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Managing Failures of Aircraft Systems by Coapplication of Parametric and Nonparametric Methods

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Analysis of failures that occur in an actual operational environment is very important for the maintenance service providers and manufacturers to offer specific maintenance solutions or product improvements tailored to the customers' needs and to survive in the highly competitive aviation market. There are mainly two methodologies for failure analysis: Parametric approach and nonparametric approach. Practitioners usually prefer one of these methodologies alone for monitoring or predicting the failure trends. However, each methodology has its own strengths and weaknesses for any application. Therefore, it may be useful to view these methods as being complementary for obtaining the most benefit from the failure analysis. This paper brings the parametric and nonparametric methodologies together for extracting valuable management information from the field failures of aircraft systems with an example of auxiliary power unit application. Opportunities of coapplication of the methodologies are described for identifying failure trends and unusual behaviors and revealing hidden information that may otherwise not be detected by the application of only one of those methodologies.

Nomenclature

K = total number of systems
$N(t)$ = total number of failures by time t
S = observation starting time
T = observation ending time
t_t = auxiliary power unit total operating hour
$u(t)$ = failure intensity (rate of occurrence of failures)
$V(t)$ = variance of cumulative number of failures at time t
β = power-law parameter
θ = power-law parameter

Subscripts

i = failure number
q = system number

I. Introduction

FOR a long time, aviation has been a business mostly between the original equipment manufacturers (OEMs) and the operators. However, a few decades earlier, new types of companies began to emerge in the market, which are usually referred to as MRO (maintenance, repair, and overhaul) service providers and PMA (part-manufacturer approval) suppliers. The primary driver behind the growing acceptance of MRO and PMA companies by operators is the significant cost savings they deliver. However, the reason behind this shift cannot be explained only by the lower prices offered. In addition to the lower prices they offer, those companies fill the gap by offering maintenance solutions or product improvements to the operators' specific problems when an OEM is not responsive or is unwilling to address those problems. Therefore, in order to compete with the others, the companies (whether an OEM, MRO, or PMA) should offer specific maintenance services or product supports that are tailored to each operator's particular operational environment in a cost-effective manner without impairing the airworthiness of the aircraft. To develop specific maintenance services or product improvements for any operator, those companies should monitor and analyze the failures that occur at operators' particular environment. Therefore, analysis of failures from the field and the methodology to be used for failure analysis has gained a central importance in the market. It is preferable that the methodology to be selected for field failure analysis is statistically valid, yet allows for identifying failure trends, misbehaving systems, unusual behaviors, and the effects of local environmental and operational conditions on the failures. It should be easy to communicate and understand so that it enables managers and field engineers to make quantifiable and rational decisions in the field, which had been usually the domain of guesswork and experience.

In terms of the failure analysis, any aircraft is a complex system. It is composed of many subsystems. Each subsystem is formed by subunits at a lower level. The failure analysis practitioners often attempt to model failures of such systems with sophisticated parametric methods that are extremely powerful but rigorous. The parametric approach for failure analysis is based on fitting a theoretical distribution to a sample of failure data. This approach is particularly useful for providing information beyond the range of the sample data. Furthermore, it allows for performing more complex analysis of the failure process. There are various parametric methods for failure modeling at different levels. Distributions based on renewal theory are used for analyzing failures at the level of individual components that are replaced by the new components when they fail. Weibull distribution [1] is the most commonly used model for this purpose. However, a distribution that uses renewal theory, such as the Weibull distribution, cannot be used to estimate the failure pattern of a system that is not replaced, but repaired, when it fails. To address the failure characteristic of a repairable system, a process is often used instead of a distribution. The most popular process model for repairable system analysis is the power-law model [2]. As the Weibull distribution

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addresses the very first failure, the power-law model addresses each succeeding failure for a repairable system. Both of these powerful parametric methods require estimation of parameters using some rigorous statistical methods such as the maximum-likelihood estimator (MLE), which makes them too complex for communicating with management, engineers, and customers. Furthermore, the parametric failure analysis is made more difficult by the highly multicensored (left and right) nature of field data and because of constant changes in the system upgrades, training, environmental issues, or operation and management conditions. Management, engineers, and field service teams that maintain and support aircraft systems may easily be intimated by such complex techniques.

Another approach for analyzing failures is the usage of a nonparametric method. Average practitioners relate more easily to the nonparametric approach than to indiscriminate modeling with various distributions. Graphical techniques based on plotting cumulative failures and mean cumulative function (MCF) [3–6] provides a nonparametric method for analysis of field failures. It can be successfully used to monitor the field failures and identify failure trends, anomalous systems, unusual behaviors, effects of various parameters (maintenance policies, environments, operating conditions, etc.) on failures, and so on. It requires minimal assumptions and provides a well-established step before moving on the assumption of an underlying distribution for parametric model.

Considerable attention has been devoted to analysis of field failures by application of parametric or nonparametric methodologies as an alternative to each other. The objective of this paper is to explore the application of the parametric and nonparametric methods as being complementary, to present effective field data analysis methodologies for aircraft systems. In the practical example presented here, it will be shown that combined application of those methods allows keeping the advantages and overcoming the disadvantages of each method. Though the discussion is presented here in the context of the auxiliary power unit (APU) system, the techniques covered are general in their applicability.

The rest of this paper is organized as follows: A brief description of the aircraft APU system is presented in the next section. In the third section the data used in the study are presented with explanations. The fourth section presents applications of nonparametric and parametric methods for monitoring and estimating failure trends. In the fifth section, further analyses of failures for extracting invaluable information from the available data are described. Finally, the paper is concluded in the sixth section.

