$

$$k, \textit{the number of times an AOE occurs in a prescribed interval of time} \tag{7}$$

$$T, \textit{the prescribed period of time} \tag{8}$$

To find the probability of $k$ occurrences of one AOE type, we use the *probability mass function* as defined by

$$P(k\ occurrences\ in\ interval) = \frac{(\lambda T)^k e^{-\lambda T}}{k!} \tag{9}$$

Where $e$ is the exponential (Euler's number), and $k!$ is the factorial of $k$ given by

$$k \times (k-1) \times (k-2) \times \ldots \times 2 \times 1$$

Figure 7 shows the Poisson Probability Mass Function (PMF) for values of $\lambda$ from 1 to 9, graphed against the probability of seeing X = $k$ events occurring, with $k$ plotted on the x-axis.

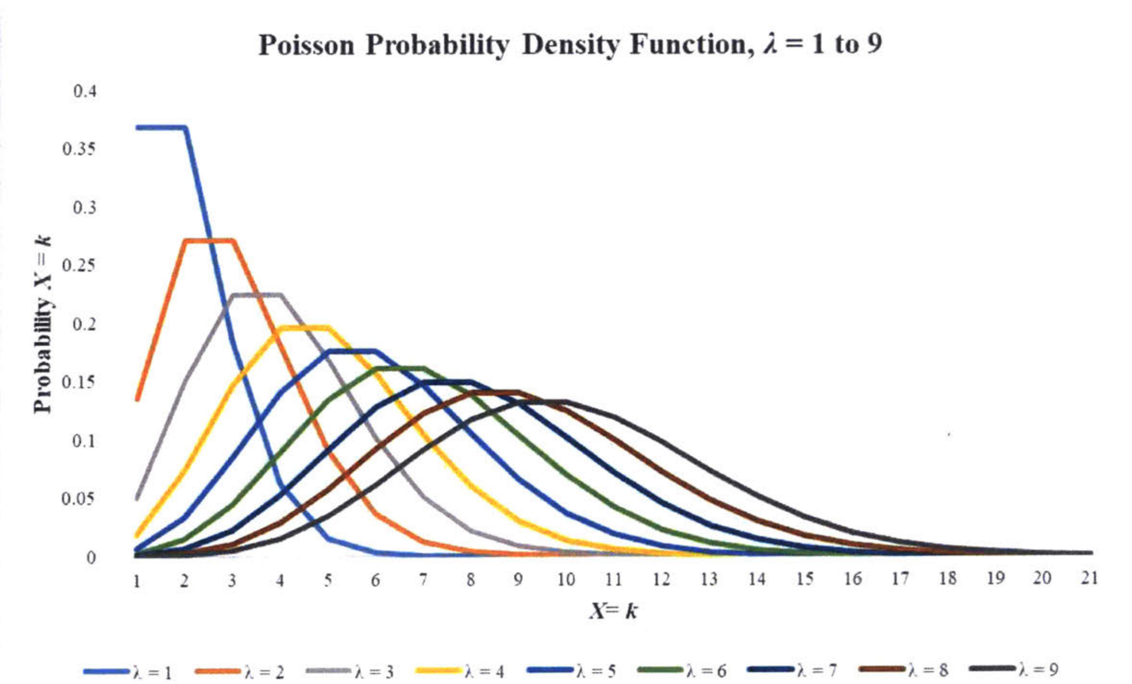



Figure 7. Probability mass functions graphed for various values of λ. The x-axis shows possible values of k, such that each curve represents the probability of seeing X = k events for a hypothetical Poisson process.

The Poisson PMF is noteworthy for approaching a normal distribution as $\lambda$ increases. Variance also increases as $\lambda$ increases, producing the long tails observed for $\lambda$ = 6 and above. For this study, we are conceptually interested in values of $k$ below $k = \lambda$, since these values represent lower incidence of engine events than the status quo.

The Poisson Cumulative Distribution Function (CDF) is given by

$$F(k;\lambda) = \sum_{k=0}^{\infty} \frac{(\lambda T)^k e^{-\lambda T}}{k!} \tag{10}$$

and defines the cumulative probability for observed occurrences up to $k$.

### **3.2.2** Formulating a Baseline Cost for Adverse Operational Events

Given that the incidence of each AOE is discrete in nature (example: 9 AOGs occurring over 1000 flight hours), the baseline cost of engine faults over any period evaluated can be computed if an average cost, $C_n$, is known for each type of AOE. If such average costs are assumed to exist for each corresponding AOE type, then the baseline cost for each of the six AOE types for a given interval of time can be computed as

$$\lambda_n C_n \tag{11}$$

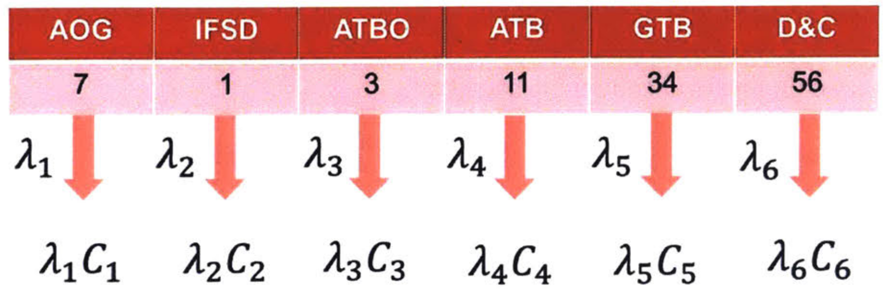
$$where\ n = 1, 2, 3, 4, 5, 6$$

and each $n$ is one of the AOEs: AOG, IFSD, ATBO, ATB, GTB, and DC. The total baseline cost can be computed as

$$\sum \lambda_n C_n \tag{12}$$

$$where\ n = 1, 2, 3, 4, 5, 6$$

This summation of baseline costs is represented pictorially in Figure 8.




$$AOE\ Costs = \sum_{n=1}^{6} \lambda_n C_n$$

Figure 8. Pictorial representation of total baseline costs across six Adverse Operational Event types.

This formulation is a simplification of the maintenance costs incurred as a result of these AOEs. Average cost for each of the AOEs is defined internally at PW as a cost range, with significant variation given that such cost data is only available on an aggregated level, and not specific to the two carriers being studied here. Nevertheless, a cost range, is useful for understanding the upper and lower bounds of AOE costs incurred because of engine faults. The advantage of having a cost range is that a sensitivity analysis can be done as the value $C_n$ varies.

### 3.2.3 Full-Flight Data Analytics for Cost Reduction

Full-flight Data Analytics (FFDA) has been described in detail in the previous chapter as a promising tool for maintenance cost reduction [42]. Although the eFAST™ system has begun flying on the GTF-powered fleet of Bombardier CSeries aircraft, a true benchmark of cost reduction has yet to be developed at PW. The problem with having no standard cost reduction model is somewhat circular; a true standard does not yet exist because the "eFAST™ ecosystem" does not have all the data it needs to form a productionized service. Yet in order to obtain such data, it needs to actively operate on revenue service aircraft. The Bombardier CSeries eFAST™ aircraft continue to inform the work done to develop and improve engine prognostics as more deliveries take to the skies.

The development of a CSeries eFAST™ product suite is outside the scope of the present study. Here, the potential for V2500 maintenance cost reduction is analyzed because the status quo of historical engine faults is widely available. The previous section described in detail the formulation of a Poisson distribution model to evaluate the probability of discrete, adverse events occurring. Since eFAST™ has not yet been formally introduced on the V2500 product line for data captured through revenue service, the analysis of FFDA here is theoretical and speculative in nature. The purpose, of course, is to provide a simple model for understanding of cost reduction. Given the wealth of V2500 engine fault data, maintenance cost reduction can be formulated as the likelihood of using FFDA to reduce the various AOE types covered above. As such, FFDA's potential for cost reduction is framed as follows: $\lambda_n$ for each AOE is assumed to be incrementally reduced through better monitoring, alerting, and detection of engine faults. Each incremental reduction corresponds to a proportional decrease in cost $C_n$. At the same time, given the Poisson nature of the AOEs, a reduction of each incidence rate $\lambda_n$ will also affect the probability mass function (Equation 9 above). Reduction in $\lambda_n$ will also exert a downward pressure on the probability of seeing $k$ occurrences of any given AOE. Therefore, the utility of modeling the cost reduction problem as a Poisson process can be summarized as follows:

$$For\ a\ given\ AOE_n\ with\ a\ defined\ \lambda_n, cost\ reduction\ occurs\ as\ a\ result\ of\ two\ factors:$$

I. $$Incremental\ Reduction\ in\ Discrete\ Events\colon \lim_{\lambda_n \to 0} \lambda_n C_n \tag{13}$$

II. $$Reduced\ probability\ of\ incidents\ in\ a\ given\ interval\colon \lim_{\lambda_n \to 0} e^{-\lambda_n} \frac{{\lambda_n}^k}{k!} \tag{14}$$

In the next section, this paradigm is applied to the AOE costs of the two airline subjects being studied, and translated into unit cost savings.

## 3.3 Airline Unit Costs

### 3.3.1 Bureau of Transportation Statistics Data Collection

The US Department of Transportation requires that commercial airlines report their quarterly financial information, including operating expenses, to the Bureau of Transportation Statistics (BTS) [43]. The most comprehensive set of data comes from the Form 41 set of reports, which include financial data as well as traffic data (scheduled departures, seats). These are publicly available data sources updated regularly by BTS. Based on the airline metrics and ratios presented in Section 2.4.4 above, the following Form 41 schedules were determined to be the most relevant for this study:

- Schedule P-5.2: Detailed operating expenses, including flying expenses, direct maintenance expenses, depreciation costs, and total operating expenses, for carriers with annual operating revenue of $20 M or more
- Schedule P-1.2: Aggregated profit and loss data, including transport-related costs, for carriers with annual operating revenue of $20 M or more
- Schedule T2: Carrier traffic data, including available seat miles, revenue seat miles, and revenue flights flown, shown by operating aircraft type

Additionally, the associated ID tables for categorical identifiers was also used to identify the lowest level of data granularity. Table 2 outlines the Form 41 schedules used and the corresponding data provided in each.

Table 2. Information Obtained from Form 41 Schedules

| DOT Form 41 Schedules Used | | |
|---|---|---|
| *Schedule P-5.2* | *Schedule P-1.2* | *Schedule T2* |
| Flying Expenses | Operating Revenue | Available Seat Miles |
| Maintenance Expenses | Operating Expenses | Revenue Seat Miles |
| Engine Labor | Net Income and Expenses | Flights Operated |
| Engine Repairs | Income Taxes | Miles Flown |
| Engine Materials | Operating Profit (Loss) | Fuel Burn |
| Depreciation Costs | | |

### 3.3.2 Airline Metric Calculations

For the airlines of interest, the following key metrics are computed: Available Seat Miles (ASM), Total Costs, Maintenance Costs, and Cost Per Available Seat Mile (CASM). Various forms of CASM are calculated, depending on the cost components included or excluded, per introduction in Section 2.4.5 above.

Granularity of data is an important issue to consider for this methodology. Schedule P-5.2 provides data to the aircraft-type level, essentially allowing isolation of only Airbus A320 family operations. Along with a filter on operating carrier, the maintenance costs for the two airlines of interest are successfully segregated. As mentioned, these two carriers are exclusive operators of the V2500 engine, allowing for a meaningful, direct analysis of maintenance costs implicated by the PW database on historical V2500 engine performance.

A summary of the approach taken to estimating maintenance cost reduction is provided in Figure 9, which shows the broad steps taken to translate engine database information into potential cost implications.

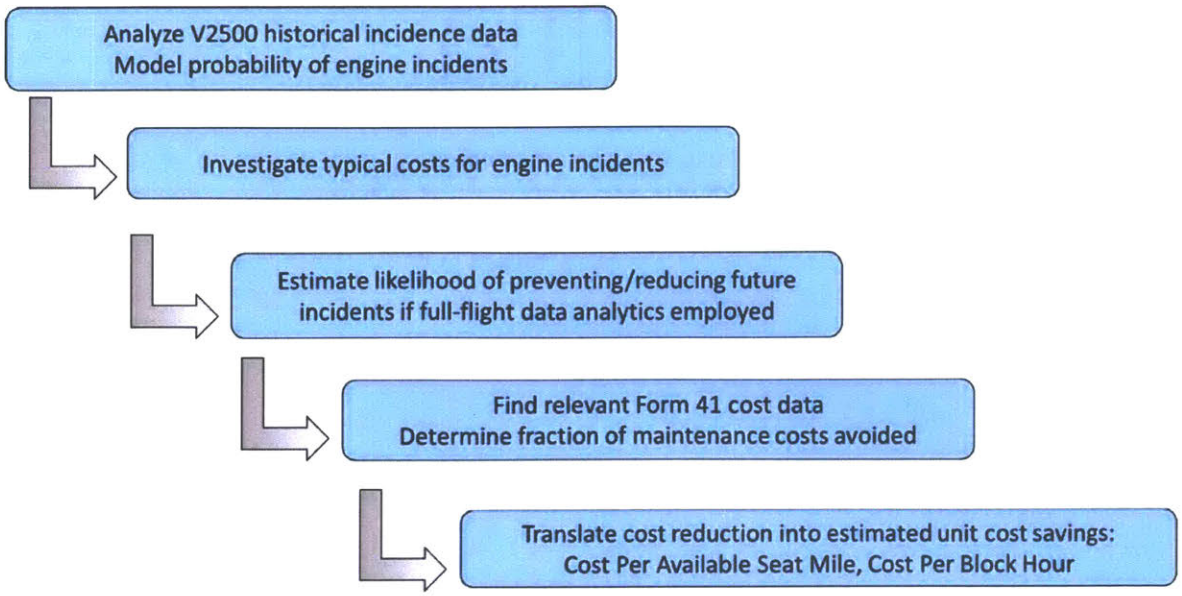



Figure 9. General approach taken to bridging engine fault data with airline cost reduction.

# Chapter 4

# Results and Analysis

## 4.1 V2500 Adverse Operational Events and Associated Costs

The physical metrics that signify engine health and performance are recorded for the V2500 across all Pratt & Whitney (PW) customers. The engine monitoring service, while individualized by carrier agreement, generally involves trending of such metrics as exhaust gas temperature (EGT) margin to component tolerance. Additionally, Adverse Operational Events (AOEs) are recorded separately in a database that compiles information on individual engine incidents, ranging from unexpected cockpit signal lights to bird strikes to inflight shutdowns. Interactions with the carrier, the location of occurrence, the suspected cause of failure, the actual cause found after investigation, and field support notes are also recorded. These engine event records are analyzed for the two carriers of interest, with particular attention to the aggregate count of six defined AOE categories. Although individual engine events can cause more than one AOE, high-disruption events are very rare, in some cases occurring only once in the five-year period evaluated. Thus, each event is assigned one category for simplicity, using a method that orders categories by descending magnitude of severity.

Independence of event occurrence between the two carriers is tested through a $\chi^2$ test for independence. Event categories are then modeled as mutually exclusive occurrences that follow a Poisson distribution, with event $\lambda$s defined for each category. These $\lambda$ parameters then allow calculation of expected annual events, expected annual cost of events, and expected cost savings based on a range of hypothetical event avoidance rates. Finally, raw cost savings are translated to proportion of unit costs saved for each carrier as an approximation for the value of this full-flight data based Engine Health Management (EHM) service.

