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Decision Support Approach to Fleet Maintenance Requirements in the Aviation Industry

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This paper discusses a decision support approach in modeling jet engine life and predicting maintenance requirements for engine restoration. The removal characteristics are estimated by collecting field data based on the engine age and operating environment. This analysis includes an example of a jet engine application illustrating how the model predictions compare to actual events. In today's highly competitive market, airlines must find more effective ways to reduce costs because the expense of engine spare parts and restoration are steadily increasing. It is critical for airlines to understand how an engine will age towards its mature time-on-wing to determine budgets, shop capacities, and spare engine and spare parts inventories. In an effort to forecast removal rates of jet engines a model was developed that incorporated statistical information obtained from field data. The probability density function for engine removal classifications was estimated by applying a hazard model with consideration of censored field data. These functions, in conjunction with simulation, were used to forecast jet engine removal patterns. This methodology provided improved performance, based on data fit and forecasting accuracy, compared with traditional techniques such as autoregressive integrated moving average and linear regression.

Nomenclature

D	=	number of differences used to discount trends with seasonality in ARIMA (p, d, q) (P, D, Q) model
d	=	number of differences used to discount trends in ARIMA (p, d, q) model
$F(t)$	=	cumulative probability density function of time t to failure
$f(t)$	=	probability density function of time t to failure
$H(t)$	=	cumulative hazard function of time t to failure
$h(t)$	=	hazard function for a distribution of time t to failure
P	=	order of the autoregressive component with seasonality in ARIMA (p, d, q) (P, D, Q) model
p	=	order of the autoregressive component in ARIMA (p, d, q) model
Q	=	order of the moving average component with seasonality in ARIMA (p, d, q) (P, D, Q) model
q	=	order of the moving average component in ARIMA (p, d, q) model
TOWmin	=	minimum time-on-wing value, h
TSSVadj	=	adjusted time since shop visit value, h
TSSVmin	=	minimum time since last shop visit

I. Introduction

HIGH bypass turbofan jet engines entered service over 30 years ago as the modern means of propulsion for commercial aircraft. The jet engine has been an economical method of transporting cargo and people throughout the world. During the past 30 years, significant improvements have been made in the area of jet engine maintenance, resulting in increased time-on-wing (TOW). This TOW improvement has permitted the majority of airlines and repair facilities to use an "on-condition" type maintenance concept for repair and troubleshooting of engines. However, the philosophy and capability of a repair facility will determine the relative "mature" TOW of its engine program.

Since deregulation, the aviation industry has considered many methods, techniques, and procedures to reduce operational costs. Kleinert [1] emphasized that operational engine cost-efficiency is a goal of all airlines. He noted that every element of cost, even if it was a small percentage of the total operating cost, required close control to maintain the cost of air travel at a level that would be attractive to a significant segment of the population. A key driver of operational cost is fuel consumption, which is impacted by performance deterioration and engine maintenance practices. Another key cost driver is the resource allocation for jet engine repairs. To effectively allocate these resources, airlines need to be able to accurately forecast engine removals. The jet engine has many failure modes that can cause the removal characteristics to have a substantial amount of variation in the expected time-on-wing leading to forecast inaccuracies. The aviation industry needs a methodology that can facilitate ways to optimize the allocation of maintenance resources and develop rational decision making criteria.

The objective of this research is to develop a decision support approach in modeling jet engine removal rates based on field data. This is accomplished by the following major steps involving 1) analysis of field data to isolate and understand removal characteristics, 2) determination of reliability estimation of engine removals, 3) development of a practical forecasting model, and 4) validation of the model's prediction capabilities through the use of simulation.

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Ghobrial [2], in a study examining forecasting of aviation activities, stated that current forecasting methodologies for airport operations varied from professional judgment to econometric modeling. Currently, modeling reliability analysis of complex machinery, such as a jet engine, tends to be approached in one of two techniques when forecasting engine removals. One method is to approach the analysis from a microbasis, which is extremely difficult when considering all of the detailed data requirements, resulting in a very labor intensive investigation at the part level. In many cases, this approach is so time-consuming that results are not available when needed and may not be cost-effective. The second approach is taken from a macrobasis with a whole engine level analysis. In this case, the TOW variation is too large to effectively forecast removal times. Individual failure model characteristics need to be considered to minimize this variation.

Renewal theory began as the study of failure and subsequent replacement of components. The ordinary renewal process is represented by a system composed of only one component. This component is assumed to be randomly taken from an infinite population. The process begins by placing one component into operation; after failure, it is replaced by another new component and is considered to be repaired to a "good-as-new" condition. If successive failures are not necessarily identically distributed (renewal process) but become stochastically smaller and smaller (deterioration) or conversely become larger and larger (reliability growth), the renewal theory would not apply. This is the case with complex machinery such as a jet engine; the systems are generally not replaced but are repaired when they fail from a specific part. As Ascher and Feingold stated, this is typically the approach because these types of systems can be restored to almost full functionality by methods other than replacing the entire system. In this case, the usual nonrepairable methodologies are simply not appropriate for repairable systems and the renewal process should not be used because the required refurbishment will typically not achieve a "same-as-new" status [3].

Modeling system deterioration or system growth requires the use of a nonhomogeneous Poisson process (NHPP) system that could improve or deteriorate with system age. The major interest in the reliability analysis of repairable systems is in the probability of system failure as a function of system age. Weckman et al. [4] developed a model to forecast jet engine removals using the NHPP but found significant limitations to the technique. In this case, the Weibull process could not predict the pattern for an airline that had a significant number of mandated removals. In many situations, the mandated removals would result in an engine being prematurely removed due to a cycle limited part versus removals due to engine deterioration or part failure. The significant number of mandated removals distorted the "counting process." These events resulted in a time since shop visit (TSSV) that was underestimated, creating in a higher than expected number of removals.