II. Auxiliary Power Unit

The APU is a self-contained gas turbine engine that supplies compressed air for main engine starting, air conditioning, and electrical power on the ground or in flight. This provides independence during turnarounds, electrical backup in the event of engine failure, and air conditioning and pressurization during an engine bleed-off. Generally, an APU consists of a load compressor, engine compressor, turbine, and a gearbox that drives the generator and other accessories. It is monitored and controlled by an electronic controller. Automatic shutdown protection is provided in the event of low oil pressure, system fault, overspeed, overtemperature, or fire.

The cooling of the oil cooler and electrical generator is provided with positive airflow by a gear-driven fan. Inlet air is ducted to the fan through a shutoff valve that opens when pressure is sensed in the bleed feeder duct. Fuel for the fuel control unit is available from the fuel tank whenever the APU is operating. In the APUs that were studied in this paper, the fuel is automatically heated, if required, to prevent icing. APU speed is automatically controlled by signals from the electronic controller to the fuel control unit, which modulates the fuel flow to control speed. A surge control valve prevents the load compressor from stall by dumping bleed air if flow demands do not match with inlet guide vanes' positions. When electrical load and air extraction combine to raise the exhaust gas temperature above acceptable levels, the inlet guide vanes to the load compressor trim to a more closed position, reducing air extraction but still maintaining the electrical load.

There are four indication lights at the cockpit for showing the system malfunctions. The fault indicator illuminates when an APU malfunction exists (such as overtemperature) and causes the APU to initiate an automatic shutdown. A low-oil-pressure indicator indicates that the APU oil pressure is low, causing the APU to initiate an automatic shutdown. The overspeed light indicates that APU speed is excessive. A maintenance indicator shows that an APU maintenance problem exists, but the APU may be operated. There are three failure modes within the APU system that cause the maintenance light to illuminate: fault of the oil quantity switch, low oil quantity, and starter/generator shorted rotating diode. By performing an APU built-in test-equipment (BITE) check, the failure mode can be determined and then a proper troubleshooting method can be applied.

III. Failure Data

The failure data analyzed here were obtained from a local aviation company in Saudi Arabia for the APUs installed in a very popular aircraft. The aircraft is used by most of the airlines around the world. The company has five aircraft in its fleet. The way airlines maintain and support their fleets is rather sensitive information. To respect the sentiments of the airline and the aircraft and APU manufacturers, their names are not disclosed and the failure data used are a few years old.

The company conducts scheduled maintenance and inspection services through preflight, postflight, transit, A, and C checks in its in-house facilities. A checks that last five working days are repeated monthly. C checks are performed annually and take 4–6 weeks. During the periods of A checks and C checks, the aircraft is grounded. Maintenance-task cards indicate that the APU system is maintained through appropriate letter checks under an on-condition maintenance process that requires inspections and checks of certain subsystems and components such as BITE check, operational check, general visual inspection of APU remote-control panel, etc. If the inspection requirements are not satisfied, necessary repair/replacement actions are taken by following the appropriate troubleshooting task recommended in the fault-isolation manual or service manual of the unit. There are no maintenance tasks that require hard-time intervals such as scheduled borescope inspection.

The failure data were collected from maintenance records of the company over a period of about five years for seven APUs. The serial numbers of the APUs are masked and they are named in serial order from 1 to 7. The APUs were new as of the beginning of the data collection. The data have the following entries: routine/nonroutine work, aircraft registration number, description of reported fault, Air Transport Association chapter number, date, description of corrective action, aircraft total time, aircraft total cycles, and APU total time. Table 1 shows summarized failure data related to APU 3. There are similar failure data records for each APU. In this study, a failure is defined as degradation below a defined level of limit set by the manufacturer's specifications. Maintenance and shop records

Table 1 Failure data for APU 3

Failure number	Failure time (APU total hours)	Component	Failure cause
1	380.2	Oil cooler	Contamination
2	760.3	Oil cooler	Contamination
3	1450.0	Rotating diode	Short
4	1950.6	Oil cooler	Contamination
5	2350.6	Compressor	Erosion
6	2628.4	Rotating diode	Short
7	3050.8	Wire harness	Short
8	3500.3	Oil cooler	Contamination
9	3800.2	Rotating diode	Short
10	4586.5	Oil cooler	Contamination
11	4900.7	Oil cooler	Contamination
12	5200.4	Wire harness	Short
13	5660.4	Oil cooler	Contamination
14	6169.6	Compressor	Erosion
End of observation	6400.1	——	——

were reviewed in detail for the APU failures. This enabled the determination of whether a field removal was a confirmed failure or a no-fault-found failure, thus eliminating false removals in the data. A total of 95 confirmed failures were observed for all APUs. In the case of 15 failures, APUs were sent to the manufacturer for repair. In all of those cases, the reasons for removal of the APU were the same and stated as "low duct pressure and surge with main engine start." The findings reports have indicated that APUs suffered from excessive erosion in the compressor section, which was most likely caused by ingestion of dust and/or sand. The rest of the failures were fixed onsite. Among the failures were electrical shorts, turbine blade walking, oil-cooler contamination, oil leakage, igniter plug failure, etc.