### **4.1.1** Statistical Independence of Events

The two operators of the V2500 being studied have each accumulated a history of engine events in the internal PW database, not all of which are necessarily adverse events. Many event records are entered as a matter of process; for example, if an airline pilot sees an engine alert on flight deck controls, any contact with PW on the matter is recorded. As such, the volume of event records itself is not an indication of the magnitude of engine failure, but rather just an archive of engine-related activities and communications with airline operators.

The AOEs are recorded as counts of events for a given period of time, in line with the assumption that they follow a Poisson distribution. Engine incidents are assumed to be Poisson events because they can be modeled by an occurrence rate $\lambda$ per unit time, with each single event occurring randomly and independently of the previous or next event. Given that each record of an engine incident is an independent occurrence, a Poisson model was used to portray the arrival of each event type over time, in this case flight hours over a full calendar year.

The carriers selected for analysis operate the V2500 exclusively on their A320 family fleet, but it is important to first understand whether or not AOE occurrence varies based on the operating carrier. That is, are there differences in the airline's operations or its fleet characteristics that could cause more AOEs to occur than statistically suggested by its ratio of flight hours? To examine these occurrences from a statistical lens, a $\chi^2$ Test of Independence was performed, with the null hypothesis being that the incidence rates of AOEs are independent of operator. Six major types of operational disruptions were included, based on data availability:

Aircraft-On-Ground (AOG), Aborted Takeoff (ATO), Air Turn-Back (ATB), Inflight Shutdown (IFSD), Ground Turn-Back (GTB), and Delay/Cancellation (DC). Events in which more than one type of operational disruption resulted were grouped up to their most severe type of disruption, based on the following convention, listed in hierarchical order:

1. Any event listing IFSD was grouped as "IFSD" regardless of additional labels
2. Any event listing AOG was grouped as "AOG" regardless of additional labels, except for IFSD (per rule #1)
3. ATO and ATB were mutually exclusive events in the data set. Any ATO, regardless of combination, was grouped as "ATO." Similarly, any ATB was grouped as "ATB" regardless of combination. Any event in combination with IFSD or AOG were grouped per rules #1 and #2 above.
4. DC in combination with GTB was grouped as "DC."
5. The remaining label was GTB, without combination, and therefore labeled "GTB."

Table 3 lists the various disruption combinations and the groups into which they were labeled for the purposes of the $\chi^2$ test.

Table 3. The Adverse Operational Event (AOE) groups used for $\chi^2$ Test of Independence.

| $\chi^2$- Group | Disruptions Listed |
|---|---|
| **IFSD** | IFSD |
| | IFSD, ATB |
| | IFSD, DC |
| **AOG** | AOG |
| | AOG, ATB |
| | AOG, DC |
| | AOG, GTB |
| | ATO, AOG |
| | ATO, AOG, DC |
| **ATO** | ATO |
| | ATO, DC |
| | ATO, GTB |
| **ATB** | ATB |
| | ATB, DC |
| **DC** | DC |
| | DC, GTB |
| **GTB** | GTB |

The groups from the $\chi^2$ test are shown below in Table 4, as well as the outcomes shown as *p*-values, with statistical significance set at $\alpha = 0.05$.

Table 4. Results from $\chi^2$ Test of Independence by airline, for each type of Adverse Operational Event (AOE).

**Observed Occurrence of Events**

| Carrier | IFSD | AOG | ATO | ATB | DC | GTB |
|---|---|---|---|---|---|---|
| Airline A | 11 | 13 | 51 | 39 | 1146 | 165 |
| Airline B | 6 | 3 | 7 | 5 | 75 | 3 |
| Total | 17 | 16 | 58 | 44 | 1221 | 168 |

**Expected Count of Events Based on Block Hour Ratio**

| Carrier | IFSD | AOG | ATO | ATB | DC | GTB |
|---|---|---|---|---|---|---|
| Airline A | 12 | 11 | 41 | 31 | 861 | 118 |
| Airline B | 5 | 5 | 17 | 13 | 360 | 50 |

**$\chi^2$ Test of Independence: Outcome**

| | | | | | | |
|---|---|---|---|---|---|---|
| *p*-value | 0.599 | 0.346 | 0.004 | 0.008 | 1.5E-71 | 3.46E-15 |

The results of the $\chi^2$ test showed statistical significance for ATO, ATB, DC, and GTB, all of which saw $p$-values below $\alpha=0.05$, suggesting that there may be differences in occurrence of these AOEs based on carrier. However, the test outcome for IFSD and for AOG were not significant. Given the conflicting statistical test outcomes, no conclusion can be drawn about the effect of carrier on occurrence of AOEs as a whole.

Given two airlines with similar networks and fleets, some variation in occurrence of engine events can still logically be expected based on differences in age of fleet, seat configuration, and scheduled utilization. The $\chi^2$ test was conducted to seek a general understanding of any possible variation, and while results suggest some statistical difference for four AOE types, there were factors for which the test did not control, such as size of each carrier's operation, fleet age, or maintenance program differences. These refinements can be done in future, more in-depth analyses, as the objective here is simply to note that these variations are possible.

As this is a first look into the occurrence of AOEs and airline cost implications, the study will proceed with AOEs pooled for both airlines. This method creates a larger sample size of engines, and also allows for better generalizability of results to other V2500 operators. Such an approach is useful in the early stages of full-flight data analyses, since the multitude of V2500 operators in the industry likely show wide variation in flight operations, and, by extension, engine performance. Future work may choose a more targeted set of data for further analysis.

### **4.1.2** Poisson Characterization

The pooled data provide a greater volume of events from which estimates of the Poisson model can be calibrated. Of course, this also means that a higher number of flight hours are used as the base time period for the $\lambda$ of each event type. The combined five-year totals of each event type, along with its $\lambda$, flight hours (divided by 1000, as is the PW convention), and flight cycles (also divided by 1000) are shown in Table 5. A flight cycle is defined as a single takeoff and landing for an aircraft. Since takeoffs and landings generally place the most strain on aircraft and engines, a count of cycles experienced by an engine is a possible indicator of its wear and tear. Therefore, event occurrence per thousand-unit cycles is another viable Poisson parameter for calibrating AOE incidence rate, though thousand-unit hours will be the base denominator used in this study.

The "blank" category was included to show the magnitude of engine event records that were not associated with an adverse operational event. As explained earlier, communications between the carrier and PW regarding an engine are recorded insofar as checks or diagnoses were suggested by the interaction, even if no operational disruption occurred.

Table 5. Poisson characterization of engine event types, from 2012-2016. Flight hours and flight cycles, each expressed as a factor of 1000, are also given.
*Number of 1000-hour units over 5 years
**Number of 1000-cycle units over 5 years

| Event Type | $\lambda$ | Flight Hour Units* | Flight Cycle Units** |
|---|---|---|---|
| IFSD | 17 | | |
| AOG | 16 | | |
| ATO | 58 | | |
| ATB | 44 | 8102.34 | 3026.09 |
| DC | 1221 | | |
| GTB | 168 | | |
| *(blank)* | *2057* | | |

Table 5 shows that $\lambda$ for the most severe events are the lowest, as expected of rare events under a Poisson distribution assumption. Note that flight hours and cycles, as given, should be interpreted as *units* of 1000 hours or cycles. Thus, a $\lambda$ of 17 for IFSD indicates that 17 such events were observed over approximately 8102 units of time, with each unit representing 1000 hours. For comparison, the "unit $\lambda$" is shown in Table 6, wherein each event's $\lambda$ is divided by its respective time and cycle units.

Table 6. Unit $\lambda$ by flight hours and cycles, per engine event type. One unit equals 1000 hours or 1000 cycles, accordingly.

| Event Type | $\lambda$ per Unit Hours | $\lambda$ per Unit Cycles |
|---|---|---|
| IFSD | 0.0021 | 0.0056 |
| AOG | 0.0020 | 0.0053 |
| ATO | 0.0072 | 0.0192 |
| ATB | 0.0054 | 0.0145 |
| DC | 0.1507 | 0.4035 |
| GTB | 0.0207 | 0.0555 |
| *(blank)* | 0.2539 | 0.6798 |

Per PW reporting convention, Table 6 provides the $\lambda$ for each engine event type, expressed as occurrences over 1000 flight hours. For all events, the count of occurrences is below one, which is consistent with a Poisson model of rare events occurring over a five-year sample. This formulation is particularly apt for a mature engine like the V2500, which has been in service for decades, and for which faults can be expressed as Poisson events. New engine models in their introductory phase are not expected to follow such a distribution, since the earliest versions of industrial products, especially in the aerospace realm, generally experience some levels of refinement in their nascent revenue service phase.

Of particular note is the count of "blank" events, which in PW's V2500 database simply means any recorded event for which an operational issue was not attributed. For continuity, these blank events are treated as-is here, since the occurrence of any record-inducing event, no matter how minor, can itself be treated as a Poisson event. This characterization is true if one is to assume that any recorded event is a random and rare event; stated differently, the label "blank" prescribed to events does not change the Poisson nature of the occurrences, since they are assumed to occur randomly and independently over a given unit of time or cycles. The "blank" events are revisited in Chapter 5, Discussion and Conclusions.

### 4.1.3 Costs Associated with Events

Perhaps the most difficult aspect of maintenance cost analysis is the high variability in cost implications from one event to the next. Indeed, there is no "typical" adverse operational event, since they are by nature unexpected; as discussed throughout this study, they are considered rare events that occur randomly. Nevertheless, the range of possibility for such costs could be estimated by turning the question back to the carriers—what has a "typical" AOG or IFSD cost in the past? PW commissioned a study to survey airlines on this subject, and received pooled responses from a sampling of carriers from around the world (all of whose identities were kept confidential to PW). The report, completed by Firm Z[1], provides that cost implications from the AOEs fall into three tiered categories based on severity of labor (particularly for flight and cabin crew), customer re-accommodation, and engine damage. They are described in detail below[2]:

- Type I: $107,000 to $533,000 cost range

  The least severe type of event, this is a "relatively minor issue" that can be recovered within the scheduled crew time. It is the most common of the three event types. Disruption to passenger service is minimal or can be resolved within the scheduled

[1] pseudonym
[2] For confidentiality, actual cost data are obscured by a random factor

buffer time. Generally, replacement and repair of engine assets is less than 10% of the event's total cost.

- Type II: $320,000 to $2,987,000 cost range

  The second tier, this event type cannot be recovered within the scheduled crew time, and incurs crew costs that can constitute up to 15% of total event cost. Longer downtime means the airline must either bring in its own spare aircraft, or re-accommodate customers on other carriers, incurring transportation costs as well as lost revenue if refunds are offered. Nevertheless, the actual repairs for hard assets is still small, at fewer than 5% of total event cost.

- Type III: $6.4M to $12.8M cost range

  Considered a major operational event, crew time is exceeded, aircraft require major component replacement(s), and ground handling costs are driven up as the aircraft is at a remote site. Downstream effects on the network are incurred as fleet have to be reshuffled, or significant purchases or leases must be made to recover hard assets and/or regular operations.

A summary of event characteristics is provided in Table 7.

Table 7. Engine event severity categories, along with cost range, cost midpoint, characteristics, and the most likely adverse operational event types corresponding to each severity. For confidentiality, true cost data have been obscured via randomly chosen factors.

| Event Tier | Cost Range in 000 | Cost Average in 000s | Characteristics | Likely Adverse Operational Event |
|---|---|---|---|---|
| Type I | $107-$533 | $337 | Recoverable within crew time | DC |
| | | | Most common event type of the three | GTB |
| | | | Operations recovered within scheduled buffer time | ATB |
| | | | Low cost of part replacement | ATO |
| Type II | $320-$2,987 | $1,739 | Cannot be recovered within crew time | ATB |
| | | | Added crew cost constitute up to 15% of event cost | ATO |
| | | | Lost passenger revenue due to refunds and rebookings to other carriers | IFSD |
| | | | Lease or charter fees may be incurred | |
| | | | Low cost of part replacement | |
| Type III | $6,401-$12,802 | $10,098 | Cannot be recovered within crew time | IFSD |
| | | | Major parts or components replacement | AOG |
| | | | Ground handling fees increase | |
| | | | Downstream network effects due to reallocating of crew and fleet | |

In Table 7, the cost ranges for each of the event severity categories are outlined, as well as the average of each range. As a matter of evaluation, these cost data points will help to define the range of costs that enhanced prognostic tools might minimize. Framed as a sensitivity analysis, the range of event avoidance is explored in the section following.

The likely AOEs to be associated with each severity category is also listed above in Table 7. Although one may argue that each AOE could result in any of the three levels of severity, the typical outcome of each AOE was considered in this classification, consistent with the hierarchical grouping of AOEs shown in section 4.1.1. As will be shown later, the groupings can be narrowed further to provide a single set of estimates.

### 4.1.4 Calculated Costs of Adverse Operational Events

The previous section provided the cost ranges of each of the Type I to III events as defined by PW commissioned surveys of airlines' historical expenses incurred from operational disruption, ranked in order of severity. As a comprehensive baseline of potential cost savings, sensitivity analyses were completed for each of the six AOE types by year, from 2012 to 2016. All three severity levels were included for each AOE type. These results appear in Table 8.

Since Poisson events are, by definition, integer in nature (i.e. one cannot have 1.7 Air Turn-Backs), Table 9 provides the same comprehensive index of costs with event counts rounded to the nearest whole number.