There are a limited number of published studies in modeling the removal of jet engines. For example, Ghobrial [2] developed a demand model based on multiple regression to forecast aircraft operations at general aviation airports. Huang [5] developed a decision model for deteriorating repairable systems for a turbine-driven pump. A different approach was proposed by Torella and Lombardo [6] in developing an artificial intelligence (AI) system for turboprop engine maintenance. In this case they used expert systems and neural networks to aid in directing the maintenance operation in diagnostics of the removed turboprop engine. Their analysis concluded that engine maintenance was a key activity performed during the operating life of a gas turbine and that careless, hurried maintenance reduces margins of safety and reliability. They believed that an AI system would be a valuable tool and could dramatically improve maintenance without causing a significant increase in costs. There are several published studies in decision making and forecasting in the aviation industry, but the analysis approach is from a more micro basis. For example, Ghobbar and Friend [7] used historical data and a mixture of statistical techniques, such as analysis of variables (ANOVA) and a general linear model, to forecast spare part requirements. In this case, the impact of part removal was driven by the type: hard-time or condition-monitored. The former is very predictable but the latter is not. Other examples of localized or micro estimating deal with the cost estimation of commercial aircraft through the use of regression in developing cost estimation relationships (CER). These CERs are based on multiple metrics such as wing area and cruise mach number [8]. Other short-term planning includes maintenance manpower, which is a very important issue to many airlines, and involves various scheduling algorithms [9]. In addition, expert knowledge is being used in developing rule-based systems such as fault diagnostics of aircraft engines [10].

As a jet engine operates in the field, its performance deteriorates due to fouling, erosion and wear. Zaita et al. [11] presented an approach to predict the performance deterioration of aircraft gas turbines. This model estimated the deterioration based on key factors such as rotating components, the aircraft mission profile, and environmental conditions. Deterioration studies performed by Pratt and Whitney and General Electric on JT9D and CF6 engines found that the major causes of turbine section performance deterioration were increases in tip clearance and flow capacity. Understanding these factors that cause performance deterioration is vital in maintaining the engines' reliability in addition to improved performance retention of new engines. They modeled the amount of engine performance deterioration as a function of the operating load, environment, and time. The model allowed the user to have the ability to input and edit mission profiles, engine characteristics, etc.

Another key problem in modeling jet engines is the fact that the life data is typically incomplete due to censoring or truncation. Fard and Chowdhury [12] presented different approaches for analyzing life data including parametric, nonparametric, and graphical methods such as the maximum likelihood estimators, cumulative hazard function, Kaplan and Meier's product-limit estimate, and graphical methods. Graphical methods are used to determine if a particular distribution is suitable for modeling a set of failure data. In another study by Lincoln and Melliere [13], the aircraft's operating environment was modeled by estimating the variations in flight severity by using the log-normal distribution. Shyur et al. [14] developed an approach using neural networks to predict component inspection requirements for aging aircraft as an aid for the safety performance analysis system developed by the Federal Aviation Administration. This approach could help identify potential problem areas for inspectors by using a neural network to predict when the number of reported problems exceeded expected levels.

II. Jet Engine Characteristics

The jet engine represents the leading edge of technology, advanced manufacturing, quality control, design evaluation, and extensive testing. This machinery, with its hardware and systems can achieve very high standards of reliability. The uncertainty of an engine failure or removal is dependent on a number of external and internal factors [15]:

1) Component-specific factors (design, manufacturing)
2) Operational factors (pressure, temperature)
3) Environmental factors (ambient conditions, temperature, humidity)
4) Maintenance factors (servicing frequency, overhaul strategy)

A major portion of systems in use today require some form of maintenance and repair. The availability of these systems and their ability to perform their functions depends not only on engineering designs, but also maintenance, the repair facilities, and the logistics of spare parts [16]. Similarly, the trend towards a mature time-on-wing for jet engine aircraft is very dependent on the maintenance, repair, and logistic practices. In preventive maintenance, parts are replaced, lubricants changed, adjustments made, etc., before failure occurs, with the objective being to increase the reliability of the system by delaying the aging effects of wear, corrosion, fatigue, etc., whereas corrective maintenance is performed after failure has occurred to return the system to service as soon as possible [17].

The major work for the retention of performance is achieved at the shop level where cost-effective workscopes are developed and implemented. A workscope planning guide is developed with the

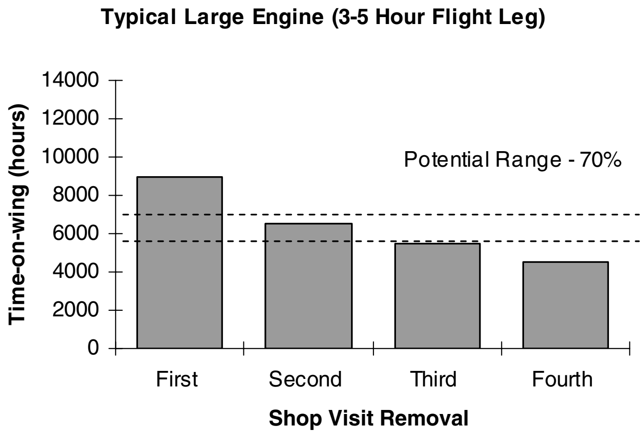

Fig. 1 Obtaining optimum SVR reliability.

engine user that identifies and defines inspection procedures in restoration. Many of these performance recovery and improvement actions are carefully developed based on a cost-effective maintenance plan as defined by Kleinert [1]. The most significant factors affecting engine maintenance costs are shop visit rate (SVR) reliability and exhaust gas temperature (EGT) margin.