IV. Analysis of APU Failures

A. Graphical Method Based on MCF

The failures of the APU are first modeled by graphical technique based on plotting cumulative failures and MCF. The main motivation of choosing this method is that it allows for monitoring system failures without resorting to complex stochastic techniques while maintaining statistical rigor. The method enables the user to analyze the failure data without assuming an underlying distribution. The ability to analyze data without assuming an underlying life distribution avoids potentially large errors brought about by making wrong assumptions about the distribution. This very efficient method has also an advantage of being appropriate for failures both at the component and system levels. It is capable of handling both right and left censoring. The graphical method uses cumulative and MCF plots that are simple and easy for reporting key figures to management. On the other hand, the resulting confidence bounds from nonparametric graphical analysis are usually wider than those obtained from parametric analysis and predictions outside the range of observations are not possible. Therefore, the parametric power-law model is also used to complement graphical method that is usually proven to be useful in practice.

In this method, the failure data of each system is first plotted against calendar time, including downtime, which produces cumulative plots over calendar time. To obtain cumulative plots over the operating time, the data are then transferred from calendar time to operating time by removing the downtime of each system. Next, it is necessary to determine the number of systems at risk as a function of operating time. Then the mean cumulative function is calculated and plotted against the operating time. MCF is calculated at each failure by using a recursive formula [6,7]:

$$\mathrm{MCF}\,(t_i) = \mathrm{MCF}(t_{i-1}) + \frac{1}{N(t_i)} \tag{1}$$

where $N(t_i)$ is the population at risk at time t_i: i.e., the number of systems in use at time t_i. Note that Eq. (1) allows for a decreasing population, and so right censored data involves no extra calculation in MCF plotting. If multiple systems have a common failure time, then these systems could be put in certain orders or sorted randomly.

MCF is a nondecreasing staircase function that is flat between failure times, but the flat portions need not be plotted. For a large number of failures the staircase curve merges to a more or less continuous curve through plotted points. Not only the magnitude, but also the shape of the MCF curve, gives important information about the average failure trend of the systems analyzed. An MCF curve with increasing slope indicates an increasing failure trend over time, which means that underlying system is deteriorating with age. A curvature with decreasing slope indicates a decreasing failure trend over time, which points to an improving system with age. A straight line through the point of origin indicates a random failure pattern with no trend. The slope of the MCF curve is known as the recurrence rate (RR) and represents the number of failures per unit time. It is also called rate of occurrence of failures (ROCOF) or failure intensity. From the corresponding continuous MCF it is possible to find and plot the local recurrence rate. The recurrence rate plot magnifies the trends in the MCF curve and identifies portions of age or calendar time where the rate of occurrence of failures is increasing or decreasing. Even though they have the same units (number of failures per unit time), recurrence rate (or ROCOF and failure intensity) should not be confused with the failure rate of a life distribution (such as Weibull distribution) for unrepaired components. The failure rate for a life distribution has an entirely different definition, meaning, and use. However, in the case of exponentially distributed component lifetimes, the failure rate is constant and the recurrence rate is equal to the failure rate.

It is possible to give a good approximation to the pointwise confidence limits to the MCF values. The approximated upper and lower confidence limits for every observed MCF value are [8]

$$\mathrm{MCF}^-(t_i) = \mathrm{MCF}(t_i) - U_{1-\frac{\alpha}{2}}\sqrt{V(t_i)} \tag{2}$$

$$\mathrm{MCF}^+(t_i) = \mathrm{MCF}(t_i) + U_{1-\frac{\alpha}{2}}\sqrt{V(t_i)} \tag{3}$$

Here, $U_{1-\frac{\alpha}{2}}$ is the $1-\frac{\alpha}{2}$ percentile of the standard normal distribution. For 80%, 90%, and 95% confidence limits, it is 1.28, 1.54 and 1.96, respectively. $V(t_i)$ is the variance of the cumulative number of failures per system at t_i and can be computed recursively by

$$V(t_i) = V(t_{i-1}) + \frac{1}{N^2(t_i)} \tag{4}$$

The confidence intervals are to be understood more as an envelope of pointwise confidence intervals on the mean rather than a prediction or tolerance interval on the MCF. Thus, if a system falls within the limits, it is definitely not an anomalous system. However, if it falls above the upper confidence limit, then visual interpretation or heuristics are used to determine if the system is experiencing a higher number of failures than the population. This approach works quite well in most practical situations (particularly in smaller sample sizes) without resorting to exact computation of prediction intervals.

In this study, the failure data of each APU system is first plotted against calendar time, including downtime, which produces cumulative plots over calendar time. To obtain cumulative plots over APU total operating time the data are then transferred from calendar time to total time by removing the downtime of each system. Next, the number of systems at risk is determined as a function of operating time. This allows for calculating the MCF and incorporating right censoring by accounting for the number of systems at risk at a particular age when failures occur. Finally, mean cumulative function is calculated and plotted against total time.

Figure 1 indicates the cumulative plots of each APU and the resulting MCF for seven APUs against APU total operating time, where the steps have been replaced with connecting lines. It can be seen that the MCF is increasing almost linearly, indicating no trend in the failures, and the recurrence rate is fairly constant. The MCF may be fitted very well ($R^2 = 0.9963$) with a straight line through the

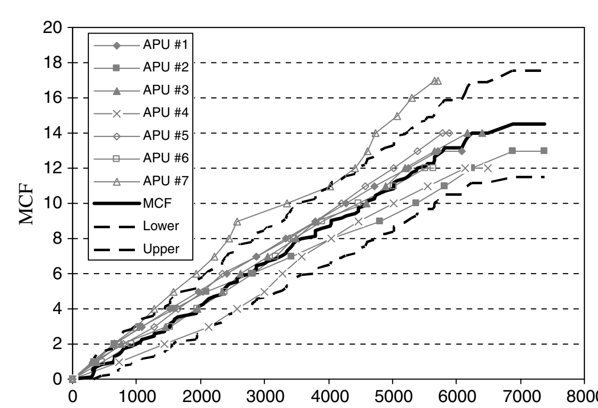

Fig. 1 Mean cumulative function with confidence intervals for the population of seven APUs.

origin, and the recurrence rate can be computed from the slope of the line as RR = 0.00220 failures/hour.