Table 8. Comprehensive cost characterizations for each adverse operational event. Each of Type I-III designations' costs are included for reference. Note: For confidentiality, cost data is obscured by a random factor.

| Event Type | λ per Unit Hours | Year | Annual Unit Hours | Expected Events | As Type I Event | | | As Type II Event | | | As Type III Event | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Min Cost | Midpt Cost | High Cost | Min Cost | Midpt Cost | High Cost | Min Cost | Midpt Cost | High Cost |
| IFSD | 0.0021 | 2012 | 1323.42 | 2.78 | $296,239 | $934,662 | $1,481,195 | $888,717 | $4,829,087 | $8,294,689 | $17,774,334 | $28,039,861 | $35,548,668 |
| | | 2013 | 1452.21 | 3.05 | $325,067 | $1,025,619 | $1,625,337 | $975,202 | $5,299,030 | $9,101,887 | $19,504,044 | $30,768,561 | $39,008,088 |
| | | 2014 | 1561.74 | 3.28 | $349,585 | $1,102,975 | $1,747,926 | $1,048,756 | $5,698,704 | $9,788,388 | $20,975,116 | $33,089,248 | $41,950,233 |
| | | 2015 | 1786.76 | 3.75 | $399,953 | $1,261,888 | $1,999,763 | $1,199,858 | $6,519,757 | $11,198,670 | $23,997,151 | $37,856,651 | $47,994,302 |
| | | 2016 | 1978.20 | 4.15 | $442,806 | $1,397,097 | $2,214,032 | $1,328,419 | $7,218,332 | $12,398,580 | $26,568,385 | $41,912,896 | $53,136,770 |
| | | Total | 8102.34 | 17.00 | $1,813,651 | $5,722,241 | $9,068,253 | $5,440,952 | $29,564,909 | $50,782,214 | $108,819,031 | $171,667,216 | $217,638,061 |
| AOG | 0.0020 | 2012 | 1323.42 | 2.61 | $278,813 | $879,682 | $1,394,065 | $836,439 | $4,545,023 | $7,806,766 | $16,728,785 | $26,390,457 | $33,457,570 |
| | | 2013 | 1452.21 | 2.87 | $305,946 | $965,288 | $1,529,729 | $917,837 | $4,987,322 | $8,566,482 | $18,356,747 | $28,958,645 | $36,713,495 |
| | | 2014 | 1561.74 | 3.08 | $329,021 | $1,038,094 | $1,645,107 | $987,064 | $5,363,486 | $9,212,600 | $19,741,286 | $31,142,821 | $39,482,572 |
| | | 2015 | 1786.76 | 3.53 | $376,426 | $1,187,660 | $1,882,129 | $1,129,278 | $6,136,242 | $10,539,925 | $22,585,554 | $35,629,790 | $45,171,108 |
| | | 2016 | 1978.20 | 3.91 | $416,759 | $1,314,914 | $2,083,795 | $1,250,277 | $6,793,724 | $11,669,251 | $25,005,539 | $39,447,431 | $50,011,078 |
| | | Total | 8102.34 | 16.00 | $1,706,965 | $5,385,638 | $8,534,826 | $5,120,896 | $27,825,797 | $47,795,025 | $102,417,911 | $161,569,145 | $204,835,822 |
| ATO | 0.0072 | 2012 | 1323.42 | 9.47 | $1,010,697 | $3,188,847 | $5,053,487 | $3,032,092 | $16,475,709 | $28,299,528 | $60,641,846 | $95,665,408 | $121,283,692 |
| | | 2013 | 1452.21 | 10.40 | $1,109,053 | $3,499,170 | $5,545,267 | $3,327,160 | $18,079,043 | $31,053,498 | $66,543,209 | $104,975,090 | $133,086,418 |
| | | 2014 | 1561.74 | 11.18 | $1,192,703 | $3,763,091 | $5,963,513 | $3,578,108 | $19,442,636 | $33,395,675 | $71,562,162 | $112,892,727 | $143,124,324 |
| | | 2015 | 1786.76 | 12.79 | $1,364,544 | $4,305,266 | $6,822,719 | $4,093,632 | $22,243,876 | $38,207,229 | $81,872,633 | $129,157,987 | $163,745,265 |
| | | 2016 | 1978.20 | 14.16 | $1,510,751 | $4,766,565 | $7,553,757 | $4,532,254 | $24,627,251 | $42,301,036 | $90,645,078 | $142,996,939 | $181,290,156 |
| | | Total | 8102.34 | 58.00 | $6,187,749 | $19,522,938 | $30,938,744 | $18,563,246 | $100,868,515 | $173,256,966 | $371,264,928 | $585,688,150 | $742,529,856 |
| ATB | 0.0054 | 2012 | 1323.42 | 7.19 | $766,736 | $2,419,125 | $3,833,680 | $2,300,208 | $12,498,814 | $21,468,608 | $46,004,159 | $72,573,758 | $92,008,318 |
| | | 2013 | 1452.21 | 7.89 | $841,351 | $2,654,542 | $4,206,755 | $2,524,053 | $13,715,136 | $23,557,826 | $50,481,055 | $79,636,275 | $100,962,110 |
| | | 2014 | 1561.74 | 8.48 | $904,809 | $2,854,759 | $4,524,045 | $2,714,427 | $14,749,586 | $25,334,650 | $54,288,537 | $85,642,758 | $108,577,073 |
| | | 2015 | 1786.76 | 9.70 | $1,035,171 | $3,266,064 | $5,175,856 | $3,105,514 | $16,874,664 | $28,984,794 | $62,110,273 | $97,981,921 | $124,220,546 |
| | | 2016 | 1978.20 | 10.74 | $1,146,087 | $3,616,015 | $5,730,436 | $3,438,262 | $18,682,742 | $32,090,441 | $68,765,232 | $108,480,436 | $137,530,463 |
| | | Total | 8102.34 | 44.00 | $4,694,154 | $14,810,505 | $23,470,771 | $14,082,463 | $76,520,942 | $131,436,319 | $281,649,256 | $444,315,148 | $563,298,511 |
| DC | 0.1507 | 2012 | 1323.42 | 199.44 | $21,276,924 | $67,130,726 | $106,384,618 | $63,830,771 | $346,842,083 | $595,753,860 | $1,276,615,415 | $2,013,921,771 | $2,553,230,830 |
| | | 2013 | 1452.21 | 218.84 | $23,347,488 | $73,663,554 | $116,737,440 | $70,042,464 | $380,595,030 | $653,729,664 | $1,400,849,281 | $2,209,906,626 | $2,801,698,561 |
| | | 2014 | 1561.74 | 235.35 | $25,108,448 | $79,219,552 | $125,542,241 | $75,325,344 | $409,301,016 | $703,036,548 | $1,506,506,888 | $2,376,586,546 | $3,013,013,777 |
| | | 2015 | 1786.76 | 269.26 | $28,726,001 | $90,633,277 | $143,630,006 | $86,178,004 | $468,271,932 | $804,328,036 | $1,723,560,077 | $2,718,998,314 | $3,447,120,153 |
| | | 2016 | 1978.20 | 298.11 | $31,803,920 | $100,344,404 | $159,019,598 | $95,411,759 | $518,446,085 | $890,509,751 | $1,908,235,181 | $3,010,332,109 | $3,816,470,361 |
| | | Total | 8102.34 | 1221.00 | $130,262,781 | $410,991,512 | $651,313,903 | $390,788,342 | $2,123,456,146 | $3,647,357,859 | $7,815,766,841 | $12,329,745,366 | $15,631,533,683 |
| GTB | 0.0207 | 2012 | 1323.42 | 27.44 | $2,927,537 | $9,236,660 | $14,637,687 | $8,782,612 | $47,722,744 | $81,971,047 | $175,652,244 | $277,099,801 | $351,304,488 |
| | | 2013 | 1452.21 | 30.11 | $3,212,431 | $10,135,526 | $16,062,154 | $9,637,292 | $52,366,884 | $89,948,062 | $192,745,847 | $304,065,776 | $385,491,694 |
| | | 2014 | 1561.74 | 32.38 | $3,454,725 | $10,899,987 | $17,273,625 | $10,364,175 | $56,316,602 | $96,732,301 | $207,283,503 | $326,999,623 | $414,567,006 |
| | | 2015 | 1786.76 | 37.05 | $3,952,472 | $12,470,426 | $19,762,360 | $11,857,416 | $64,430,536 | $110,669,214 | $237,148,315 | $374,112,790 | $474,296,630 |
| | | 2016 | 1978.20 | 41.02 | $4,375,969 | $13,806,601 | $21,879,846 | $13,127,908 | $71,334,105 | $122,527,140 | $262,558,158 | $414,198,030 | $525,116,315 |
| | | Total | 8102.34 | 168.00 | $17,923,134 | $56,549,201 | $89,615,672 | $53,769,403 | $292,170,870 | $501,847,764 | $1,075,388,067 | $1,696,476,021 | $2,150,776,133 |

Table 9. Results from Table 8, with events rounded up nearest integer to better represent actual operational disruptions, which cannot happen in fractions. Note: For confidentiality, cost data is obscured by a random factor.

| Event Type | λ per Unit Hours | Year | Annual Unit Hours | Expected Events | As Type I Event | | | As Type II Event | | | As Type III Event | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Min Cost | Midpt Cost | High Cost | Min Cost | Midpt Cost | High Cost | Min Cost | Midpt Cost | High Cost |
| IFSD | 0.0021 | 2012 | 1323.42 | 3 | $320,056 | $1,009,807 | $1,600,280 | $960,168 | $5,217,337 | $8,961,567 | $19,203,358 | $30,294,215 | $38,406,717 |
| | | 2013 | 1452.21 | 3 | $320,056 | $1,009,807 | $1,600,280 | $960,168 | $5,217,337 | $8,961,567 | $19,203,358 | $30,294,215 | $38,406,717 |
| | | 2014 | 1561.74 | 3 | $320,056 | $1,009,807 | $1,600,280 | $960,168 | $5,217,337 | $8,961,567 | $19,203,358 | $30,294,215 | $38,406,717 |
| | | 2015 | 1786.76 | 4 | $426,741 | $1,346,410 | $2,133,706 | $1,280,224 | $6,956,449 | $11,948,756 | $25,604,478 | $40,392,286 | $51,208,956 |
| | | 2016 | 1978.20 | 4 | $426,741 | $1,346,410 | $2,133,706 | $1,280,224 | $6,956,449 | $11,948,756 | $25,604,478 | $40,392,286 | $51,208,956 |
| | | Total | 8102.34 | 17 | $1,813,651 | $5,722,241 | $9,068,253 | $5,440,952 | $29,564,909 | $50,782,214 | $108,819,031 | $171,667,216 | $217,638,061 |
| AOG | 0.0020 | 2012 | 1323.42 | 3 | $320,056 | $1,009,807 | $1,600,280 | $960,168 | $5,217,337 | $8,961,567 | $19,203,358 | $30,294,215 | $38,406,717 |
| | | 2013 | 1452.21 | 3 | $320,056 | $1,009,807 | $1,600,280 | $960,168 | $5,217,337 | $8,961,567 | $19,203,358 | $30,294,215 | $38,406,717 |
| | | 2014 | 1561.74 | 3 | $320,056 | $1,009,807 | $1,600,280 | $960,168 | $5,217,337 | $8,961,567 | $19,203,358 | $30,294,215 | $38,406,717 |
| | | 2015 | 1786.76 | 4 | $426,741 | $1,346,410 | $2,133,706 | $1,280,224 | $6,956,449 | $11,948,756 | $25,604,478 | $40,392,286 | $51,208,956 |
| | | 2016 | 1978.20 | 4 | $426,741 | $1,346,410 | $2,133,706 | $1,280,224 | $6,956,449 | $11,948,756 | $25,604,478 | $40,392,286 | $51,208,956 |
| | | Total | 8102.34 | 16 | $1,706,965 | $5,385,638 | $8,534,826 | $5,120,896 | $27,825,797 | $47,795,025 | $102,417,911 | $161,569,145 | $204,835,822 |
| ATO | 0.0072 | 2012 | 1323.42 | 9 | $960,168 | $3,029,421 | $4,800,840 | $2,880,504 | $15,652,011 | $26,884,702 | $57,610,075 | $90,882,644 | $115,220,150 |
| | | 2013 | 1452.21 | 10 | $1,066,853 | $3,366,024 | $5,334,266 | $3,200,560 | $17,391,123 | $29,871,891 | $64,011,194 | $100,980,716 | $128,022,389 |
| | | 2014 | 1561.74 | 11 | $1,173,539 | $3,702,626 | $5,867,693 | $3,520,616 | $19,130,236 | $32,859,080 | $70,412,314 | $111,078,787 | $140,824,628 |
| | | 2015 | 1786.76 | 13 | $1,386,909 | $4,375,831 | $6,934,546 | $4,160,728 | $22,608,460 | $38,833,458 | $83,214,553 | $131,274,930 | $166,429,106 |
| | | 2016 | 1978.20 | 14 | $1,493,595 | $4,712,433 | $7,467,973 | $4,480,784 | $24,347,573 | $41,820,647 | $89,615,672 | $141,373,002 | $179,231,344 |
| | | Total | 8102.34 | 58 | $6,187,749 | $19,522,938 | $30,938,744 | $18,563,246 | $100,868,515 | $173,256,966 | $371,264,928 | $585,688,150 | $742,529,856 |
| ATB | 0.0054 | 2012 | 1323.42 | 7 | $746,797 | $2,356,217 | $3,733,986 | $2,240,392 | $12,173,786 | $20,910,324 | $44,807,836 | $70,686,501 | $89,615,672 |
| | | 2013 | 1452.21 | 8 | $853,483 | $2,692,819 | $4,267,413 | $2,560,448 | $13,912,899 | $23,897,513 | $51,208,956 | $80,784,572 | $102,417,911 |
| | | 2014 | 1561.74 | 8 | $853,483 | $2,692,819 | $4,267,413 | $2,560,448 | $13,912,899 | $23,897,513 | $51,208,956 | $80,784,572 | $102,417,911 |
| | | 2015 | 1786.76 | 10 | $1,066,853 | $3,366,024 | $5,334,266 | $3,200,560 | $17,391,123 | $29,871,891 | $64,011,194 | $100,980,716 | $128,022,389 |
| | | 2016 | 1978.20 | 11 | $1,173,539 | $3,702,626 | $5,867,693 | $3,520,616 | $19,130,236 | $32,859,080 | $70,412,314 | $111,078,787 | $140,824,628 |
| | | Total | 8102.34 | 44 | $4,694,154 | $14,810,505 | $23,470,771 | $14,082,463 | $76,520,942 | $131,436,319 | $281,649,256 | $444,315,148 | $563,298,511 |
| DC | 0.1507 | 2012 | 1323.42 | 199 | $21,230,379 | $66,983,875 | $106,151,897 | $63,691,138 | $346,083,352 | $594,450,626 | $1,273,822,769 | $2,009,516,239 | $2,547,645,539 |
| | | 2013 | 1452.21 | 219 | $23,364,086 | $73,715,922 | $116,820,430 | $70,092,258 | $380,865,599 | $654,194,407 | $1,401,845,158 | $2,211,477,670 | $2,803,690,317 |
| | | 2014 | 1561.74 | 235 | $25,071,051 | $79,101,560 | $125,355,256 | $75,213,153 | $408,691,396 | $701,989,432 | $1,504,263,069 | $2,373,046,815 | $3,008,526,139 |
| | | 2015 | 1786.76 | 269 | $28,698,352 | $90,546,042 | $143,491,761 | $86,095,057 | $467,821,215 | $803,553,861 | $1,721,901,131 | $2,716,381,248 | $3,443,802,261 |
| | | 2016 | 1978.20 | 298 | $31,792,227 | $100,307,511 | $158,961,133 | $95,376,680 | $518,255,472 | $890,182,344 | $1,907,533,594 | $3,009,225,323 | $3,815,067,189 |
| | | Total | 8102.34 | 1221 | $130,262,781 | $410,991,512 | $651,313,903 | $390,788,342 | $2,123,456,146 | $3,647,357,859 | $7,815,766,841 | $12,329,745,366 | $15,631,533,683 |
| GTB | 0.0207 | 2012 | 1323.42 | 27 | $2,880,504 | $9,088,264 | $14,402,519 | $8,641,511 | $46,956,033 | $80,654,105 | $172,830,225 | $272,647,932 | $345,660,450 |
| | | 2013 | 1452.21 | 30 | $3,200,560 | $10,098,072 | $16,002,799 | $9,601,679 | $52,173,370 | $89,615,672 | $192,033,583 | $302,942,147 | $384,067,167 |
| | | 2014 | 1561.74 | 32 | $3,413,930 | $10,771,276 | $17,069,652 | $10,241,791 | $55,651,594 | $95,590,050 | $204,835,822 | $323,138,290 | $409,671,644 |
| | | 2015 | 1786.76 | 37 | $3,947,357 | $12,454,288 | $19,736,785 | $11,842,071 | $64,347,156 | $110,525,996 | $236,841,419 | $373,628,647 | $473,682,839 |
| | | 2016 | 1978.20 | 41 | $4,374,098 | $13,800,698 | $21,870,491 | $13,122,295 | $71,303,605 | $122,474,752 | $262,445,897 | $414,020,934 | $524,891,794 |
| | | Total | 8102.34 | 168 | $17,923,134 | $56,549,201 | $89,615,672 | $53,769,403 | $292,170,870 | $501,847,764 | $1,075,388,067 | $1,696,476,021 | $2,150,776,133 |

Tables 8 and 9 provide a comprehensive reference for the possible costs incurred in each year if one is to consider the pooled flight hours as a single operator of the V2500. Importantly, they provide an estimate for events regardless of their severity. However, in order to provide a more specific assessment of full-flight data value, a narrowed grouping is created as follows:

| | |
|---|---|
| IFSD | Type II |
| AOG | Type III |
| ATO | Type II |
| ATB | Type II |
| DC | Type I |
| GTB | Type I |

In considering each AOE's category, the annotations provided by PW field support in the event logs were evaluated to understand the severity of issues, particularly those AOEs with small $\lambda$ over the five-year period. Details provided of events informed an assessment on the range of severity, leading to assignment of the appropriate Type label corresponding to the Type definitions provided above in Section 4.1.3.