After the engines have flown, typically 3–4 years before removal from the aircraft, the hardware will undergo wear, fretting, fatigue, erosion, corrosion, distortion, and other forms of distress. Some of these deterioration factors, if not refurbished properly, can limit the ability of the engine to stay on-wing during its second and subsequent installations. When the cause for removal requires penetration into a module (standardized breakdown of the engine into workable sections) then it is classified as a shop visit (SV). It is at this point that different maintenance philosophies and initial engine designs produce various levels of restored reliability. With good workscope planning and shop methods, an engine can be restored and achieve a subsequent TOW of approximately 70% of first run (new) capability (see Fig. 1 adapted from Kleinert [1]). However, in many cases the TOW will deteriorate to as low as 50% of first run capability as the engine ages [1]. The types of performance deterioration for turbine jet engines are [18]

1) Recoverable with cleaning/washing (accumulation dirt, dust, pollen, particles in gas path, etc.)

2) Nonrecoverable with cleaning/washing (deposits remain after cleaning/wash, flow path damage, erosion, corrosion, etc.)

3) Permanent not recoverable after refurbishment (as closely to "as new" but loss due to eccentricity in clearances, increase leakage paths, surface roughness, distortion in platforms, etc.)

These factors account for the inability to restore the reliability of a jet engine as it ages, resulting in a condition not "same-as-new." Love and Guo define this condition as imperfect repair [19].

III. Example: Jet Engine Application

Maintenance data from two different airlines, with different operating conditions, were analyzed. These airlines were referred to as "Airline A" and "Airline B" to maintain confidentiality of the operators, and the data was masked and scales on graphs were omitted due to proprietary reasons. The engine removal data spanned eight years and included over 800 engine removals. The database includes key information such as time since new (TSN), time since last shop visit measured in flying hours (TSSV or TOW), cycle values, measured as cycles since new and cycles since shop visit (CSN and CSSV), shop visit removal number (SV), removal cause codes, engine delivery, and removal dates (event). In addition to past events, the database also includes all current engine locations with up-to-date time and cycle values. The current engine location data (operating aircraft) is essential information when determining the censored impact on estimating reliability distributions. All of the historical data was used to develop the model, whereas a more recent update of removal statistics for the following 27 months of the airline's operation was used to evaluate the effectiveness of each forecasting methodology.

A. TOW Behavior

To better understand how the engines performed, the removals for Airline A's entire fleet of aircraft were plotted to determine the frequency with respect to time since last shop visit (see Fig. 2).

However, analyzing the characteristics for first run engines along with refurbished engines can be misleading. Throughout the life cycle of an engine, each resulting shop visit restores the subsequent TOW to a lesser degree of its first run capability. This loss of capability was observable from field data collected over the time period as the engine aged (see Fig. 3). By trending the data according to removal number, the average TOW of a first run (new) engine was compared with refurbished engines. Another key factor was the amount of censoring of the data.

B. Censored Data

In life testing there are many occasions when the analysis will include censored data. Censored data will arise when units are 1) removed from test or service before failure, 2) still operational at the time of the data analysis, and 3) removed from test or service due to an extraneous cause. When using field data, rather than test data, the analyst will frequently encounter problems in deficiencies of the reported data. In the reliability field, misinterpretation of data appears to be widespread due to analysis in which only failure times have been analyzed and the censoring times ignored. This is typically due to the fact that the analyst is unaware of the importance of censoring information. By neglecting unfailed components, a bias is introduced in the modeling of failure [20,21].

There are four major classes of censored data that are encountered in the analysis of reliability data: singly censored type I, singly censored type II, multiply censored and doubly censored data (see

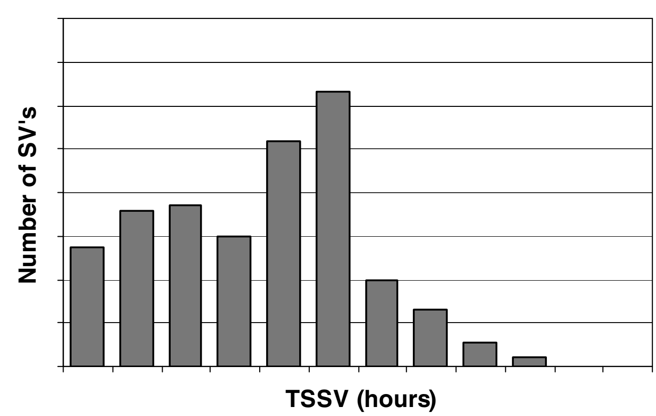

Fig. 2 All shop visit removals.

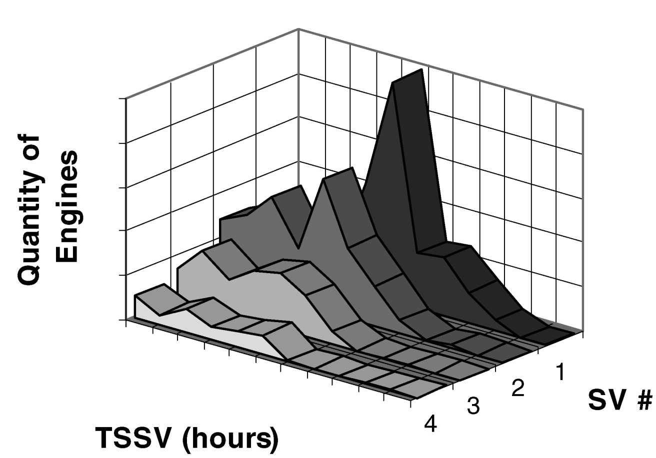

Fig. 3 TSSV by shop visit number.