Calculating the MCF allows an estimate of the population mean cumulative number of failures by some specified time, which can be read directly from the curve. For example, from Fig. 1 the estimate of this by 3000 h is about 6.57 failures (on average) per APU system. Therefore, one can expect 46 failures (or unscheduled maintenance actions) for the entire APU fleet at 3000 h. The average number of failures per APU system for the entire observation period of 6880 h is 14.51 with 95% confidence bounds of [11.50–17.53].

As mentioned previously, MCF cannot be used to make predictions or extrapolations beyond the observation period. For instance, it cannot answer a question such as how many failures would be expected in the next year after the observation period. However, MCF can effectively be used to estimate the number of failures for the new systems of the same model to be purchased by the company. It is expected that a new APU of the same model would exhibit failure behavior similar to that predicted by the MCF for the population at hand. For instance a new APU will experience about 6.57 failures by the time it reaches 3000 h of operation. This allows management to estimate additional maintenance cost, manpower, and spare support required for the new systems to be purchased.

Figure 1 also shows the 95% confidence intervals of MCF for seven APU systems that can be used to identify anomalous systems. As can be seen from Fig. 1 the cumulative plot of APU 7 goes slightly beyond the upper confidence level, which means that APU 7 is experiencing a higher number of failures than the population at large. Visual inspection of data confirms that APU 7 is the system with the highest number of failures (17 failures) in the population. A cumulative plot of the same APU suggests that its failures occur randomly as they occur in the other APUs. However, they occur at a higher constant rate than the rest of the fleet. Therefore, for engineering purposes, one can say that there is an anomaly with this APU compared with the rest of the population. This anomaly has nothing to do with the failure trend and will be investigated later. This simple technique allows the maintainers to monitor failures by aircraft/system serial numbers and see if there are any unusual behaviors and then zoom into the systems in question. The same technique can also be used by an MRO company to compare different subsets of aircraft or systems in a more versatile way. The subsets can be aircraft/systems from different customers, sites, environments, operating conditions, maintenance policies, etc.

B. Power-Law Model

Since the MCF model discussed in the previous section cannot be used for predictions beyond the observation period, a parametric method would be required for this purpose. The power-law model is one of the most popular parametric processes for repairable system analysis. The model approximates the cumulative number of failures for a system under minimal repair using a power function of the form [5,9]

$$N(t) = \theta t^{\beta} \tag{5}$$

The derivative of the power function is the intensity function $u(t)$ (or ROCOF). This function gives the expected number of failures per unit time:

$$u(t) = \theta\beta t^{\beta-1} \tag{6}$$

The parameters can be determined by using least-squares fitting or MLE. If $\beta < 1$, failure intensity is decreasing; if $\beta > 1$, failure intensity is increasing; and if $\beta = 1$, failure intensity is constant. The latter is the special case that represents a homogenous Poisson process, because there is no change in the intensity function. Nonparametric analysis in the previous section points out that a power function with $\beta \approx 1.0$ would be expected for the APUs at hand. The general MLE for θ and β can be obtained from [10]

$$\theta = \frac{\sum_{q=1}^{K} N_q}{\sum_{q=1}^{K} (T_q^{\beta} - S_q^{\beta})} \tag{7a}$$

$$\beta = \frac{\sum_{q=1}^{K} N_q}{\theta \sum_{q=1}^{K} [T_q^{\beta} Ln(T_q) - S_q^{\beta} Ln(S_q)] - \sum_{q=1}^{K} \sum_{i=1}^{N_q} Ln(t_{iq})} \tag{7b}$$

The failure of the APU is modeled by the power-law model described above. MLE is used to determine parameters. Goodness of fit is tested by the Cramér–von Mises method. A Laplace test is used to test for trend. To determine if the failure data for the systems should be combined into a single superposition (equivalent) system that can be used to estimate the reliability metrics of interest, a common beta hypothesis (CBH) test [11] is employed. A CBH test compares the rate of occurrences of failures of each system by comparing the β of each system in order to determine if the interarrival rates of failures across the systems are fairly consistent. In other words, CBH tests the hypothesis H_o, such that $\beta_1 = \beta_2 = \beta_3 = \cdots = \beta_q$. A likelihood ratio procedure is used for the CBH test of the systems.

Estimated β values for APUs range from [0.8835–1.10648], and θ values range from [0.00052–0.0025]. All system have passed the Cramér–von Mises test. The Laplace tests show no trend in failure data for each system. The CBH test indicated that APUs can be combined into a single superposition system at a 5% significance level. Estimated parameter values for the superimposed system are $\beta = 1.06404$ with a 95% confidence interval of [1.03297–1.07510] and $\theta = 0.00128$ with a 95% confidence interval of [0.00117–0.00139]. Therefore, the resulting power function is

$$N(t) = 0.00128 t^{1.06404} \tag{8}$$

The fitted function can be used directly to estimate the expected number of failures over a specified time window with a confidence interval. For example, the estimated number of APU failures at 3000 h is 6.41 per system, which is in very good agreement with the number estimated by the MCF method. The total number of failures per system at 6880 h is 15.50. The function also allows for predicting the future number of APU failures in a window of time that can be effectively used for shaping the maintenance schedule for the future. For example, in the next 3000 h after the end of the observation period, it is expected that each APU system will suffer about 7.3 failures.