In the spirit of approximation, these event severities were assigned based on the data available at the time of writing. As more work is done to elucidate the intricacies of operational disruptions, particularly in ways that offer greater specificity of cost estimations (for example, if there are more severity types than the three found), the model presented here can be adapted to incorporate new information. Tables 8 and 9 above are provided as a comprehensive sensitivity analysis, allowing each AOE to be valued at each of the severity levels. For more specific needs, the reader is encouraged to consider the various severity levels presented and the cost ranges that provide bounds by which different conclusions can be drawn.

### 4.1.5 Event Cost Estimates for Prescribed Severity Levels

Having determined a Type label for each AOE, a more refined calculation of event costs was done by using the average of each prescribed cost range. Again, the $\lambda$ per unit hours was used, with occurrence determined by multiplying with the reported 1000-unit hours of each year. Results are shown in Table 10.

Table 10. Expected cost, by year, of each operational disruption based on average cost of prescribed severity type. Expected costs have been inflation-adjusted to 2016 dollars.

| Event Type | Year | Expected Events | Expected Cost |
|---|---|---|---|
| | 2012 | 3 | $5,479,083 |
| | 2013 | 3 | $5,397,336 |
| IFSD | 2014 | 3 | $5,361,543 |
| | 2015 | 4 | $7,101,957 |
| | 2016 | 4 | $6,956,449 |
| | 2012 | 3 | $31,814,029 |
| | 2013 | 3 | $31,339,372 |
| AOG | 2014 | 3 | $31,131,540 |
| | 2015 | 4 | $41,237,167 |
| | 2016 | 4 | $40,392,286 |
| | 2012 | 9 | $16,437,248 |
| | 2013 | 10 | $17,991,121 |
| ATO | 2014 | 11 | $19,658,991 |
| | 2015 | 13 | $23,081,359 |
| | 2016 | 14 | $24,347,573 |
| | 2012 | 7 | $12,784,526 |
| | 2013 | 8 | $14,392,897 |
| ATB | 2014 | 8 | $14,297,448 |
| | 2015 | 10 | $17,754,892 |
| | 2016 | 11 | $19,130,236 |
| | 2012 | 199 | $70,344,352 |
| | 2013 | 219 | $76,259,139 |
| DC | 2014 | 235 | $81,287,909 |
| | 2015 | 269 | $92,439,984 |
| | 2016 | 298 | $100,307,511 |
| | 2012 | 27 | $9,544,209 |
| | 2013 | 30 | $10,446,457 |
| GTB | 2014 | 32 | $11,068,992 |
| | 2015 | 37 | $12,714,793 |
| | 2016 | 41 | $13,800,698 |

By using the systematic method described above to categorize each AOE with its severity level, and by using the average cost of its respective level, one specific set of cost estimations was calculated in Table 9. The growing cost of each event type over time can be attributed to the increasing flight hours reported by these two pooled carriers, which is logical given their continuous growth in fleet size over these five years. A single, generalized $\lambda$ per 1000-unit hours was used, since the rate of occurrence is assumed to be Poisson in nature for every year.

### 4.1.6 Reducing Event Occurrence in a Poisson Process

The Poisson model for engine events is appropriate given the rare and random nature of occurrence. It is also a useful tool for considering what level of engine event reduction is possible. The discrete event Poisson model provides the probability of observing exactly $X = k$ events for a given $\lambda$, based purely on chance. Therefore, if no tools, devices, or interventions were implemented to the existing fleet of engines, and we assume that the Poisson model holds for future years, the probability of observed annual occurrences of each engine event type can be found. In particular, the probability distribution of each adverse operational event would follow those found in Figure 8, which provides a normalized x-axis for event occurrence expressed as the $z\%$ $of\,\lambda$ events.

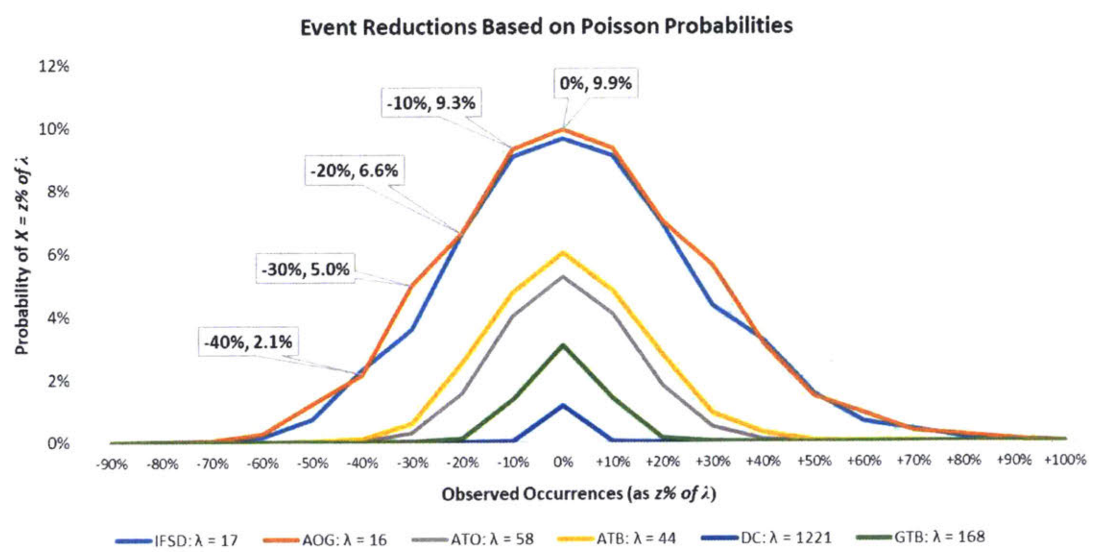



Figure 8. Poisson probability distribution for each adverse operational event type. The x-axis is observed occurrences, X = k, as before, but has been normalized as a percentage of λ. Therefore, k = z% of λ = number of observed occurrences expressed as a proportion of λ.

In Figure 8, the x-axis has been normalized to express each $X = k$ observation as a percentage of $\lambda$. That is, $k = z\%\ of\, \lambda$, where z ranges from -100% to +100% (a range representing complete elimination of events for that given AOE, up to a doubling of the number of events). These probabilities are, again, the likelihood of observing a particular number of occurrences simply due to randomness. By logic, full-flight data provides value only when the observed occurrences $k$ is smaller than $\lambda$. Consequently, $k = z\%\ of\, \lambda$, for values of z between 0 and 1, defines occurrences in the left half of the probability curve. The data labels shown in Figure 8 are a few possible reduction levels (shown as first term), and the Poisson probability of observing that amount of reduction is provided as the second term in the data label.

In the next section, we analyze the expected costs incurred should FFDA enable diagnostics or other tools that reduce engine event occurrence. Based on the Poisson probabilities alone, achieving 20% to 30% reduction only has a 5 to 6% likelihood, if no full-flight data analytics tools are used for the V2500. Of course, since FFDA is a deliberate intervention for catching these events sooner, it is expected that likelihood of achieving reductions will be greater than by pure chance alone. The possible magnitudes of reduction depend on the FFDA capabilities achieved, and thus a range of volumes is considered here.

### 4.1.7 Prospective Reductions in Engine Events

In this nascent stage of full-flight data analytics for the V2500 program, algorithmic and procedural techniques for prognosticating engine faults continue to be developed and refined. Therefore, cost reductions are conceptual in nature, and take on varying levels of "benefit" as preliminary estimates of cost reduction from the status quo. It is the author's opinion that engine event reductions of 20% or less are reasonable expectations. Based on the equation for the Poisson cumulative distribution function, we can find the likelihood of observing events between two values of $k$. From Figure 8, for the AOG probability mass function (PMF), the cumulative probability between $k = \lambda - (0.2\lambda)$ and $k = \lambda$ is the area under the PMF between these two $k$'s. For $\lambda = 16$, this area is $0.56 - 0.20 = 0.36$. Given that there is a 36% probability that the observed number of occurrences would represent a 0 to 20% reduction just by chance, it follows that a targeted prognostics effort through full-flight data could produce results within these bounds.

Nevertheless, for a complete analysis, we consider cases in which each AOE observes 5%, 10%, 20%, 30%, 50%, 70%, or 90% reduction in the $k$ count of events in each year. The logic, therefore, is that the higher the percentage of event reduction, the more favorable it will be for cost avoidance. Having a range will also allow for a better understanding of the sensitivity of cost results to this input.

No further commentary will be made about where on the spectrum these reductions will occur for the eFAST™ product. Rather, as an academic and exploratory method of understanding the relationship between engine events and maintenance cost, many different scenarios are calculated and provided for the reader's consideration. Table 11 summarizes the calculations performed for this spectrum of event reduction percentages.

Table 11. Dollar estimates of cost savings with varying degrees of event reduction. Per Poisson distribution assumptions, all event counts are rounded to the nearest whole. Dollars are nominal. Note that confidential cost data continue to be obscured by a random factor.

| Event Type | Year | Expected Events | 5% Reduction | 10% Reduction | 20% Reduction | 30% Reduction | 50% Reduction | 70% Reduction | 90% Reduction |
|---|---|---|---|---|---|---|---|---|---|
| IFSD | 2012 | 3 | $0 | $0 | $1,739,112 | $1,739,112 | $3,478,225 | $3,478,225 | $5,217,337 |
| | 2013 | 3 | $0 | $0 | $1,739,112 | $1,739,112 | $3,478,225 | $3,478,225 | $5,217,337 |
| | 2014 | 3 | $0 | $0 | $1,739,112 | $1,739,112 | $3,478,225 | $3,478,225 | $5,217,337 |
| | 2015 | 4 | $0 | $0 | $1,739,112 | $1,739,112 | $3,478,225 | $5,217,337 | $6,956,449 |
| | 2016 | 4 | $0 | $0 | $1,739,112 | $1,739,112 | $3,478,225 | $5,217,337 | $6,956,449 |
| | Total | 17 | $1,739,112 | $3,478,225 | $5,217,337 | $8,695,562 | $15,652,011 | $20,869,348 | $26,086,685 |
| AOG | 2012 | 3 | $0 | $0 | $10,098,072 | $10,098,072 | $20,196,143 | $20,196,143 | $30,294,215 |
| | 2013 | 3 | $0 | $0 | $10,098,072 | $10,098,072 | $20,196,143 | $20,196,143 | $30,294,215 |
| | 2014 | 3 | $0 | $0 | $10,098,072 | $10,098,072 | $20,196,143 | $20,196,143 | $30,294,215 |
| | 2015 | 4 | $0 | $0 | $10,098,072 | $10,098,072 | $20,196,143 | $30,294,215 | $40,392,286 |
| | 2016 | 4 | $0 | $0 | $10,098,072 | $10,098,072 | $20,196,143 | $30,294,215 | $40,392,286 |
| | Total | 16 | $10,098,072 | $20,196,143 | $30,294,215 | $50,490,358 | $80,784,572 | $111,078,787 | $141,373,002 |
| ATO | 2012 | 9 | $0 | $1,739,112 | $3,478,225 | $5,217,337 | $8,695,562 | $10,434,674 | $13,912,899 |
| | 2013 | 10 | $1,739,112 | $1,739,112 | $3,478,225 | $5,217,337 | $8,695,562 | $12,173,786 | $15,652,011 |
| | 2014 | 11 | $1,739,112 | $1,739,112 | $3,478,225 | $5,217,337 | $10,434,674 | $13,912,899 | $17,391,123 |
| | 2015 | 13 | $1,739,112 | $1,739,112 | $5,217,337 | $6,956,449 | $12,173,786 | $15,652,011 | $20,869,348 |
| | 2016 | 14 | $1,739,112 | $1,739,112 | $5,217,337 | $6,956,449 | $12,173,786 | $17,391,123 | $22,608,460 |
| | Total | 58 | $5,217,337 | $10,434,674 | $20,869,348 | $29,564,909 | $50,434,257 | $71,303,605 | $90,433,841 |
| ATB | 2012 | 7 | $0 | $1,739,112 | $1,739,112 | $3,478,225 | $6,956,449 | $8,695,562 | $10,434,674 |
| | 2013 | 8 | $0 | $1,739,112 | $3,478,225 | $3,478,225 | $6,956,449 | $10,434,674 | $12,173,786 |
| | 2014 | 8 | $0 | $1,739,112 | $3,478,225 | $3,478,225 | $6,956,449 | $10,434,674 | $12,173,786 |
| | 2015 | 10 | $1,739,112 | $1,739,112 | $3,478,225 | $5,217,337 | $8,695,562 | $12,173,786 | $15,652,011 |
| | 2016 | 11 | $1,739,112 | $1,739,112 | $3,478,225 | $5,217,337 | $10,434,674 | $13,912,899 | $17,391,123 |
| | Total | 44 | $3,478,225 | $6,956,449 | $15,652,011 | $22,608,460 | $38,260,471 | $53,912,482 | $69,564,493 |
| DC | 2012 | 199 | $3,366,024 | $6,732,048 | $13,464,095 | $20,196,143 | $33,660,239 | $46,787,732 | $60,251,827 |
| | 2013 | 219 | $3,702,626 | $7,405,252 | $14,810,505 | $22,215,757 | $37,026,262 | $51,500,165 | $66,310,670 |
| | 2014 | 235 | $4,039,229 | $8,078,457 | $15,820,312 | $23,898,769 | $39,719,081 | $55,539,394 | $71,359,706 |
| | 2015 | 269 | $4,375,831 | $9,088,264 | $18,176,529 | $27,264,793 | $45,441,322 | $63,281,248 | $81,457,777 |
| | 2016 | 298 | $5,049,036 | $10,098,072 | $20,196,143 | $29,957,612 | $50,153,755 | $70,349,898 | $90,209,439 |
| | Total | 1221 | $20,532,745 | $41,065,491 | $82,130,982 | $123,196,473 | $205,664,057 | $287,795,039 | $369,926,021 |
| GTB | 2012 | 27 | $336,602 | $1,009,807 | $1,683,012 | $2,692,819 | $4,712,433 | $6,395,445 | $8,078,457 |
| | 2013 | 30 | $673,205 | $1,009,807 | $2,019,614 | $3,029,421 | $5,049,036 | $7,068,650 | $9,088,264 |
| | 2014 | 32 | $673,205 | $1,009,807 | $2,019,614 | $3,366,024 | $5,385,638 | $7,405,252 | $9,761,469 |
| | 2015 | 37 | $673,205 | $1,346,410 | $2,356,217 | $3,702,626 | $6,395,445 | $8,751,662 | $11,107,879 |
| | 2016 | 41 | $673,205 | $1,346,410 | $2,692,819 | $4,039,229 | $7,068,650 | $9,761,469 | $12,454,288 |
| | Total | 168 | $2,692,819 | $5,722,241 | $11,444,481 | $16,830,119 | $28,274,600 | $39,719,081 | $50,826,960 |

Finally, in order to understand the magnitude of the combined reduction of all event types, the cost reductions by year were summed and are shown in Table 12.