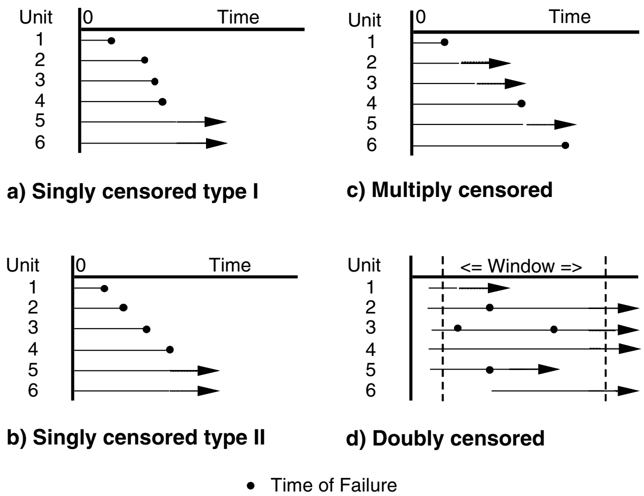

Fig. 4 Types of data.

Figs. 4a–4d). Failure times that are known only to be beyond their present running times are referred to as "censored on the right." The "unfailed" units are called run-outs, survivors, removals, or suspensions [22]. Singly censored (type I) occurs when units of observation are started at the same time, then at a predetermined time the test is discontinued, and observations are made of the number of units that have failed (time is fixed).

The term "singly censored" refers to the one censoring characteristic. Singly censored (type II) is observed in a situation where the test is carried out until a predetermined number of failures have been obtained (failures are fixed). All runout units have the same runout times which are equal to the time of the last failure. Multiply censored data occurs when units come into service at various times during the data collection interval. Data, if censored on the right, would have differing running times intermixed with failure times (also called progressively or arbitrarily censored) [22,23]. Doubly censored data occurs when a system is observed in which some of the ages are unknown and some of the units are unfailed, resulting in both left and right censoring. This situation occurs only when a window exists for data collection, which is typical of sequential replacement problems where field data have residual life and right censored observations [24–26].

C. Failure Modes

Many products fail from more than one cause. The key to analyzing complex machinery was to breakdown the failure data into common individual population categories (failure modes). Because of proprietary reasons, the removal types will be coded A through F. Mandated removal types can typically be scheduled by the airlines. Because this removal type can be scheduled, they were separated from unscheduled removals. The results were then plotted as a Pareto chart to illustrate their relative importance within engine removals (see Fig. 5).

These types of events are considered competing failure modes and can typically be modeled by a series system. The series-system model assumes [27] 1) each unit has M potential times to failure: one from each mode, 2) the M times are statistically independent, and 3) the time to failure of a system is the smallest of its M times, where M represents the number of failure modes. For each independent part, a different probability density function (PDF) should be established with its own dataset.

D. Premature Removals

Another concern involves units from different production periods that may have different life distribution due to differences in design, raw materials, environment, usage, etc. Typically, at the introduction of any new engine program, a distinct event pattern arises. This pattern has a very high initial failure rate (engine removals) in the first years of the program. These removal events are usually the result of

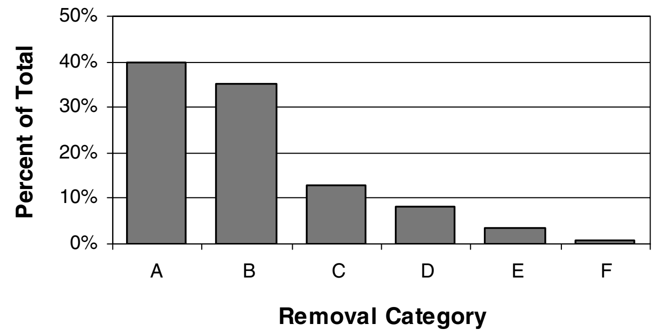

Fig. 5 Pareto chart of removal categories.

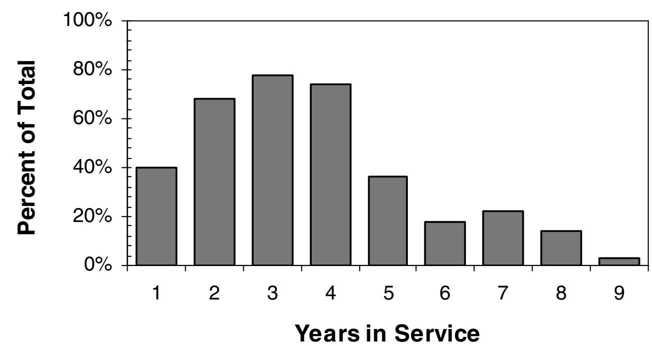

Fig. 6 Percentage breakdown of removals by year.

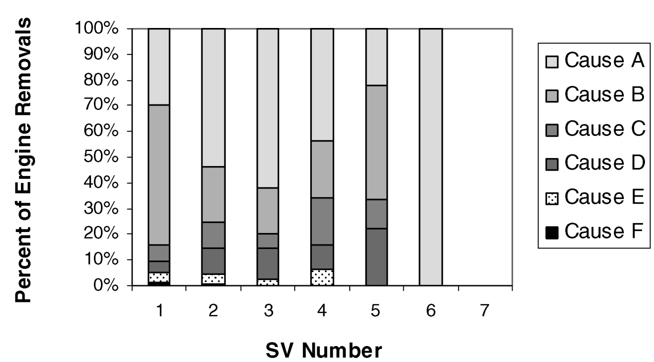

Fig. 7 Removal category by year.

early design or procedural problems and are classified as infant mortality or premature removals (see Fig. 6). It was necessary to identify these events, which are premature in nature, to estimate the PDF for the current and future populations. Figure 7 illustrates that the key contributor, Cause B, did indeed, result in a substantially higher number of engine removals in the early SV number (indicative of the early years of operation) than in later SVs. Figure 8 breaks down a few key component failures by year.