An estimated β value of 1.06404 indicates a very slight increase in the failure intensity of APUs. However, in general, it can be said that the model predicts that the failures of the APUs occur randomly with a fairly constant rate that is consistent with the result obtained from the MCF method. Although both models suggest that the failures are hardly age-related, it may be useful to plot the variation of failure intensity and RR over time to clearly see the potential information to be extracted from each model. Figure 2 indicates local recurrence rate vs total operating hours based on the MCF for seven APUs, along with the instantaneous failure intensity predicted by the power-law model. The local recurrence rate is estimated by numerical differentiation of the cumulative average number of failures vs age. The degree of smoothness of the curve is controlled by the number of points used in calculating the tangent at each point in the MCF plot.

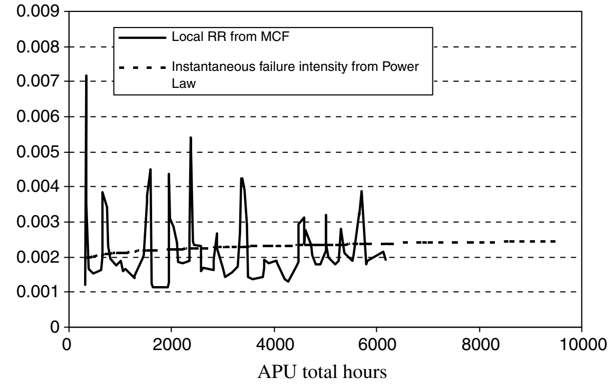

Fig. 2 Instantaneous failure intensity and local recurrence rate.

Spreadsheets have a slope function that can be used to calculate the local recurrence rate.

Figure 2 reveals that both methods suggest that there is almost no trend in failures with operating hours, and failures occur randomly, as previously predicted. However, many distinctive spikes can be observed in the local recurrence rate. These spikes can occur in cases when there is a clustering of failures in a short period of time. This usually points to poor diagnostics, imperfect repair, or spares that are "dead on arrival." On the other hand, the spikes at the beginning, which are clearly seen in Fig. 2, may provide clues as to potential failure modes such as early-life problems or learning-curve issues with the maintenance personnel. Learning-curve issues are fairly common with aircraft operators, due to constant evaluation of technology. Thus, local recurrence plot is more explanatory than the failure intensity plot and provides extremely valuable information that may otherwise not be revealed by parametric approach. On the other hand, instantaneous failure intensity by power law enables analysts to predict the change in the failure intensity beyond the observation period. For the case under investigation, Fig. 2 indicates that the failure intensity remains almost constant at around a value of 0.0024. Therefore, for practical purposes, one can expect that the failures would continue to occur randomly at the same rate after the observation period. Since the failure intensity is fairly constant, one may also apply the conventional notion of mean time between failures (MTBF), which is estimated as 416.67 h. It should be noted that under all other situations in which rate of failures depends on time, the traditional notion of a single MTBF to describe all periods has very limited applicability.

It is also possible to plot cumulative recurrence rate and cumulative failure intensity over operating time, as shown in Fig. 3. This is useful for indicating the long-term average rate of occurrences of the failures. As the figure suggests, both methods predict almost the same trend in the cumulative failures. After an increase in the early life, the cumulative recurrence rate tends to stabilize at about 0.00215. The same trend can also be observed in the cumulative failure intensity, which seems to be stabilized at about 0.0023 in 10,000 h.

V. Further Analysis of APU Failures

A. Component Failures

It is also possible to apply parametric and nonparametric methodologies for analyzing the failures of interesting subsystems, modules, or individual components in order to do a more thorough analysis and prioritize maintenance tasks. Some components may be replaced with the new ones and others may be repaired when they fail. The parametric approach requires application of different models for analyzing failures, depending on whether the component is repairable or unrepairable. For the case studied here, the oil/air separator was replaced when the oil cooler failed, but the compressor was repaired in response to the failure. Thus, although the compressor is a subunit, like the oil cooler in an APU system, its failures cannot be modeled by parametric methods that use renewal theory. This may be confusing for an average practitioner who tries to analyze the failures at a lower level. Using the nonparametric MCF method may eliminate such confusion.

The failure data indicate that the oil cooler is the component with the most observed failures (48 failures). Electrical components (rotating diodes, wires, etc.) have failed 22 times. A compressor that has failed 15 times follows the electrical components. Figure 4 indicates the MCF plots over total operating hours for these components, which are normalized by the number of APUs. The plots reveal the time evolution of components' failures and/or customer problems by addressing the variation of failures over time. The oil cooler fails at an almost constant RR with no trends. Its MCF may be fitted very well ($R^2 = 0.9889$) with a straight line, which produces an $\mathrm{RR} = 0.0011$. Therefore, one can say that oil-cooler failures are dominated by random failures, which are usually externally induced. Since the oil-cooler failures occur at a constant rate, the MTBF can be estimated as 900 h. In maintenance records of the company, the causes of all failures of the component were recorded as dirt contamination. According to manufacturer's recommendations, the oil cooler should be replaced if 25% of the total area of the fins is blocked. In the maintenance program, there is no dedicated hard-time inspection task to check the condition of the APU oil cooler, as the maintenance of the oil cooler is on condition. In the event that the cooler becomes blocked and fails to provide an adequate level of oil cooling, the oil temperature will eventually rise to the point where the APU electronic control unit will trigger a protective APU automatic shutdown and a fault indicating that maintenance is required. Since the APU eductor uses unfiltered intake air to cool the oil cooler, the level of contamination buildup on the oil-cooler surface is mostly influenced by the local environment in which the aircraft (APU) is used. Therefore, it is quite likely that the oil-cooler problem experienced by the company is not a general problem for all operators and that it results from the local environmental conditions in which the company operates. Since it is a local problem, the manufacturer cannot be expected to add a requirement in the maintenance manual for a dedicated hard-time inspection of the oil cooler, because this will penalize those operators who may have no contaminant-buildup problems. A customized solution is needed for addressing this specific problem of the company. It seems that the company is experiencing an undesirable level of contaminant buildup on the APU oil cooler that would warrant a dedicated hard-time inspection. Therefore, adding such an inspection (at an interval of about 900 h) to the company's approved maintenance program with the concurrence of their local periodic maintenance inspection tasks would be recommended. Of course, a PMA may also come up with a solution of adding an intake-air filtering system, if it is possible and feasible both technically and economically.