Table 12. The cost reduction sums shown by year and by level of event reduction. Five-year totals are also provided for each level of reduction. Amounts are inflation-adjusted to 2016 dollars.

| | Event Reduction Percentage | | | | | | |
|---|---|---|---|---|---|---|---|
| **Year** | **5%** | **10%** | **20%** | **30%** | **50%** | **70%** | **90%** |
| 2012 | \$3,888,381 | \$11,782,974 | \$33,817,134 | \$45,600,108 | \$81,597,092 | \$100,803,339 | \$134,620,473 |
| 2013 | \$6,325,910 | \$12,303,605 | \$36,852,780 | \$47,357,274 | \$84,210,054 | \$108,469,050 | \$143,522,718 |
| 2014 | \$6,629,865 | \$12,913,824 | \$37,646,103 | \$49,118,651 | \$88,551,935 | \$114,033,677 | \$150,238,504 |
| 2015 | \$8,705,624 | \$14,203,913 | \$41,924,454 | \$56,128,367 | \$98,396,463 | \$138,201,785 | \$180,126,238 |
| 2016 | \$9,200,465 | \$14,922,706 | \$43,421,708 | \$58,007,811 | \$103,505,233 | \$146,926,941 | \$190,012,046 |
| Total | \$34,750,246 | \$66,127,022 | \$193,662,178 | \$256,212,211 | \$456,260,778 | \$608,434,791 | \$798,519,980 |

Tables 12 provides the detailed outcome of the various scenarios that could be realized under a full-flight data enabled prognostics system that could prevent the number events that constitute the status quo of the V2500. These simplified scenarios assume a single percentage reduction across all engine event types. Of course, as full-flight data capabilities improve over time, it is likely that PW's prognostics ability will not increase uniformly; some engine event types may receive more attention depending on data availability or customer need. It must be acknowledged here that prognostics capabilities are not a singular tool, but a suite of capabilities that depend on the relationship between PW and the airline customer. Therefore, while a singular percentage reduction of events is unlikely, it is a helpful approximation as to the value proposition to the airline's maintenance costs.

Table 12 provides a condensed summary, with cost savings of all events added together. By definition, cost savings increase as event reduction increases. However, because engine events are discrete, the values in practice should appear more stepwise in nature. As an example, if a certain adverse operational event occurred 13 times in a year, and full-flight data prognostics were to have an efficacy of 50%, there would be 6.5 events prevented. However, engine events are discrete in nature, and there is no notion of a "partial event," so either 6 events were avoided, or 7 events, but not 6.5 events.

## 4.2 Airline Unit Costs

### 4.2.1 Historical CASM

Cost data for the two carriers of interest were obtained from Form 41 Schedule P-1.2, which contains both operating revenue and expenses for all mainline US carriers. Generally, in order to find operating expenses for a carrier's mainline operations, the "transport-related costs" are subtracted from total operating expenses to exclude expenses associated with capacity purchase from regional carriers. Although the two carriers chosen for analysis in this study have neither subsidiaries nor seat purchase agreements, for consistency, their reported transport-related costs were subtracted, and the result was slightly lower than the reported total operating expenses (as shown in Table 13). This small discrepancy could possibly be attributed to one-time leases, charters, or other exceptional expenditures; in all cases, the difference is negligible given the total reported operating expenses. Nevertheless, for consistency, the "total operating costs" from here on will mean the ex-transport operating expenses.

Table 13. Total Operating Expenses, as reported from Form 41 Schedule P-1.2, alongside the same costs excluding transportation expenses. The resulting cost total is essentially the same, given the two carriers' lack of contracted regional service. Figures are reported as 000s of $ USD, and inflation-adjusted to 2016 dollars. Cost have been inflation-adjusted to 2016 dollars using the Bureau of Labor Statistics' Seasonally-Adjusted Consumer Price Index [44].

| Year | Total Operating Expenses | Total Operating Expenses (Ex-Transport) |
|---|---|---|
| 2012 | $6,056,014 | $6,012,234 |
| 2013 | $6,620,173 | $6,579,043 |
| 2014 | $7,075,607 | $7,051,498 |
| 2015 | $6,993,390 | $6,987,979 |
| 2016 | $7,202,613 | $7,200,538 |

Having completed the total cost calculation, the available seat miles (ASM) were obtained through Form 41 Schedule T-2. Below in Table 14, the total costs, ASMs, and mainline CASM area shown.

Table 14. Total Mainline CASM for Carriers A and B, from 2012 to 2016. Dollars have been inflation-adjusted to 2016 dollars.

| Year | Ex-Transport Total Cost | ASM | CASM |
|---|---|---|---|
| 2012 | $6,012,234,434 | 51,371,552,309 | 11.70¢ |
| 2013 | $6,579,042,676 | 56,659,847,664 | 11.61¢ |
| 2014 | $7,051,498,482 | 61,394,302,317 | 11.49¢ |
| 2015 | $6,987,978,788 | 70,645,499,502 | 9.89¢ |
| 2016 | $7,200,537,830 | 79,277,701,952 | 9.08¢ |

It should be noted that the ASMs and CASM shown above are inclusive of aircraft type other than the Airbus A320 family, as Form 41 Schedule P-1.2 does not distinguish aircraft type in the reporting process. This is not expected to be problematic for the remainder of the analysis, as Schedule P-5.2, which contains the detailed maintenance costs of interest, does present data at the aircraft type level.

### 4.2.2 Unit Costs: CASM and Cost Per Block Hour

Another unit cost measure considered here is the Cost Per Block Hour (CBH), which is the analog to CASM using scheduled aircraft utilization in the denominator rather than available seat miles. When two or more airlines are evaluated, CBH may be a good tool for equalizing the effects of route network, which may skew representation via differing stage length. CBH mitigates this difference by using a unit time as a base. Using the same cost totals as in the previous section, CBH is shown in Table 15. "Block hours" is defined as the scheduled origin gate to destination gate ("gate to gate") time of a flight. "Flight hours" is defined as total airborne time, also known in industry parlance as "wheels-up to wheels-down." Form 41 Schedule T-2 provides both time measures: block hours are called ramp-to-ramp hours, while flight hours are called airborne hours. For the purposes of this study, block hours will be used as the basis for the cost-per-hour metric.

Table 15. Unit cost defined as Cost Per Block Hour. Dollars have been inflation-adjusted to 2016 dollars.

| Year | Ex-Transport Total Cost | Block Hours | Cost Per Block Hour |
|---|---|---|---|
| 2012 | $6,012,234,434 | 942,136 | $6,381.49 |
| 2013 | $6,579,042,676 | 1,037,276 | $6,342.62 |
| 2014 | $7,051,498,482 | 1,108,380 | $6,361.99 |
| 2015 | $6,987,978,788 | 1,237,385 | $5,647.38 |
| 2016 | $7,200,537,830 | 1,351,011 | $5,329.74 |
| Total | $32,991,836,240 | 5,676,188 | $5,812.32 |

### 4.2.3 Maintenance Component of Total Costs

DOT requires airlines to abide by its specific Form 41 accounting conventions. For Schedule P-5.2, total aircraft operating costs are reported, as described above in section 2.4.3. These include expenses related for flying operations (pilot compensation and benefits, fuel, insurance for flight equipment), direct maintenance (distinguished between airframe and aircraft engine for labor, outsourced repairs, and repair materials), and depreciation and amortization. Importantly for this study, direct maintenance expenses are reported at the aircraft type level, allowing isolation of data to the individual A320 family variant. For this analysis, the aircraft selected are the A319, A320, and A321, all of which are powered by the V2500 engine on the two carriers of interest. In Table 16 that follows, the maintenance cost accounts from Form 41 Schedule P-5.2 relevant to this study are shown, and include expenses associated with engine repair and logistics.

Table 16. Definition of cost accounts specific to engine maintenance costs from Form 41 Schedule P-5.2.

| Cost Account | Category | Description and/or Included Items |
|---|---|---|
| 5225.2 | Labor - Aircraft Engines | *"Apprentice mechanic, chief mechanic, cleaner, crew chief, electrician, engineer, foreman, inspector, lead mechanic, mechanic, mechanic helper"* |
| 5243.2 | Aircraft Engine Repairs - Outside | Outsourced engine repairs |
| 5246.2 | Maintenance Materials - Aircraft Engines | *"Materials used to repair aircraft engines"* |
| 5279.6 | Applied Maintenance Burden - Flight Equipment | *"This consists of maintenance overhead, expenses related to the administration of maintenance stocks and stores, record keeping, scheduling, controlling, planning and supervising maintenance operations."* |

For Applied Maintenance Burden, which serves as an overhead for both airframe and engine maintenance, the proportion attributable to engines was calculated by summing the labor, repairs, and materials cost accounts for both airframe and engine, and then finding the percentage of that sum coming from the engine categories. This breakdown is shown in Table 17.

Table 17. Percentage of total aircraft maintenance (labor, repairs, and materials accounts) attributable to engines. These factors were used to apportion the Applied Maintenance Burden to engine-specific costs only.

| Year | Engine Percentage of Total Aircraft Maintenance |
|---|---|
| 2012 | 36.02% |
| 2013 | 40.94% |
| 2014 | 44.42% |
| 2015 | 45.76% |
| 2016 | 47.33% |
| Overall | 43.56% |

The reported amounts in each of the maintenance cost categories shown above were obtained for the two carriers of interest. The sum of the four cost categories is total maintenance costs, and is shown in Table 18.

Table 18. The four maintenance cost categories from Form 41 Schedule P-5.2. Figures shown are in $USD (000s) and inflation-adjusted to 2016 dollars.

| Carrier | Year | Engine Repairs | Applied Maintenance Burden | Engine Materials | Engine Labor | Total Maintenance Costs |
|---|---|---|---|---|---|---|
| Airline A | 2012 | $134,308 | $29,670 | $44 | $0 | $164,022 |
| | 2013 | $148,215 | $33,700 | $53 | $0 | $181,967 |
| | 2014 | $157,209 | $36,046 | $59 | $0 | $193,313 |
| | 2015 | $190,042 | $37,518 | $65 | $0 | $227,625 |
| | 2016 | $239,587 | $40,931 | $98 | $0 | $280,616 |
| Airline B | 2012 | $71 | $0 | $2,336 | $0 | $2,292 |
| | 2013 | $3,911 | $0 | $26,217 | $0 | $29,124 |
| | 2014 | $7,536 | $0 | $38,385 | $0 | $44,686 |
| | 2015 | $8,703 | $0 | $40,899 | $0 | $48,586 |
| | 2016 | $14,945 | $0 | $36,249 | $0 | $51,193 |

Note that in Table 18, the maintenance cost totals are reflective only of A320 family aircraft, and thus only revenue service powered by the V2500. This is a critical step in the methodology, as Form 41 does not specify the engine OEM used by each airline. By virtue of management decisions at these two carriers, the entire fleet of A320 family aircraft are operated on PW-monitored V2500 engines (all thrust ratings included). This allows for proper analysis of maintenance cost outcome, as reported to the DOT, given the internal PW data warehouse of V2500 engine faults and events.

The fleet size of Airline A is several times higher than that of Airline B in the time period analyzed. This fleet disparity is one main factor that explains the difference in magnitude of maintenance spending at the two carriers. Interestingly, the amount spent on maintenance does not appear to scale linearly based on fleet size. Table 19 summarizes the fleet size ratio and maintenance cost ratio ($\frac{Airline\ A}{Airline\ B}$) in the time period studied.

Table 19. Fleet Size Ratio and Maintenance Cost Ratio between Airline A and Airline B. From Form 41, Schedule B-43 and Schedule P-5.2. *Indicates an outlier value likely due to misreporting from DOT BTS database.

| Year | Fleet Size Ratio | Maintenance Cost Ratio |
|---|---|---|
| 2012 | 4.00 | 68.16* |
| 2013 | 3.59 | 6.04 |
| 2014 | 3.12 | 4.21 |
| 2015 | 2.72 | 4.59 |
| 2016 | 2.39 | 5.48 |

The ratios showing the fleet size and maintenance cost disparities between the two carriers is interesting, as Airline A appears to be spending many times more on maintenance than its fleet size would suggest. For the years 2013-14, the fleet ratio and cost ratio gap narrowed as Airline B grew its fleet size faster, but its incurred costs still remained lower on a proportional basis. There is, perhaps, some evidence that Airline A is spending more on maintenance while not reaping proportionally higher benefits, based on its higher than expected incidence of Ground Turn-Backs, Delays/Cancellations, Air Turn-Backs, and Aborted Takeoffs. Without further data on cost details available for study, no judgment will be made on the efficacy of maintenance spending.

Nevertheless, it appears that maintenance activity for both carriers do not occur in-house. Returning to Table 18 above, it is apparent that neither airline incurs Engine Labor cost in these years. This is likely due to outsourcing of engine maintenance, which many carriers do as part of their business model. Another noticeable trend is the lack of applied maintenance burden for Airline B, whereas Airline A does spend quite a bit on this category. Since applied maintenance burden refers to the "overhead" associated with maintenance activities, one can likely conclude that Airline A expends more resources for maintenance overhead—which is not surprising given the disparity between its fleet ratio and cost ratio—though specific details are not known, as "applied maintenance burden" is a commingled category.

Ultimately, what can be concluded is that both carriers opted to contract out their repair services, but the cost differences seen in the other categories (relative difference, not absolute difference) could be due to strategic management decisions or, in rare cases, incorrect cost accounting on the part of the airline. For evaluative purposes, this study will assume that the sum of all engine maintenance cost items captures the true maintenance burden.