IV. Methodology

The model development was divided into the following key steps: 1) failure category and SV separation, 2) PDF estimation, 3) seasonal effect, and 4) simulation design.

A. Category and SV Separation

The first step in the methodology was to separate the database into the key removal categories and shop visit number while including the censored data. This separation resulted in the need for up to 20 different pdfs in order to characterize this model. Figure 9 illustrates this breakdown for two of the failure modes.

Next, for each of these removal categories, the impact of censored data needed to be added to analyze the complete picture. In this analysis, the censored data was combined with the removal data (see

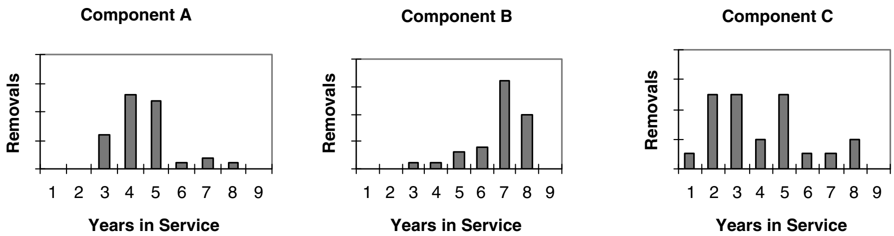

Fig. 8 Removals by key components.

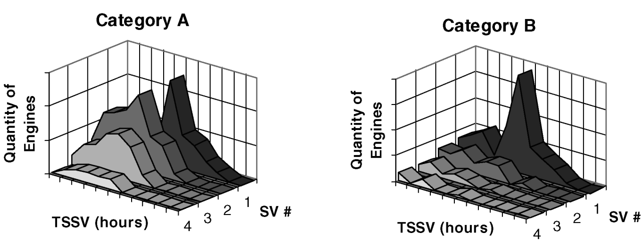

Fig. 9 Shop visit removals by removal category.

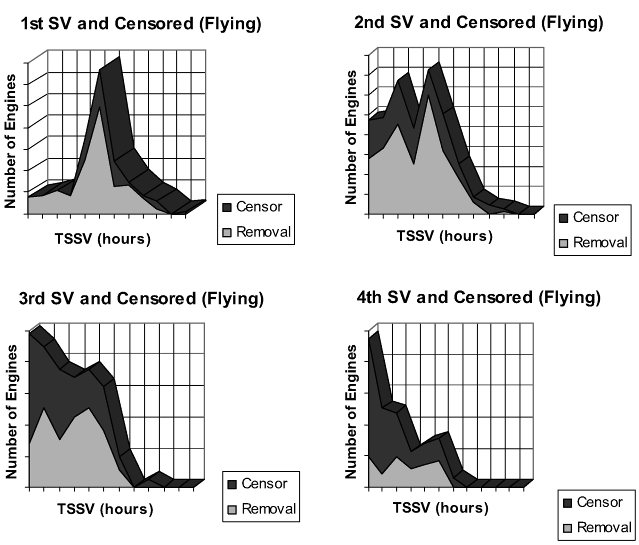

Fig. 10 Censored impact.

Table 1). This combination allowed each PDF to consider the TSSV of engines that were still flying and allowed these times to influence the value of the parameters. In many cases the mean parameter would be understated if the censored data was not considered, because a significant portion was beyond the mean value. As illustrated in Fig. 10, the TSSV of engines still flying has a significant impact on the final frequency distribution for refurbished engines.

After the removals and censored data were combined, the parametric values were estimated, using a graphical technique known as hazard plotting.

B. PDF Estimation

The hazard rate is popular in reliability work because it takes into account the information continuing in the censored times of the unfailed units in determining the appropriate plotting positions for each failure. This methodology is frequently used as criteria in decision making, especially in burn-in estimation of complex equipment or replacement situations where alternatives such as drill wear versus downtime, scrap cost, or replacement cost [28,29]. The $H(t)$ of a distribution is [23]:

$$H(t) = \int_{-\infty}^{t} h(t)\,\mathrm{d}t = -\ell_n[1 - F(t)] \tag{1}$$

Table 1 Combination of removals and censored data

Removal: SV number	Censored: last SV number
1	0
2	1
3	2
4	3

The scales represented on the graph paper used for a theoretical distribution are constructed so that the $H(t)$ and time t are linearly related to each other as:

$$F(t) = 1 - \exp[-H(t)] \tag{2}$$

This relationship between $H(t)$ and $F(t)$ is shown in the construction of all hazard papers. The scales on hazard paper for a specific theoretical distribution are chosen to produce a straight line. The basis for this relationship is the assumption that the sample cumulative hazard function (sum of the conditional failure probabilities) approximates the theoretical cumulative hazard function (integral of the conditional failure probabilities). The conditional failure probability of unit k is represented by $1/k$ where k is its reverse rank and is initially set equal to the number of units (both failed and unfailed). As an example, Table 2 illustrates how the data was organized to determine the Weibull parametric values to "best fit" the part failure removal category. In this example the data included 226 censored and 37 removal observations. By applying the hazard plotting technique, the "best" PDF was chosen for each of the five categories. Figure 11 is an example that illustrates the Weibull PDF by SV removal number for the Category B classification. The basic model logic assumed that the five PDFs could be combined as a series system in which the minimum TSSV time would result in removal of the jet engine. The model design was then programmed using ProModel, a discrete event simulation software package.