Electrical component failures also seem to occur randomly, but with a lower constant rate. On the other hand, the MCF for the compressor indicates that the recurrence rate tends to increase slightly with age. This may also explain the slightly increasing failure trend estimated by the power-law model at system-level analysis. One may say that wear-out starts to dominate the failure pattern of this component toward the end of the observation period. This usually points to problems such as aging, erosion, or imperfect repair. Considering the design life of the compressor, the wear-out seems to somehow start early. Therefore, tear-down reports for the system at each compressor failure were reviewed. In all cases it was seen that the compressor suffered from excessive erosion, causing a surge condition under load, and the observed erosion was most likely caused by ingestion of dirt and/or dust, in addition to the normal service wear. Therefore, it is very probable that the sand/dirt on the ramps/taxiways/runways from the desert surrounding the airports served by the company's fleet are sucked by the APU and accelerate the wear-out process in the compressor.

It is possible to extract other invaluable information from Fig. 4, as discussed in Sec. IV.A. For example, in 1300 h of operation (average operating hours per system annually) the oil cooler has failed an average of 1.5 times per system. Therefore, one can expect that 10 oil coolers will be needed annually to service the entire fleet. However, the company may want to protect against shortages and keep more oil

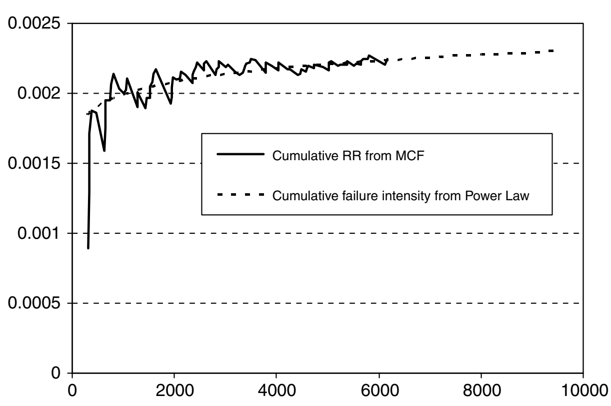

Fig. 3 Cumulative failure intensity and recurrence rate.

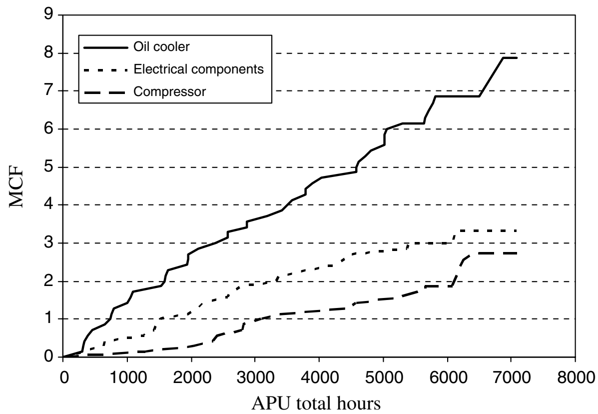

Fig. 4 APU components' failures.

coolers as spares. Setting the appropriate number depends on the relative costs of being short vs having a surplus of oil/air separators on hand.

The same procedure discussed above can also be used in other ways. For example, a keen practitioner may plot failure causes of the APU (contamination, electrical short, misinstallation, low resistance, etc.) as a function of operating hours by mapping each failure event by cause. This enables the practitioner to see which causes are remediated and which causes are still trending badly, which may help to develop repair procedures. For greater understanding, failure-cause plots can be plotted akin to the MCF by normalizing by the number of APUs. Thus, one can show the MCF at the system level and show the failure-cause MCFs that add up to the system MCF in one plot.

B. Impact of Ground and Flight Operation Hours

Manufacturers commonly report the maintenance indexes (such as mean time between failures and time interval between consecutive inspections or replacements) of aircraft components and systems in terms of aircraft flight hours or cycles (number of landings). On the other hand, the same indexes for some particular systems, such as APUs, are expressed in terms of its own operating hours or cycles. However, primarily for the convenience and ease of scheduling, these time intervals may be converted to calendar-time intervals based on average daily usage of the aircraft by the operator.

In relation to operating time, note that the APU distinguishes itself from other systems on the aircraft. Their total operation time consists of ground operation time and flight operation time and they are operated on different proportions of time on the ground and in flight, due to being exposed to quite different environmental and operating conditions. It is quite likely that their reliability indexes are sensitive to these changes in operating conditions. Therefore, predictions based merely on the total operation hours, ignoring the fact that APU operates on the ground and in flight for different parts of its total operating hours, can result in missing developing trends and drawing erroneous conclusions. Thus, a good methodology that enables the analyst to evaluate the impact of ground and flight operating hours on APU failures and to estimate the rate of occurrences of failures based on quantitative operating time on the ground and in flight is very important for choosing better operation and maintenance plans for the system.