The specific maintenance accounts used here constitute a putative cost basis that full-flight data analytics can impact. It must be emphasized that these particular categories of maintenance costs are not *all* maintenance costs realized by these carriers. Indeed, depreciation and other less operationally-associated cost accounts are not represented. This point is further emphasized below with a look at Schedule P-1.2's maintenance cost category, which as mentioned, is a commingled category for all maintenance activity. As such, maintenance appears to constitute a larger proportion of aircraft operating costs in Table 20 than in Table 18.

Table 20. Total operating costs, maintenance costs (as defined Schedule P-1.2), and the proportion of maintenance that constitutes total operating costs. Figures are reported in 000s and inflation-adjusted to 2016 dollars.

| Year | Ex-Transport Costs | Total Maintenance Costs | Maintenance Proportion of Total Cost |
|---|---|---|---|
| 2012 | $6,012,234 | $576,032 | 9.6% |
| 2013 | $6,579,043 | $662,609 | 10.4% |
| 2014 | $7,051,498 | $660,228 | 9.6% |
| 2015 | $6,987,979 | $743,956 | 10.9% |
| 2016 | $7,200,538 | $855,724 | 11.9% |

It should be noted that Table 20 provides general evidence that maintenance of all forms constitute about 10-11% of total mainline costs. This outcome is consistent with previous literature showing that maintenance is about 10-12% of an airline's costs [28]. For further granularity on maintenance specific to the V2500 engine, the sum of engine-related costs (from Table 18) are shown below in Table 21 as a percentage of Aircraft Operating Costs (AOC), which, as noted earlier, comprise the costs incurred for flying the aircraft.

Table 21. Aircraft operating costs and engine maintenance costs, as defined previously as engine-specific cost accounts from Form 41 Schedule P-5.2. Figures shown are in $USD (000s) and inflation-adjusted to 2016 dollars.

| Year | Aircraft Operating Costs (AOC) | Engine Maintenance Costs | Engine Maintenance as Percentage of AOC |
|---|---|---|---|
| 2012 | $3,356,259 | $166,429 | 5.0% |
| 2013 | $3,631,635 | $212,095 | 5.8% |
| 2014 | $3,854,318 | $239,234 | 6.2% |
| 2015 | $3,506,751 | $277,227 | 7.9% |
| 2016 | $3,441,327 | $331,810 | 9.6% |

While AOC has climbed progressively in the five years shown, engine maintenance costs appear to have increased at a higher rate, constituting 5% in 2012 but reaching 10% in 2016. The increase of $173.3 million in engine maintenance over five years, in light of AOC increasing only $245.4 million, might suggest that 69% of the AOC increase is due to engine maintenance alone. However, it is important to note that within this same time frame, the global oil industry declined significantly, resulting in record low fuel prices that reduced airlines' AOC. Thus, it is useful to look at AOC excluding fuel (ex-fuel) costs. Table 22 below shows each year's ex-fuel AOC, the engine-specific maintenance costs, the proportion of ex-fuel AOC attributable to engine maintenance, and the year-over-year growth of each.

Table 22. Aircraft operating cost, excluding fuel, along with engine-specific maintenance cost as defined above from Schedule P-5.2 cost items. Year-over-year growth is also shown for each AOC ex-fuel and engine maintenance cost, to show pattern of cost increase. The final column shows the percentage makeup of AOC due to engine maintenance. Figures shown are in $USD (000s) and inflation-adjusted to 2016 dollars.

| Year | Aircraft Op Cost Ex-Fuel | Aircraft Op Cost Ex-Fuel Growth | Engine Maintenance Cost | Engine Maintenance Cost Growth | Engine Maintenance as Percentage of AOC |
|---|---|---|---|---|---|
| 2012 | $1,416,591 | | $166,429 | | 11.7% |
| 2013 | $1,580,571 | 11.6% | $212,095 | 27.4% | 13.4% |
| 2014 | $1,758,802 | 11.3% | $239,234 | 12.8% | 13.6% |
| 2015 | $2,005,639 | 14.0% | $277,227 | 15.9% | 13.8% |
| 2016 | $2,188,209 | 9.1% | $331,810 | 19.7% | 15.2% |

The data from Table 22 show that ex-fuel growth in AOC has decreased over this time period, while engine maintenance cost has moved more sporadically: starting at 27%, it drops by half before climbing again to about 20%. In spite of this nonlinear growth, engine maintenance costs have stably constituted 12-15% of ex-fuel AOC in this time period.

### 4.2.4 Engine Event Cost Reductions and CASM

Having determined an estimate of the cost reductions by percentage improvement on the status quo occurrence of events, attention will now turn to estimating these cost reduction effects on CASM and Cost Per Block hour (CBH). Reductions in unit costs are almost always expressed as percentage decreases, since raw CASM itself means little unless given a reference point. The calculation is as follows:

$$\%Improvement = \frac{Old\ CASM - New\ CASM}{Old\ CASM} \tag{15}$$

$$\%Improvement = \frac{Old\ CASM - \frac{Total\ cost - Cost\ Savings}{ASM}}{Old\ CASM} \tag{16}$$

The calculation for CBH reduction is similar to that of CASM above.

Table 23. CASM reduction by percent, with proportion of engine events reduced as variable. Based on equations 15 and 16 above.

| | | Percentage of Engine Events Avoided | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Year | 5% | 10% | 20% | 30% | 50% | 70% | 90% |
| CASM Reduction | 2012 | -0.06% | -0.20% | -0.56% | -0.76% | -1.36% | -1.68% | -2.24% |
| | 2013 | -0.10% | -0.19% | -0.56% | -0.72% | -1.28% | -1.65% | -2.18% |
| | 2014 | -0.09% | -0.18% | -0.53% | -0.70% | -1.26% | -1.62% | -2.13% |
| | 2015 | -0.12% | -0.20% | -0.60% | -0.80% | -1.41% | -1.98% | -2.58% |
| | 2016 | -0.13% | -0.21% | -0.60% | -0.81% | -1.44% | -2.04% | -2.64% |

Table 23 shows that CASM is reduced by 0.5-0.6% if 20% of status quo V2500 events are prevented or mitigated. In general, a CASM reduction range of 0.5% to 1.5%[3] can be expected if the event avoidance rate is 20-50%, a reasonable lower- to mid-range that does not overpromise FFDA's prognostic capabilities. On the surface, it is difficult to assess the significance of a 0.5-1.5% decrease in CASM for an airline, as unit cost changes are interpreted in the context of the airline's quarter-to-quarter cost trends, as well as its performance relative to the industry. Moreover, CASM change must also be considered alongside an airline's capacity and route network changes. An increase in ASMs through increased stage length, for example, would lower CASM by virtue of spreading fixed costs over more ASMs, making that CASM change less noteworthy. Nevertheless, it is noted that at 20% event reduction, cost implications

[3] Range will vary depending on true event cost data used; see footnote 1

are significant on an annual basis, with a range of $33.8M to $43.4M of potential raw savings[4]. Implications of this magnitude of change on CASM are discussed further in the Discussion section below.

For CBH, percentage improvement is identical to that of CASM, as the amount of cost savings is identical for either case. Since the denominator includes the old CBH value, it is a self-controlled metric that reflects the impact of the engine event cost savings. Perhaps more interesting are the raw dollars per flight hour saved, which are shown below.

Table 24. Reduction of block hour cost in raw dollars. Values are inflation-adjusted to 2016 dollars.

| | | Percentage of Engine Events Avoided | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Year | 5% | 10% | 20% | 30% | 50% | 70% | 90% |
| Cost Per Block Hour | 2012 | -$4.13 | -$12.51 | -$35.89 | -$48.40 | -$86.61 | -$106.99 | -$142.89 |
| | 2013 | -$6.10 | -$11.86 | -$35.53 | -$45.66 | -$81.18 | -$104.57 | -$138.37 |
| | 2014 | -$5.98 | -$11.65 | -$33.96 | -$44.32 | -$79.89 | -$102.88 | -$135.55 |
| | 2015 | -$7.04 | -$11.48 | -$33.88 | -$45.36 | -$79.52 | -$111.69 | -$145.57 |
| | 2016 | -$6.81 | -$11.05 | -$32.14 | -$42.94 | -$76.61 | -$108.75 | -$140.64 |

The cost savings per block hour presented in Table 24 provide another set of estimates by which to value FFDA prognostic services. For event reductions in the 20-50% range, cost savings vary from $30 to $80 per block hour. Given that maintenance costs constitute approximately 10% of total costs, as shown in Table 20, these dollar values represent 6-15% of the maintenance component of block-hour costs, a relatively significant share of the approximately $533 attributed to maintenance per block hour.

In order to provide further perspective on realistic CASM savings, the two airlines' individual unit costs can be evaluated separately using the same method. In particular, because Airline A operates aircraft types other than the A320 family, the unit cost reductions above may

[4] Given the engine event cost ranges used

be diluted by additional seat-miles and flight hours. In the following examples, the full unit cost reduction procedure is completed and summarized for each carrier.

Table 25. Estimates of percent reduction of CASM as well as Cost Per Block Hour shown for Airline A.

| | | Percentage of Engine Events Avoided | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **Year** | **5%** | **10%** | **20%** | **30%** | **50%** | **70%** | **90%** |
| CASM Reduction | 2012 | -0.07% | -0.20% | -0.33% | -0.79% | -1.16% | -1.49% | -2.07% |
| | 2013 | -0.06% | -0.19% | -0.35% | -0.75% | -1.10% | -1.44% | -2.00% |
| | 2014 | -0.06% | -0.19% | -0.34% | -0.72% | -1.07% | -1.40% | -1.93% |
| | 2015 | -0.06% | -0.20% | -0.40% | -0.80% | -1.24% | -1.57% | -2.17% |
| | 2016 | -0.10% | -0.21% | -0.61% | -0.82% | -1.46% | -1.85% | -2.45% |

| | | Percentage of Engine Events Avoided | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **Year** | **5%** | **10%** | **20%** | **30%** | **50%** | **70%** | **90%** |
| Cost Per Block Hour Savings | 2012 | $4.03 | $12.25 | $19.86 | $47.86 | $70.94 | $90.80 | $126.42 |
| | 2013 | $3.75 | $11.81 | $21.47 | $46.20 | $67.67 | $89.14 | $123.53 |
| | 2014 | $3.60 | $11.72 | $21.38 | $45.09 | $66.86 | $87.84 | $121.21 |
| | 2015 | $3.73 | $11.70 | $23.39 | $46.29 | $71.61 | $90.77 | $125.36 |
| | 2016 | $5.64 | $11.63 | $33.73 | $45.01 | $80.55 | $102.01 | $135.39 |

Similarly, Airline B's specific results are calculated, and shown in Table 26.

Table 26. Estimates of percent reduction of CASM as well as Cost Per Block Hour shown for Airline B.

| | | Percentage of Engine Events Avoided | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **Year** | **5%** | **10%** | **20%** | **30%** | **50%** | **70%** | **90%** |
| CASM Reduction | 2012 | -0.06% | -0.18% | -0.32% | -0.80% | -2.19% | -2.49% | -3.11% |
| | 2013 | -0.07% | -0.17% | -0.47% | -0.74% | -2.08% | -2.40% | -2.97% |
| | 2014 | -0.06% | -0.17% | -0.45% | -0.71% | -1.91% | -2.24% | -2.78% |
| | 2015 | -0.10% | -0.21% | -0.60% | -0.83% | -2.16% | -2.66% | -3.29% |
| | 2016 | -0.11% | -0.29% | -0.60% | -0.87% | -2.10% | -2.68% | -3.26% |

| | | Percentage of Engine Events Avoided | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **Year** | **5%** | **10%** | **20%** | **30%** | **50%** | **70%** | **90%** |
| Cost Per Block Hour Savings | 2012 | $3.53 | $10.58 | $19.40 | $48.21 | $131.41 | $149.05 | $186.68 |
| | 2013 | $4.39 | $10.25 | $28.07 | $44.43 | $124.00 | $143.04 | $177.22 |
| | 2014 | $3.80 | $10.12 | $26.78 | $42.18 | $113.46 | $132.44 | $164.50 |
| | 2015 | $5.01 | $10.03 | $29.42 | $40.45 | $105.13 | $129.36 | $159.78 |
| | 2016 | $5.23 | $14.08 | $29.04 | $42.25 | $101.93 | $130.10 | $158.27 |

As can be deduced from Tables 25 and 26 above, there is varying effect of the tentative cost reductions when the two constituent carriers' data are segregated. In particular, Airline B appears to benefit more simply because its smaller size and fewer flight hours. This difference is manifested in its higher percentage in CASM reduction, and higher reduction in CBH. In fact, the higher the percentage of engine events avoided, the greater its benefit on unit costs.

At 20% and 30% event reduction, both carriers show very similar reductions in CASM, ranging from 0.3-0.6%, and 0.7-0.9%, respectively. However, there appears to be an inflection at 50% event reduction, at which Airline A's CASM reduction ranges from 1.1% to 1.5%, but Airline B's CASM reduction range is higher on average by almost half a percentage point: 1.9% to 2.2%. At 70% and 90% reduction, this trend for Airline B continues, with its CASM reduction nearly one full percentage point higher than that of Airline A. Thus, it appears that the 50% inflection point marks the threshold at which event reduction impacts CASM more significantly between these two carriers. With lower ASMs, Airline B gets the benefit of a higher unit cost reduction when the hypothetical efficacy of FFDA prognostics is higher than 50%.

This 50% efficacy inflection point is interesting and worthy of further analysis with data comparing other airlines. It is unclear if such an inflection point exists for all CASM reduction tables generated through the same methodology, but if so, then it would have significant implications on how full-flight data EHM services are marketed, executed, and delivered. In particular, this finding suggests that the value promised by FFDA to PW customers may be difficult to generalize beyond a certain efficacy threshold. This idea is explored further in the next chapter.

# Chapter 5

# Discussion and Conclusions

The present study seeks to define the potential value of full-flight data analytics in the context of engine event reduction. It forms a part of the growing body of work internally at Pratt & Whitney (PW) that is done to evaluate and affirm the business case for the EngineWise™ suite of Engine Health Management (EHM) services and products, with the Enhanced Flight Data Acquisition, Storage and Transmission (eFAST™) system being a particular focal point. Having introduced the Flight Data Acquisition, Storage and Transmission (FAST) service on Pratt & Whitney Canada's turboprop fleet, eFAST™ is PW's foray into full-flight data acquisition, storage, analysis, diagnostics, and prognostics for its jet engine products. The eFAST™ hardware was first introduced as a default option on PW's Geared Turbofan (PW1500G series) aboard the Bombardier CSeries aircraft, though that EHM arrangement is brokered through Bombardier to airline operators. Seeking to generalize the eFAST™ product, PW is looking into offering the hardware as an add-on to its most popular engine to date, the International Aero Engines V2500, which powers the Airbus A320 family of aircraft. Introduction of eFAST™ onto the V2500 is only in trial stages, and as such, the full-flight data warehouse itself has not yet been established. Therefore, the approach taken in this study was to characterize the benefits of full-flight data analytics (FFDA) in terms of its improvement over the status quo, which is represented by the current database of engine-induced operational disruptions to airline customers. Event reductions were then translated to cost reductions, which in turn were applied to publicly available airline costs as reported to the US Department of

Transportation (DOT). Cost reductions were further interpreted as unit cost reductions, as an outcome of the overall cost avoidance model based on inputs from the Poisson parameters, expected flight hours, and the magnitude of disruption events. In this section, the implications of this study will be discussed in further detail, beginning with a review of the assumptions made.