C. Seasonal Effect on Removals

A goal of the model was to forecast the removals on a monthly basis; therefore the potential of seasonal effects was investigated. The outside ambient temperature has an impact on the engine's EGT. Typically, as the outside temperature increases, so does the EGT and vice versa. High EGT is often a cause for engine removals. For key airports, the average daily maximum (ADM) were recorded on a monthly basis within a typical year to track ambient temperatures. In analyzing the field data, the seasonality impact of temperature was not as obvious as the ADM characteristic. This would imply that the impact of temperature, as a seasonality factor, was at a small enough level that other factors or "noise" mask this phenomenon. The seasonal effect was placed into the simulation model to reflect the change in temperature during different months of the year. The adjustment factor was determined for each month and applied to the TSSV of the engine flying. From a modeling aspect, the influence of ADM temperature was used in the simulations by calculating a ratio for each month and weighting this ratio with respect to TSSV as:

$$\text{Seasonal Factor}_{\text{June}} = \text{ADM Temperature}_{\text{June}}/\text{AverageADM}_{\text{Year}} \tag{3}$$

Table 2 Hazard plotting technique: part failure class for SV #2

Removal category	Censor	Reverse rank	Hazard value	Cumulative hazard value	TSSV
Flying	1	263	0	0	——
Flying	1	262	0	0	——
Flying	1	261	0	0	——
D	1	260	0	0	——
Flying	1	259	0	0	——
D	1	258	0	0	——
F	1	257	0	0	——
⋮	⋮	⋮	⋮	⋮	⋮
Flying	1	248	0	0	——
B: Component B	0	247	0.404858	0.404858	800
B: Component J	0	246	0.406504	0.811362	925
B: Component A	1	245	0	0.811362	——
B: Component G	0	244	0.409836	1.221198	1200
Flying	1	243	0	1.221198	——
⋮	⋮	⋮	⋮	⋮	⋮
Flying	1	3	0	53.61224	——
C	1	2	0	53.61224	——
Flying	1	1	0	53.61224	——

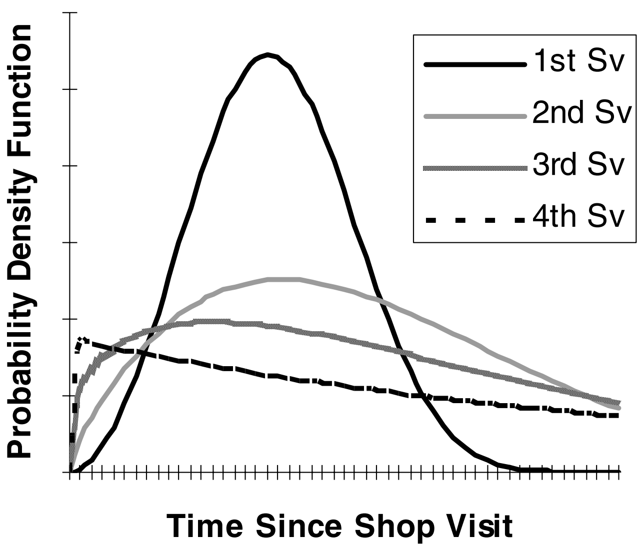

Fig. 11 Weibull PDF by SV removal number for Category B.

$$\text{TSS V}_{\text{June}} = \text{TSSV} * (1 + \text{Seasonal Factor}_{\text{June}} * \text{Weighting Factor}) \tag{4}$$

The weighting factor was added to allow the ADM temperature effect on TSSV to be proportionally raised or lowered for a given simulation run. Through this method, the seasonality was considered as to how it influenced the life of a jet engine within the simulation phase.

D. Simulation Design

The basic model logic assumed that the removal PDFs could be combined as a series system in which the minimum TSSV time would result in removal of the jet engine. This assumes that each removal category was independent of each other. The basic model design considered a number of factors as illustrated in Fig. 12. Figure 13 illustrates the logic used in the model to determine the removal time (event) of an engine, while taking into consideration factors such as seasonal impact, spares influence, and premature and mandated removals (life limited hardware).