To explore the effect of proportions of ground and flight time on the rate of occurrence of failures, the data were rearranged to reflect the ground operation hours and flight operation hours. APU ground operating time is calculated by subtracting aircraft flight hours from the APU total operating hours at each failure. When the APU was installed on a different aircraft, the flight hour of the aircraft at the time of installation was noted and APU flight hours and ground hours were calculated accordingly. Sample data for APU 3 are presented in Table 2.

When the APU was installed on a different aircraft, the flight hour of the aircraft at the time of installation was no evaluate the impact of ground and flight operating hours on APU failures and to estimate the rate of occurrences of failures based on quantitative operating time on the ground and in flight evaluate the impact of ground and flight operating hours on APU failures and to estimate the rate of occurrences of failures based on quantitative operating time on the ground and in flight ted and APU flight hours and ground hours were calculated accordingly. Sample data for APU 3 are presented in Table 2.

As shown in the previous section, both methods have indicated that the APU failures occur randomly with a constant rate. However, it is very likely that APU failures occur at different constant rates on the ground and in flight. Therefore, a two-state analysis may be considered to enable a more accurate forecasting of failures. Let the recurrence rate during in-flight operation be λ_f, and during on-the-ground operation let it be designated by λ_g. The APU operates in flight during a fraction of T_f of the total operating hours and operates on the ground during a fraction of T_g, where $T_f + T_g = 1$. Then the cumulative recurrence rate at any operating hour should be equal to

$$\mathrm{RR} = \lambda_f T_f + \lambda_g T_g \tag{9}$$

It is possible to write Eq. (8) in terms of a fraction of operation hours on the ground as follows:

$$\mathrm{RR} = \lambda_f + (\lambda_g - \lambda_f) T_g \tag{10}$$

A simple linear regression model [12] has been used to find the relationship between the proportion of APU ground time and the rate

Table 2 Total time, flight time, and ground time at failures for APU 3

Aircraft serial	Failure number	APU total hours	APU flight hours	APU ground hours
NCCC	1	380.2	217.3	162.9
NCCC	2	760.3	434.6	325.7
NCCC	3	1450.0	1009.3	440.7
NCCC	4	1950.6	1385.8	564.8
NCCC	5	2350.6	1626.8	723.8
NCCC	6	2628.4	1753.0	875.4
NDDD	——	2628.4	1753.0	875.4
NDDD	7	3050.8	2021.3	1029.5
NDDD	8	3500.3	2325.5	1174.8
NDDD	9	3800.2	2461.7	1338.5
NDDD	10	4586.5	3128.1	1458.4
NEEE	——	4586.5	3128.1	1458.4
NEEE	11	4900.7	3277.9	1622.8
NEEE	12	5200.4	3413.9	1786.5
NEEE	13	5660.4	3732.3	1928.1
NEEE	14	6169.6	4124.0	2045.6
NCCC	——	6169.6	4124.0	2045.6
NCCC	End of observation	6400.1	4224.1	2176.0

of occurrence of failures. The proportion of APU ground time is selected as the explanatory variable, and the cumulative recurrence rate is considered as the response variable. The recurrence rate in flight (λf) is the constant (intercept), and the coefficient ($\lambda_g - \lambda_f$) is the slope and represents the difference in recurrence rates in flight and on the ground. The root-mean-squared error (rmse) for the regression model was calculated using

$$\text{rmse} = \sqrt{\frac{\sum_{i=1}^{N}(\text{RR}_i - \overline{\text{RR}}_i)^2}{N}} \tag{11}$$

where RR_i is the actual cumulative recurrence rate, and $\overline{\text{RR}}_i$ is the predicted cumulative recurrence rate. The following regression function was obtained with an rmse of 0.000056:

$$\text{RR} = 0.00054 + (0.00521)T_g \tag{12}$$

A plot of predicted recurrence rate versus actual recurrence rate is shown in Fig. 5. Although some points have deviations from the ideal line $y = x$, the points appear to be clustered around the ideal line and the model seems to capture the trend in the data.

The model predicts that the recurrence rate for in-flight operation is 0.00054, and the recurrence rate for on-the-ground operation is 0.00575, which is almost 10 times higher than the recurrence rate in flight. This remarkable difference in the rate of occurrence of failures may be attributed to the difference in contamination loads to which APUs are exposed during ground and flight operations. The company essentially provides flight services to remote areas in deep desert that are not served by other carriers. It is quite likely that APUs are exposed to more severe contaminating conditions, such as fine sand, dust, etc., from the desert surrounding the airports during the ground runs, which incur a higher rate of failures.

At this point it may be interesting to find the relation between the APU operating hours t and ground hours t_g for the entire fleet, to test the model's performance. It is obvious that the APU ground operation hours are proportional with the APU operation hours: i.e., $t_g \propto t$. Using the data, it is found that the average ratio of ground hours to operating hours is 0.3287 for the entire fleet in the observation period. If this value is substituted in Eq. (12), one obtains an RR of 0.00225, which is in very good agreement with the values predicted by MCF and power-law models. However, neither MCF analysis nor the parametric power-law method based on total operation hours can detect the variation of occurrences of failures for ground and flight operations. This hidden information, which is revealed by applying the simple regression technique, is invaluable for an MRO. It allows an MRO to pinpoint the problems that are specific to the customer and to develop flexible customized solutions that meet operators' specific requirements. For example, in the case of the APUs studied here, a reduction of 10% in ground operation hours would result in an 8.7% reduction in failures. Therefore, the suggestions of keeping the APU ground operation time to a minimum and wider usage of ground support equipment as an alternative to APUs would be useful, depending on the relative costs of the failures vs having some ground support equipment at hand. In addition, good housekeeping on the ramp/parking areas or smart aircraft parking orientation to avoid exposure to blowing sand/dirt may alleviate some of the APU problems experienced by the company. Furthermore, the operator would also want to consider the increased maintenance costs in reevaluating ticket prices; if operating in remote areas increases maintenance costs, due to more frequent APU failures, then an increase in ticket price per passenger would help recover those costs of operating in the more remote locations, especially when APUs must be used because no ground power units are available.