## 5.1 Review of Framework and Assumptions

### 5.1.1 Grouping of Adverse Operational Events

The architecture of PW's V2500 database lent itself well to a Poisson characterization of engine events, since each individual record can be treated as a rare, random occurrence that is mutually exclusive of any other record. For each individual record, a determination was made at the time of data entry as to which, if any, operational disruptions arose as a result of that particular engine event. Although a protocol exists, there is a significant level of subjectivity and variability in the event-recording process.

First, each record is input by one or several PW field specialists, introducing variability into the event recording based on person-to-person variation in style, level of detail, and even urgency—one could speculate that a more severe event might affect an employee's sense of urgency, such that he/she rushes through without providing detail, or conversely that this person may be compelled to over-provide details if he/she feels the event must be avoided in the future.

Here, it is worthwhile to discuss the fidelity of the V2500 database as an objective dataset befitting a strict Poisson characterization of the engine incident process. It was shown in Table 5 (Chapter 4) that 2,057 events from the five-year set showed "blank" under event type, meaning that no operational disruption was noted for that record. Yet upon inspection of the "narrative" field of these records, which contains textual input from the employee recording the event, some of these "blank" events appeared to have incurred operational disruptions that were not labeled as one of the Adverse Operational Events (AOE). Although further review of the blank entries confirmed that such mistakes were rare, it was also found that many "blank" events provided very limited details in the "narrative" field, suggesting that there could be more operational disruptions than were officially recorded. If this is the case, then the database itself could very well be underreporting the engine incidents that occur, and, in the context of this study, causing the estimated cost results to be lower than actual. Of course, any database in which inputs are not automated will be subject to this type of human variability, and these outliers alone do not delegitimize the dataset. Rather, this evidence points to one part of the cost valuation framework that can be further refined through a more standardized reporting protocol.

Further standardization in reporting could also help to elucidate the incidence rate of AOEs occurring in combination. In Section 4.1.1 of Chapter 4, individual engine events were grouped according to their perceived level of severity in order to reduce the number of possible categories. This grouping process was aided by the fact that very few events—often, only single occurrences in two to three year windows—were reported with multiple AOEs in combination. In practice, the labeling of events in combination is another area of subjectivity that exposes the dataset to possible under- or over-reporting. For example, if a flight does a Ground Turn-Back (GTB), wherein it returns to the gate after having begun its taxi toward takeoff, it is almost certain to be delayed, but we do see an entire set of GTB-labeled events recorded alone without any other AOEs in combination. The same would apply for aborted takeoffs that don't have any GTB recorded, but it is logical to assume that at least some of these aborted takeoffs did return to the gate, and also consequently experienced a delay/cancellation. The difficulty of categorizing events in combination reflects the complicated nature of operational disruptions. Indeed, as described in Section 4.1.3 regarding the Type I-III severity labels, the cost range of events can vary widely because there are so many different elements that comprise an operational disruption, and so many different costs can be incurred. Crew time-outs and ferrying of new crew, for example, always occur together, but spare parts may or may not need to be ferried depending on where an engine incident takes place. For costs with such variation and ambiguity, estimates are better expressed as ranges than specific values, as shown in this study. The literature suggests that studies of airline operational disruptions often focuses on the logistics of disruption management, rather than detailed cost reduction measures [45]. Moreover, work has generally been done on specific and visible types of disruptions, such as passenger delay costs [46], which was observed to be the largest AOE by volume, but not the most individually costly events from a maintenance perspective.

### 5.1.2 Poisson Distribution and Characterization

The V2500 database of engine events provides a record of individual incidents across five years for two operators, each event of which can be considered a rare, mutually exclusive, randomly arising event. These characteristics are befitting of a Poisson set of occurrences, which are defined by the typical number of occurrences over a given time period or space [38]. A possible counterargument to application of a Poisson model could be that engine events, in their current state, have been actively monitored and improved for years by PW, and are not akin to "naturally occurring" events not monitored for incidence rate, such as the number of arrivals at a hospital emergency room over a week—that is, PW is actively monitoring and trying to reduce engine events around-the-clock, but presumably no one is actively monitoring emergency room arrivals since the hospital cannot predict and prevent patient accidents. Yet, the Poisson model has in fact been applied to adverse events that are monitored and targeted for reduction, such as cancer survival [40] and, more relevant, air transportation accidents [47]. Moreover, given the maturity of the V2500 program, major engine faults are rare and random, lending themselves well to a Poisson model. Along with the accuracy and availability of information on flight hours experienced by each engine, the occurrence of disruptions is very fitting of the Poisson parameter, $\lambda$.

### **5.1.3** Poisson Parameter Pooling

This study's methodology called for the pooling of two carriers' engine events over five years of records. In order to explore the possibility of non-random variation in event incidence between the carriers, a $\chi^2$ Test of Independence by airline was conducted for each of the adverse operational events to determine if the null hypothesis of independence between the two carriers would be rejected. Four of the six AOEs tested, namely Aborted Takeoff (ATO), Air Turn-Back (ATB), Delay/Cancellation (DC), and Ground Turn-Back (GTB), were statistically significant in the $\chi^2$ test, potentially raising concern about whether the two carriers really do operate differently enough that the same engine type results in statistically different incidence of engine faults. However, since the remaining two AOEs, Aircraft-On-Ground (AOG) and Inflight Shutdown (IFSD) were not statistically significant, there remains some uncertainty as to the independence of the carriers. In other words, the difference across all AOEs could not be attributed to operator variation alone.

Nevertheless, one may argue that pooling two separate airlines' data, no matter how closely their route networks align, is inappropriate. This concern was addressed earlier with the reasoning that a pooled approach makes for a larger sample size that is likely more applicable to other PW customers of the V2500. Should this model for cost reduction be used on raw data of other carriers, a pooled Poisson parameter is likely to be more robust than if based on one carrier's data alone. Indeed, pooling of the Poisson parameter is not uncommon in the literature for adverse events such as automobile accidents [48]. For this study in particular, the commonalities between the two carriers selected, which lent themselves to better access to Form 41 data, provided further confidence for combining the data sets.

The approach taken to apply the Poisson event parameter, $\lambda$, was to make use of five years' worth of V2500 event records, and then to recalculate each year's event totals by finding the product of $\lambda$ and the 1000-unit hour totals for each year. Such an approach may appear counterintuitive, given that the true number of events of each year are *already* known. The justification for this modified methodology is to establish a general framework that can be applied to any given year, and not necessarily these five specific years. The use of such a generalized $\lambda$ parameter is, perhaps, more useful if considered as a tool to predict future years' count of engine events. Suppose that a given airline customer has a planned number of flight hours for an upcoming year, which airlines often do forecast when budgeting and investor guidance is prepared for the upcoming calendar year. Given the planned number of 1000-unit flight hours, one can apply $\lambda$ to predict the likely number of each AOE type, and quantify the potential cost range over which FFDA can have an effect. As eFAST™-based EHM services mature and stabilize, this method will likely become even more useful.

### **5.1.4** Event Reduction Estimation

Full-flight data analytics was assumed to reduce adverse operational events induced by engine faults. The Poisson characterization of engine events is helpful for quantifying the status quo, but with respect to engine event reduction, it only provides the probability of observing a certain number of occurrences, given a known $\lambda$ and a period of time over which events are observed and counted. The Poisson model itself does not tell us how likely FFDA can reduce costs, it simply provides a baseline expectation for how often events should occur under random conditions. This includes the probability of observing a count of events greater than $\lambda$, which, although counterintuitive, is embedded by definition because the Poisson probability model accounts for event counts both above and below the $\lambda$ parameter. In Section 4.1.7, a simple model of event avoidance was used, whereby the V2500 status quo of event faults was reduced by a given percentage. These percentages, ranging from 5% to 90%, essentially cover the lower half of the Poisson distribution for each given adverse operational event. That is, we have $P(X = k)$ for all $k < \lambda$, but in turn $k$ has been defined as some fraction of $\lambda$ such that

$$k = z\lambda \tag{17}$$

where $0 < z < 1$.

The $z$ here is the ratio ascribed to each $k$ such that any $k$ will never exceed $\lambda$. Implicitly, we want to see occurrences of events below $\lambda$, so *(1-z) %* is the amount by which $\lambda$ is reduced. The underlying Poisson process does not itself limit observances to only those less than $\lambda$, but since the focus is on event avoidance and EHM process improvement, it is not necessary to consider the upper half of the distribution (where $k > \lambda$). FFDA prognostics, however, should decrease the number of events that are manifested in practice, since it is expected to detect, prevent, or minimize unexpected failures. Comparable work in the medical field has tried to characterize medication errors as a Poisson process, with review of individual events as preventable or non-preventable as a motivation for reducing $\lambda$ for these adverse events [49]. Work has also been done to characterize engine failure as a Weibull process for two airlines, though without suggestion for reducing failure rates [50]. For the study here, the Poisson distribution of engine events was used as motivation for understanding the incidence rate of unexpected engine failures, but we do not estimate Poisson probabilities because the objective of FFDA prognostics is to proactively prevent failures and ultimately minimize randomness in the occurrence of such failures.

## 5.2 Translation of Engine Maintenance to Airline Costs

### 5.2.1 Form 41 Data Reliability

One of the vestiges from the pre-deregulation era of airlines is that the DOT continues to require all airlines to report very extensive cost, revenue, traffic, and capacity data, beyond that which is required of typical 10K filings of publicly traded companies. In addition to collecting the data, the DOT has made this information publicly available, allowing for airline business research. For the purposes of this study, the Form 41 schedules detailing operating expenses proved to be the most useful, particularly since maintenance costs are detailed quite comprehensively in Schedule P-5.2. The availability of this data is fortuitous, but the fidelity of the information is highly dependent on the consistency with which airlines report their data. While there is no reason to believe that unscrupulous activity is occurring, it remains the case that Form 41 data is not audited in an official capacity. Therefore, much of the information available must be accepted as is. Nevertheless, Form 41 is and continues to be the standard used by professionals and academics alike [22], including the airlines themselves in competitive analysis. Thus, this commentary is provided here for transparency, rather than to cast doubt on data credibility.

### 5.2.2 Nuances of Form 41 Data Fields

Form 41 contains many schedules and tables that present airline financial and operational data by different cross sections. Importantly, Schedule P-5.2 allowed for maintenance expense data to be disaggregated by source (airframe or engine), making the data significantly more useful than if estimations were made on the proportion of maintenance attributable to engines. Moreover, other than operating airline, a key identifying field in this Schedule is aircraft type, which allowed for selection of not just A320 family aircraft, but the variants themselves (A319, A320, A321). In this study, with the ability to segregate maintenance data on only the two airlines of interest and only their A320 family fleet, we are able to pinpoint the reported maintenance costs specific for the V2500, since the two carriers operate it exclusively for their A320 family. Internally, PW's V2500 database of course also allows for only these two carriers' engines to be analyzed. Therefore, the level of specificity afforded by these data sources lend confidence to the outcomes of the analysis.

It should be noted here that this study's cross-source data analysis, that is, the use of publicly available Form 41 data, along with the internal PW V2500 database of engine events, is limited by the fact that they are disparate sources. On the one hand, the reader must keep in mind that internal and external data, especially when reported by different sources, introduce multiple layers of variation. On the other hand, the ability to pinpoint operating airline, aircraft type, and engine-specific cost within the Form 41 fields by using PW's V2500 data set mitigates much of the uncertainty, particularly since engine fault rate is external to Form 41 itself. Indeed, this type of internal-external hybrid maintenance cost evaluation is a unique feature of this study, enabled by access to PW's engine database and extensive study of DOT airline data.

### 5.2.3 Unit Cost Reduction Estimation

To the knowledge of the author, this is the first study to bridge the raw data of engine fault events with the realized engine maintenance costs publicly reported to the US DOT. Despite the perceived potential from so-called "big data" analytics enabled by such technologies as eFAST™, interest on the airline side is limited by each carrier's relationship to the original equipment manufacturer (OEM), which can vary based on contract terms and the associated EHM services elected. Using the two carriers of interest, it has been shown here that the potential for unit cost reduction can vary widely. The higher the proportion of engine events avoided, the higher the expected cost savings. As presented in Table 23 (Chapter 4), the model here predicts about a half-percentage decrease in annual CASM in the assumed ideal scenario of 20% engine event avoidance. A more optimistic scenario of 20-50% engine events avoided yields CASM reductions up to 1.5%. Such a figure could carry broader significance for an airline customer that not only wishes to reduce costs, but also minimize disruption to operations that carry with it negative customer sentiment, media portrayal of inefficiency, and other intangible damages caused by irregular operations. On raw dollars, the 2016 estimates of 50% event reduction translates to a full year cost savings of $104 million, which is not trivial for a mid-sized carrier like the hypothetical combination of Airline A and Airline B studied here. With many of the smallest US carriers facing total costs of at least $1 billion annually, cost savings in the tens of millions would be a boon to an industry with little control over its largest cost component, fuel expense.

With regards to fuel expense, an appropriate method for evaluating the magnitude of savings calculated here is to compare it to the year-over-year change in CASM that each airline has experienced over time. Figure 9 presents ten major US carriers and their mainline CASM changes from 2010 to 2016. An "Airline Composite" is included as a single proxy for the industry that encompasses industry total cost and industry ASMs.

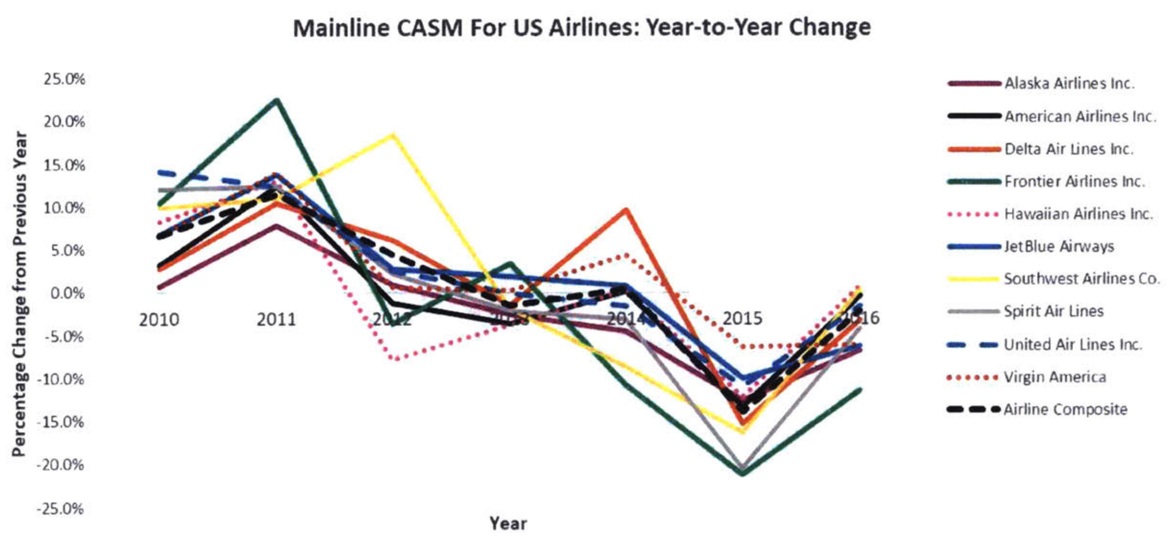



Figure 9. Mainline CASM Year-over-Year Change in Percent, 2010 to 2016.