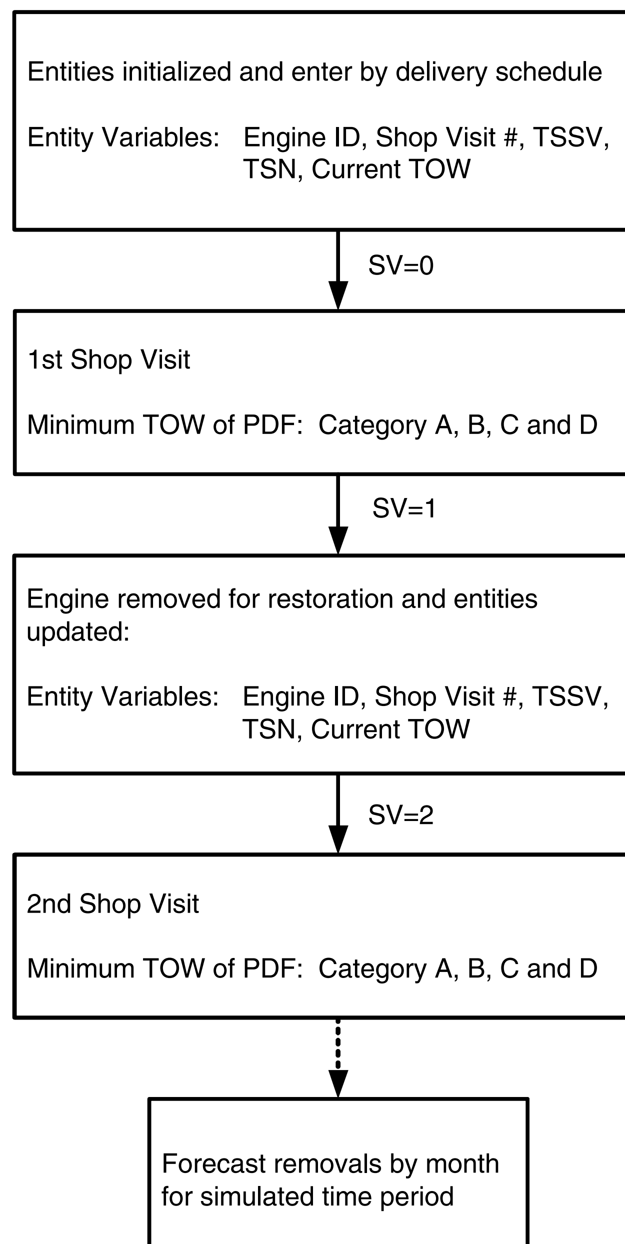

Fig. 12 Simulation design.

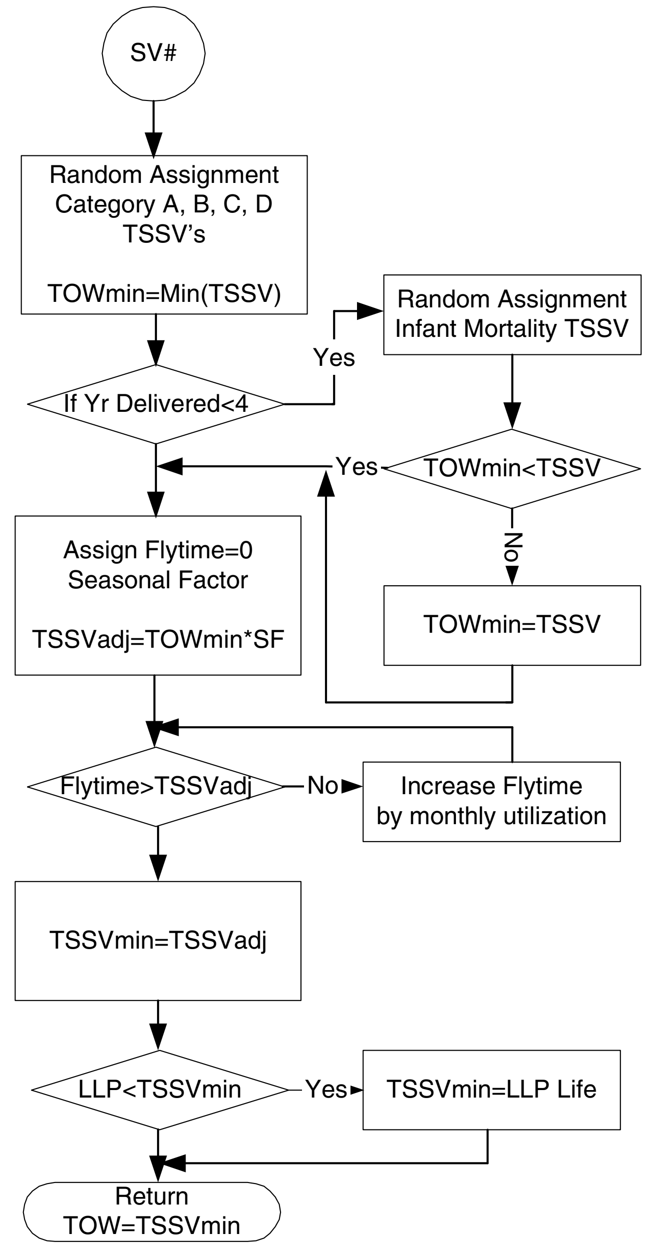

Fig. 13 Flowchart of model logic.

V. Baseline Comparison: ARIMA and Linear Regression

A. Linear Regression

This technique was included as a baseline, in the sense that today this methodology was typical of the type of analysis that many airlines would consider using. Based on linear regression technique, an equation was calculated to fit the removal data of each airline based on least squares. A forecast for future removals was calculated once the best fit line was determined.

B. ARIMA

One of the main advantages of applying Box–Jenkins's techniques to repairable systems is the great flexibility of their autoregressive integrated moving average (ARIMA) model. These methodologies can be used to model the wearout process, actual failure times, times between failures, interactions between failure times, and maintenance times of complex systems [30]. This general model includes autoregressive, moving average parameters, and differencing in the design or formulation. The abbreviated form for the model is ARIMA (p, d, q) (P, D, Q).

The first step in the analysis is model identification. Identification of the models was determined by analyzing the autocorrelation and partial autocorrelation functions. When the autocorrelation function dies down gradually, the process is considered nonstationary and requires differencing until it becomes stationary. In this case, the data was a nonstationary process and became a stationary process after one differencing.

After the data was differenced, the autocorrelation and partial autocorrelation functions can be analyzed to see what type of ARIMA model best fits the data. Based on the characteristic of these two functions, an ARIMA model was determined based on the following guidelines. For Airline A the model chosen would be the best between a moving average [ARIMA (0,1,1)] or an autoregressive [ARIMA (1,1,0)]. Seasonal models used the same identification criteria, but also looked for a repeating pattern in the autocorrelation function. In addition, nonseasonal models typically cut off after lag *k<* =2 in the partial autocorrelation function. Even though the data did not suggest a seasonal influence based on the guidelines above, the ARIMA (0,1,1) (0,1,1) was chosen.