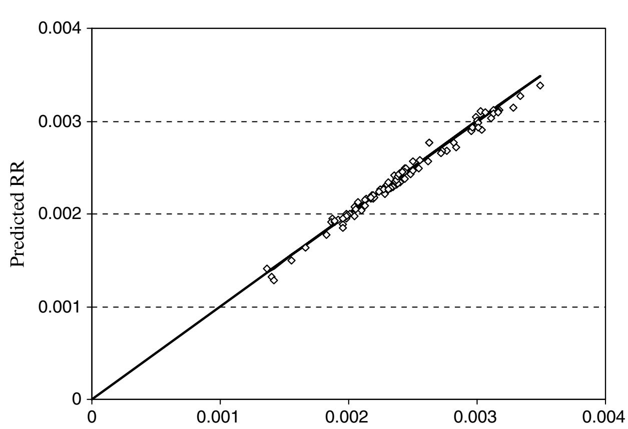

Fig. 5 Actual and predicted recurrence rates.

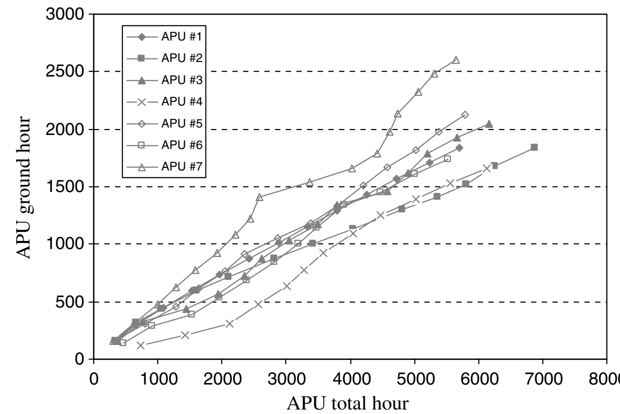

Fig. 6 APU's total and ground operation hours.

Since the ground operation hours seem to be an important factor affecting the rate of occurrences of failures, it may also be the reason for the misbehavior of APU 7, which was detected in Sec. IV.A. Therefore, ground operation hours versus total operation hours are plotted for each APU, as shown in Fig. 6. Figure 6 clearly indicates that APU 7 has the highest ratio of ground hours to total hours, compared with the others. If the data for each APU are fitted with a straight line through the origin, one can see that APU 7's ratio of ground hours to total hours is 0.4533, whereas the same ratio ranges from [0.2592–0.3637] for the other APUs. Therefore, the higher RR experienced by this APU can be attributed to the fact that it has operated on the ground at a higher rate than the others.

VI. Conclusions

The analysis of aircraft systems' failures does not have to be performed by either parametric or nonparametric methodologies. Coapplication of these complementary methodologies provides a very powerful and versatile tool for extracting invaluable information and prevents any missing information or trend that may result from application of either method alone. Nonparametric MCF technique provides a simple and very effective method for measuring and monitoring field failures of aircraft systems. It also serves as a well-established intermediate step toward more highly structured parametric models for reliability experts. The parametric power-law process is particularly useful for providing information beyond the range of the sample data, which are not possible to obtain by the nonparametric approach. However, one should note that such predictions make the implicit assumption that the failure process remains unchanged (which, in turn, implies that the operating environment is constant). The further out in time one goes, the less certain it is that these predictions will prove valid.

The parametric method also allows for performing more complex analysis of the failure process using some rigorous statistical methods such as the maximum-likelihood estimator (MLE). Therefore, coapplication of both methods enables the analyst to not only monitor the current status of failures, but to also estimate for future trends of failures. It also provides a way to validate the analysis by cross-checking the consistency of the results obtained from each method.

A practitioner may also prefer to use the MCF method for quickly identifying unusual behaviors and misbehaving systems and for comparing different subsets of the systems. Then he/she may zoom into the system with the anomaly and carry out more thorough parametric analysis for exploring the reasons of anomaly. Coapplication of these methods also allows for revealing important hidden information or relations that may not be captured by application of only one of the methods or that may not be evident in MCF or parametric plots at the system level.

MRO companies can use this approach for developing customized solutions, repair procedures, or alternate methods of compliance for their customers. It also allows fine-tuning of maintenance schedule, prioritizing maintenance tasks and following the performance of letter checks, overhauls, system modifications, etc. OEMs and PMA companies can also benefit from the same approach for product improvement and design feedback.

MRO companies, OEMs, and PMA companies may also need to use MCF as a complement to a parametric analysis for the purpose of communicating with the customers. Showing a parametric MLE equation is usually not the fastest or most effective way to gain credibility with the customers, who are mostly not familiar with these complex statistical methods. The graphical analysis based on MCF provides those organizations with a very handy tool for expressing their findings and justifying their proposed solutions to customers' management/engineers in very easy, effective, and most revealing presentations that speak to them in the professional language with which they are familiar.

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