Figure 9 shows that year-over-year CASM change can vary widely, first in response to fuel spiking around 2010-11, and then tumbling beginning in 2014 and onward, which was marked by a period of unprecedented profitability for airlines. In these later years, a savings of up to $104 million would have been less substantial in comparison, but that fuel-driven cost advantage has slowly crept back up in the couple years since 2016. Without the effect of major fuel swings, the years between 2012 to 2014 showed year-over-year CASM converging around +/- 5%. If FFDA-enabled reductions were to constitute 1.5 percentage points of cost savings in the +/- 5% CASM range, then these values would be quite significant for an airline's earnings reports and investor outlook.

With respect to cost per flight hour, the 20-50% reduction scenario translates to \$30-\$80 saved per block hour. These figures may appear more compelling for airlines, if only because a Cost Per Block Hour (CBH) reduction is a concrete value distilled to a unit of aircraft utilization time. The CBH metric may also be more useful for both parties to reach an agreement on EHM service costs, especially if existing contracts already establish a cost-per-flight-hour charge in a fleet management program.

Some limitations should be explained in the context of the two carriers' data used for these conclusions. First, the two carriers chosen are not large, network legacy carriers, and thus their fleets are simple and uniform. Such fleet decisions were, of course, intentionally made with cost considerations in mind, as is typical of the low-cost carrier model [51]. There may thus be a "self-selecting" issue at play, in which the carriers themselves have already maximized their cost reduction potential. If so, the inputs used from their DOT-reported maintenance data could represent a low baseline from which more reductions are not easily achieved. Second, both carriers primarily outsource their maintenance operations, as evidenced by the lack of engine labor costs in Table 18 (Chapter 4). This type of maintenance and repair operations (MRO) structure was also decided with costs in mind, as it minimizes complexity at each airline. For both carriers, these business choices reduce the utility of the cost reduction model presented in this study, though the framework remains useful for other carriers operating more complicated fleets or MROs, assuming the relevant data inputs are available.

Of course, data availability itself dictated the selection of these two carriers for study, so while the magnitude of cost reduction ranges from low to moderate *based on the inputs used*, the various components of this model can be made more robust with data inputs that are specific to the airline customer. With individual contracts and relationships, the methodology here can be honed and refined so that fewer assumptions need to be made. For example, a tailored conversation would allow for the model to be adapted to a particular carrier's sub-fleet of PW engines, eliminating the dependence on a generalized formula that is not representative of that carrier's particular operations. Even broader, the applicability of this study's model to the industry at-large is at yet uncertain given the inability to obtain all specific data inputs on aircraft type, engine type, and incidence of adverse operational events for all engines other than the IAE V2500. To the extent that the airframe manufacturer cooperates or wishes to be involved, the FFDA methodology would be influenced by all three stakeholders: PW, the airframe manufacturer, and the airline customer. The procedures presented in this study should motivate airlines to share more engine performance data in order to produce a more widely applicable model of unit cost reduction.

Ultimately, the annual cost saving presented here ranged from $8-9 M in annual cost savings, up to $104 M if half of all engine events were avoided (based on the cost inputs used, which can vary depending on an airline's particular experience with AOEs and engine disruptions).

### 5.2.4 Cost-Benefit Analysis of an Engine Prognostics Product

The value of the services promised by full-flight data analytics and prognostics is best summarized by Table 12 (Chapter 4), which is reproduced again below in abridged form.

Table 27. Estimated cost savings from 20% and 50% reduction of adverse operational events.

| Year | 20% Reduction | 50% Reduction |
|---|---|---|
| 2012 | $33,817,134 | $81,597,092 |
| 2013 | $36,852,780 | $84,210,054 |
| 2014 | $37,646,103 | $88,551,935 |
| 2015 | $41,924,454 | $98,396,463 |
| 2016 | $43,421,708 | $103,505,233 |

As described in Chapter 4, a scenario with 20% reduction is a simplifying assumption made on the best approximation for prognostics efficacy. Based on Year 2016 costs, a hypothetical airline could see about $43 million in cost savings across its fleet if 20% of all AOEs were avoided or mitigated. Economic reasoning provides that this airline will, all other factors being equal, be indifferent between business-as-usual, or paying $43 million to avoid such engine events. The carriers studied here, Airline A and Airline B, have a combined fleet size of about 300 narrow-body aircraft. Therefore, on average, an airline of this size would be willing to pay $\frac{\$43M}{300\ aircraft}$ = $143,333 per aircraft per year to avoid 20% of engine-induced disruptions.

Is this a reasonable assumption to make? Continuing on the same line of reasoning, the airline is equivalently willing to spend $393 per aircraft per day, and $39.30 per hour if each aircraft were assigned 10 hours per day of block hour utilization, a reasonable industry standard [52]. This method can be extended further for the 50% event reduction case to produce the following table.

Table 28. Airlines' Theoretical Per-Hour Willingness-to-Pay for Engine Health Management Program. Assumes fleet of 300 aircraft with average daily utilization of 10 hours.

| | 20% Reduction | 50% Reduction |
|---|---|---|
| Annual Cost Savings | $43,421,708 | $103,505,233 |
| Per Aircraft Per Year | $144,739 | $345,017 |
| Per Aircraft Per Day | $397 | $945 |
| Per Aircraft Per Block Hour | $40 | $95 |

Based on the simplified analysis in Table 29 for airlines' theoretical willingness-to-pay, an EHM program that produces 20% reduction in engine events would cost the airline $43 million annually, but on a per block hour basis would cost $40. With block hour costs of $3200 per hour (in Year 2016 for pooled Airlines A and B), a $40 EHM block hour fee represents a 1.25% increase. Indeed, we found that the block hour cost reduction for 20% event reduction is about $34, roughly on the same order as the $40 estimated here. The rough calculation presented here is, in fact, a simplified version of the CBH savings, and is shown here as a heuristic for a potential pricing model that PW or any other prognostic service provider could consider.

In this simplified estimate for pricing strategy, it should be noted that an airline customer is unlikely to pay the direct equivalent of the engine disruption costs avoided, because those costs are themselves estimates predicated on (1) a constant rate of engine event occurrence, namely $\lambda$ of the Poisson process model shown above, (2) a guarantee that the service provider will reduce disruptions at the promised level, and (3) that cost estimates for events are accurate. All three of these assumptions must be satisfied to some degree in order for the provider to offer a theoretical Engine Health Management product for which the airline is willing to pay, but absolutes are unlikely to be possible. In economic terms, a more likely pricing strategy for the provider would be to price lower than the estimated savings to the customer but higher than average cost. For example, if the hypothetical cost of prognostics EHM to PW were $20 per block hour, then a price between $20 and $40 per block hour to the customer would be a reasonable charge that allows both the airline and the EHM provider to reap some economic surplus.

## 5.3 Full-Flight Data in Its Current State

At present, the widespread availability and use of data, particularly from social media channels that can aggregate large amounts of personal information, have undoubtedly had spillover effects into all types of industries that can benefit from data acquisition and analysis. In the aerospace sector, data has always been prevalent, but the ability to capture, store, and maintain data at the scale of continuous capture for, say, a 15-hour intercontinental flight is now very real and tangible. Pratt & Whitney's traditional ADEM platform for engine health monitoring and management has proven to be a valuable part of its aftermarket services. It follows, therefore, that continued advancements in data acquisition and storage through cloud platforms will not only be adopted, but received emphatically.

This study has shown that a paradigm for applying engine health management to airline operations cost is not only viable, but likely to be expected in the coming years. While the cost reduction results shown here vary widely depending on cost inputs, the creation of a baseline model and set of procedures by which data can flow, from the recording of engine incident reports, to the aggregation of engine events over time via a statistical distribution model, to cross-source integration with airline cost information, are the most valuable result of this study. A visual representation of this paradigm is shown in Figure 10.

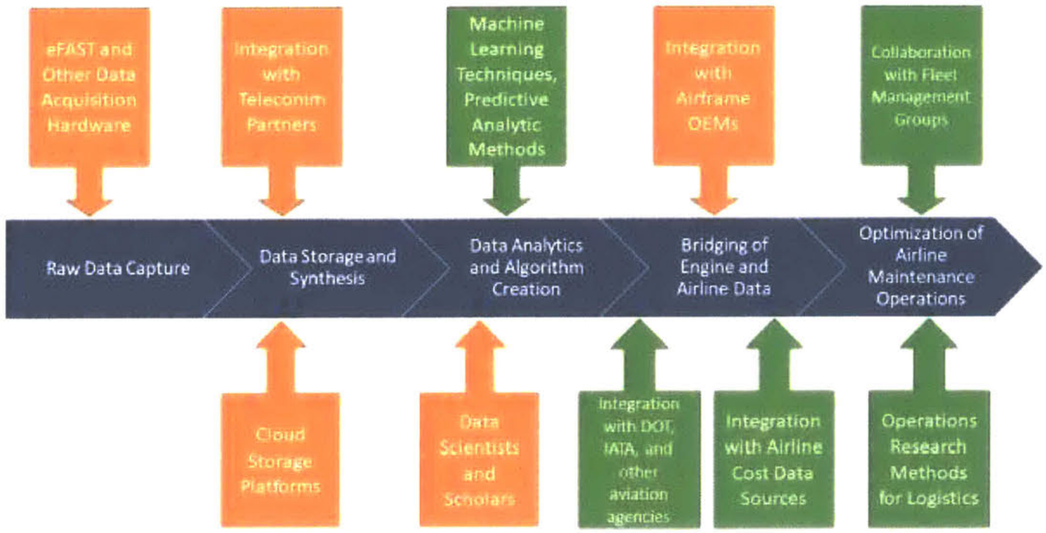



Figure 10. Paradigm for data and process flow for a full-flight data engine health management service. Orange inputs are those already in place, while green inputs are planned and awaiting initiation.

Figure 10 above is very much in line with PW's plans for a mature, productionized EHM service that will arise from its EngineWise™ brand of aftermarket services. As expected from a culture of science and engineering, PW has been working steadfastly on ensuring hardware production and integration with aircraft is done precisely and carefully. The soft products that arise from this EHM paradigm will be introduced bit by bit. With the advent of the Geared Turbofan, which is only in its nascent stages of commercial passenger service, the development of full-flight data tools will occur in tandem with the maturation of PW's newest and most advanced single-aisle engine product to date. Of course, one should not discount the reliable and iconic IAE V2500, which is the main focus of this study precisely because it is a reliable and mature engine. The benefit of having an established dataset that is *not* full-flight in nature created a baseline for this study. Given the availability of engine event records as the status quo, the first step in defining a value for FFDA is to delineate the process by which the status quo can be improved and eventually replaced by a new status quo that promises fewer operational disruptions to the customer. From the most minor at-gate delay to the most unexpected aircraft-on-ground complication, proactive prevention with the sufficient tools to provide prognostic guidance to the airline operator is the service promise. Integration with the MRO network at PW and at the airlines will further improve efficiency in responding to events and optimizing maintenance schedules to maximize aircraft utilization.

The use of full-flight data in EHM services for MRO optimization is only a question of time, if not for the sake of cost reduction, then for the general principle that more data also equates to better safety. In a post-Malaysia Airlines MH370 world, lack of data is both inconceivable and unacceptable in times of emergency, whether from the airframe or the engines of a commercial passenger aircraft. Although 2017 was one of the safest in commercial airline history [53], the threat of unscrupulous individuals in fomenting fear and terrorism continues to exist, whether domestic or international. The availability of data, then, can be said to have inherent safety value that is not yet fully quantified.

## 5.4 Next Generation Products at Pratt & Whitney and the Airline Industry

Pratt & Whitney has invested heavily to create a full-flight data analytics platform that supports a comprehensive engine health management service for airline customers, both current and future. On the horizon are efforts to bring the data services out to a tangible medium for the customer, namely airlines, to access quickly and easily. The current ADEM system offers a customer user interface platform for airline fleet managers to access engine health information, and has been the standard offering for years. As FFDA matures, platforms for analyzing and using the data will be provided across multiple channels in an effort to expedite decision-making and operations optimization. In particular, there are prospects for leveraging the so-called "Internet-of-Things" method to bring the same sets of data, analysis, conclusions, and recommendations to the mobile application space [12], [54]. Though envisioned as a product farther down the line, the emphasis here is on accessibility, ease, and speed of delivery. The pace at which commercial aviation moves and evolves requires that those in charge are equipped with the tools to streamline the operations of the business. At its heart, an airline is a complex and intricate operations puzzle that is always subject to change, delay, and surprises. FFDA aims to deliver greater *control* to the decision-makers that work to ensure the puzzle fits together precisely and quickly.

## 5.5 Implications on Security and Privacy

With large data comes large responsibility. As more and more data is compiled, worry turns toward the threat of cybersecurity and the unauthorized use of aviation data by individuals to potentially shut down an aircraft or its engines as an act of terrorism. These are considerations that fall in tandem with the security needs of the "connected world," whereby IoT and artificial intelligence provide powerful tools for accomplishing great tasks, such as predicting when an engine will need proactive maintenance, but also presents vulnerabilities that might be exploited by unscrupulous individuals.

The existing snapshot method of data transmission through the ACARS system has persisted for decades without breach of security because it has not, so far, tapped into the more open and vulnerable internet networks on which full-flight data will necessarily depend. This is of course not an issue localized to PW's systems, but to all aerospace systems now and hereafter that make use of cloud-based platforms that involve, by default, remote data storage and processing. Fortunately, research is being done to better understand the risks of cyberattacks into integrated networks that contain highly sensitive information [55], [56]. Although this study does not aim to provide prescriptions for cybersecurity in the aviation space, the author cautions and urges the technology of data acquisition to occur alongside the technology of data encryption and safety monitoring.

## 5.6 Conclusions and Applications

This study has established a model by which full-flight data analytics can create value for the airline customer operating Pratt & Whitney engines. Existing incidence rates of adverse operational events were quantified, and the potential for cost avoidance was evaluated through various scenarios of event prevention. Using publicly available cost data for two carriers that operate the V2500 engine, the cost avoidance estimates were translated to potential unit cost savings, which are metrics of value to airlines in determining operational efficiency, business outlook, and investor confidence.

When applied to other operators of the V2500, the event avoidance and cost savings will vary based on their historical engine event incidence rates. Given the variety of EHM services possible, which are based on individual airline agreements, the realized value of flight-flight data analytics will also vary. Nevertheless, the model presented here offers a baseline on which individual airline datasets can iterate and refine. Importantly, successful implementation of engine health prognostics will rely on cooperation between Pratt & Whitney and airline customers to capture, transmit, and share the most accurate data possible. The stakeholders must seek alignment on data integrity and availability, so as to ensure that the outcome is reliable, replicable, and ever-growing in intelligence.

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