VI. Results

A. Model Fit to Historical Data

Linear regression was used as a forecasting baseline to compare the PDF and ARIMA models. The analysis completed for all three methodologies resulted in the list of models shown in Table 3. These were fit to historical data, and listed along with their respective mean square error (MSE) and mean absolute deviation (MAD) values for each airline (see Table 3).

Overall, the models obtained a MSE in the range of 4.7–5.7 and a MAD in the range of 1.5–1.7 (excluding the linear regression model with MAD of 5.0) for Airline A. The models obtained MSE in the range of 1.7–2.5 and a MAD in the range of 1.0–1.2 (excluding the linear regression model with MAD of 2.9) for Airline B. As expected, the MSE values for Airline B are about half those of Airline A, because Airline B's number of aircraft and removals are about half of those for Airline A.

B. Model Fit to Forecasted Data

After model selection, the next step was to compare their forecast to actual results. In this case, an analysis was made for all of the models by comparing their forecast to actual removals over an additional 27 month period. Each airline had a different removal trend over this time period. Airline A's removal pattern flattened off from the prior months' rate of increase, whereas Airline B's removal pattern continued at a steady rate of increase. Table 4 lists their respective MSE and MAD values.

Overall, the models obtained a MSE in the range of 11.3–15.8 and a MAD in the range of 2.8–3.4 for Airline A. Based on these measurements, the following models appeared to have the best forecast:

1) PDF: 1.25% seasonal weight for Airline A
2) PDF: no seasonal weight for Airline B

To measure overall accuracy of the various models, the differences between the quantity of removals was calculated based on cumulative absolute deviation (CAD):

$$\mathrm{CAD} = \mathrm{CAR} - \mathrm{CFR} \qquad (5)$$

where CAR is the cumulative actual removals and CFR is the cumulative forecasted removals. The cumulative absolute deviation was calculated to compare overall forecasting error as shown in Table 5.

VII. Conclusions

These results indicate that the PDF model can be used to predict jet engine removals. The accuracy of the PDF model for both airlines was within 3–8% and averaged 5.5%. The accuracy for the linear regression and ARIMA model varied from one airline to the next

Table 3 Fit to historical data

Airline A				Airline B			
Model		MSE	MAD	Model		MSE	MAD
PDF	No seasonal effect	4.9	1.6	PDF	No seasonal effect[a]	2.1	1.1
	1.25% seasonal weight[a]	4.7	1.6		2.5% seasonal weight	2.3	1.1
	2.50% seasonal weight	5.2	1.6		5.0% seasonal weight	2.4	1.1
Time series	Linear regression	5.0	5.0	Time series	Linear regression	2.3	2.9
	ARIMA (0 1 1)	5.0	1.5		ARIMA (0 1 1)	2.3	1.2
	ARIMA(0 1 1)(0 1 1)	5.7	1.5		ARIMA(0 11)(0 1 1)	2.3	1.1

[a]"Best fit" by model type based on MSE and MAD.

Table 4 Fit to forecasted data

Airline A				Airline B			
Model		MSE	MAD	Model		MSE	MAD
PDF	No seasonal effect	13.7	3.1	PDF	No seasonal effect[a]	4.6	1.8
	1.25% seasonal weight[a]	11.3	2.8		2.5% seasonal weight	4.4	1.7
	2.50% seasonal weight	14.0	3.0		5.0% seasonal weight	5.0	1.7
Time series	Linear regression	15.1	3.3	Time series	Linear regression	4.6	1.7
	ARIMA (0 1 1)	11.4	2.9		ARIMA (0 1 1)	6.6	1.8
	ARIMA(0 1 1)(0 1 1)	15.8	3.4		ARIMA(0 11)(0 1 1)	5.1	1.7

[a]"Best fit" by model type based on historical data.

Table 5 Model accuracy

Best model	Airline A		Airline B		Overall model average error
	CAD	%	CAD	%	
PDF	24 SV	8	5 SV	3	5.5%
ARIMA (0 1 1)	16 SV	5	60 SV	32	18.5%
ARIMA (0 1 1)(0 1 1)	36 SV	12	19 SV	10	11.0%
Linear regression	55 SV	19	8 SV	4	11.5%

between forecasting periods. This is in part due to the fact that the linear regression and ARIMA methodology "fits" the testing (historical) data without fully understanding the underlying process. In this case the pattern is difficult to identify for both airlines by the linear regression and ARIMA models due to hidden phenomena in the series.

Although this PDF model also requires a substantial amount of data and time to establish, it is the most flexible in its ability to predict the impact of product improvements or part failure problems. They can be introduced by changing the PDF parameters that are affected and the period of time. These changes can be accomplished in the simulation model with few modifications. When using the PDF model, this methodology presented nullifies the limitations of existing methods as discussed previously by identifying subgroups (removal classifications) and analyzing the variations within each group to better predict the removal rates (engine life) with a much higher level of accuracy. Because each removal classification is analyzed separately, the overall variation is reduced, allowing for a more accurate forecast. In addition, many of the engine parts can be grouped together according to the cause of removal, thus reducing the amount of labor needed and the requirements for data collection. Both of these changes result in the ability to obtain the results of the analysis within a more reasonable time frame. These new methodologies of applying existing techniques allow for the practicality of forecasting reliability of complex machinery where previous methods simply were not cost-effective or sufficiently accurate. As noted, the PDF model can account for planned improvements and predicted failure modes. This is a limitation of using the ARIMA and linear regression models.

For the aviation industry, this level of forecasting accuracy would represent significant savings for an airline. This is best illustrated by the impact of maintaining additional spare engines to account for inaccuracies in current forecasting methods. Present day feelings among airlines agree that current methodologies provide very inadequate forecasting of engine removals.

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