APU FMEA Validation Using Operation and Maintenance Data

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ABSTRACT

FMEA(Failure Mode and Effects Analysis) is a systematic method of identifying and preventing system, product and process problems. As a standard document, FMEA is produced during the design of products or systems. However, FMEA documentation is rarely validated or updated in practice after it was generated. FMEA validation remains a challenge. In this technical report, we propose to validate FMEA using historical operation and maintenance data. First, we need to verify linkages between FMEA and corresponding operational and maintenance data. Based on statistical results obtained from historic operational data, we update useful FMEA parameters such as Failure Rate and Failure Mode Probability. The updated FMEA can provide more reliable information that could benefit the decision-making process and making maintenance a more efficient practice. The paper briefs the initial investigation and some preliminary results from APU FMEA case study*.

1. INTRODUCTION

Failure Mode and Effects Analysis (FMEA) has been used for fault identification and prevention in maintenance industry as a systematic method, since it was originally developed by NASA to enhance the reliability of space program hardware (Chen 1996). Theoretically, FMEA provides a foundation for qualitative reliability, maintainability, safety and logistic analysis; it documents the relationships between failure cause and failure effects. In particular, FMEA contains useful information such as Severity of Failure, Failure Rate, and Failure Mode Probability (FMP) for determining the effects of each failure mode on system performance. Such information is also useful for determining the policy of maintenance. Currently, some research focuses on how to use FMEA information to develop intelligent fault diagnostic systems (Murri, et al. 2005, Abajo et al. 2004). Other research concentrates on developing techniques for automatically generating FMEA documents (Peter, et al 1999, Teoh, et al. 2005), or modeling the manufacturing processes (Bouti, et al. 1994) and the failure modes (Ruiz, et al. 2000), in order to improve the FMEA quality and save costs.

Not surprisingly, FMEA is hardly validated or updated in practice after the system or product design process. This constricts the wide utility of FMEA in maintenance practice since some information may not be accurate or the lack of verification support. To promote FMEA application to real-world problems, it is necessary to validate the FMEA information or parameters using domain expertise or readily available maintenance data and operation data, such that FMEA can be reliable and accountable in practice. For this purpose, we initiated a project to investigate FMEA validation by using operation and maintenance data. In particular, we focus on APU (Auxiliary Power Unit engine) FMEA validation. Firstly, we tried to verify the existence of potential linkages between the FMEA information and APU maintenance data. Then we updated some FMEA information using these results and APU operation data.

This study relies on an "in-house" representation of APU FMEA prepared by domain experts based on a full FMEA received from the OEM. The operation and maintenance data are from a commercial airline using a similar APU. The APU used in the aircraft is also from the same OEM, but it is not the same model as the one described by the FMEA available. Nevertheless, we consider the two APUs to be sufficiently similar to warrant this study. To constrain the study, we decided to focus on components related to the “Inability to start” failure effect. In this technical report, we present our initial investigation and some preliminary results.

The next section describes the investigation of relationships between APU FMEA and maintenance data; following that, we present some results for updating FMEA information by using the operation data. The final section is the discussion and some remark on future work.

2. LINKAGES BEWTEEN FMEA AND MAINTEANCE DATA

The first challenge is to try to relate APU FMEA information with maintenance data available. To link the failures that caused the “Inability to start” effect for APU with maintenance data, we performed a comprehensive search of the airline’s maintenance data to retrieve occurrences of replacement of the components identified in the FMEA as contributors to the failure effect “Inability to Start”. The search consists of three steps:

- Identify relevant part numbers and part names
- Identify occurrences of part replacements
- Write an aircraft maintenance story around each replacement

The first step is to determine which part number(s) and part name(s) the technicians use to refer to a given FMEA component. This is a difficult task for a number of reasons: part numbers change over time and we often ended up with several numbering schemes, data entry errors or omission errors, technicians personal preference when entering part names when referring to a given component, and sometimes a component is mentioned in the textual description of the repair without being actually replaced. For example, in database, we found that “ignitor”, “igniter”, “ignitor plug”, ‘ignition exciter’ and “ignition unit” are referred to component “Igniter”. All of these difficulties need to be taken into account when establishing part names (part description) and part IDs for a given component. The second step uses the part numbers and part names identified to retrieve from the maintenance data all occurrences of replacement of the given part (the so-called failure events). This step results in a list of occurrences of part replacements with detailed event information (e.g., repair date, aircraft identification number, and reason for replacement). Further validation is needed to remove duplicates and irrelevant entries from the list of occurrences. In the third step, we reconstruct the maintenance history around each occurrence of replacement in order to get insights on other potentially related fixes (or components). To reconstruct this story, we considered all APU maintenance repairs in the 60 day interval around each replacement event (i.e., up to 30 days before the given replacement and up to 30 days after the replacement). A number of software tools were developed to help automate these three steps but manual validation is still needed.

FMEA Part	***AMTAC data***		
	Identified Instances of Part Replacements (Failures)		
	by Part Number	**by Des-cription**	**Total Failures (*NFc*)**
Starter	49	158	207
Igniter	16	140	156
Fuel Control Assembly	46	19	65
Fuel Flow Divider	9	5	14
Low Oil Pressure Switch	1	10	11
Fuel Pump	19	6	25
EGT Thermocouple	0	1	1
Monopole Speed Sensor	1	3	4
Oil Pump Assembly	0	4	4
Isolation Valve	0	0	0
O-Ring Seal	0	0	0
Fuel Manifold	0	0	0

Table 1, Instances of Replacements for components

Table 1 shows the preliminary results obtained. The left column lists the components contributing to the failure effect considered (Inability to start) based on the FMEA. The other three columns show the number of replacement occurrences found using the part numbers only, the part name only, and the two of them, respectively. From Table 1, we observe that we have been able to retrieve a significant number of occurrences of replacement for some FMEA components contributing to the selected failure effect. However, we retrieved very few replacements or even no replacement for some FMEA contributing components such as Fuel Manifold and O-Ring Seal. This is surprising as the operator’s maintenance database covers more than 10 years of operation for a fleet of over 100 aircraft. A couple of hypotheses may be proposed to explain this situation. It is possible that some of the contributing components mentioned in the FMEA simply never failed during the period of

Component Name	Original APU FMEA Information					Updated Information		
	Severity Class	FMP (%)	Failure Rate	MTBF (hours)	Risk Priority Number	FMP (%)	Failure Rate	Risk Priority Number
Starter	4	1.96	9.75	500,000	0.76	41.4	47.61	78.842
Igniter	3	16.67	27.78	36,000	13.89	31.2	35.88	33.584
Fuel Control Assembly	3	16	20	50,000	9.60	13	14.95	5.831
Fuel Flow Divider	3	0.8	20	50,000	0.48	2.8	3.22	0.270
Low Oil Pressure Switch	4	4.44	22.22	45,000	3.95	2.2	2.53	0.223
Fuel Pump	3	0.02	2.0	500,000	0.00	5	5.75	0.863
EGT Thermocouple	2	5.0	20.0	50,000	2.00	0.2	0.23	0.001
Monopole Speed Sensor	3	20.0	20.0	50,000	12.00	0.8	0.92	0.022
Oil Pump Assembly	3	4.25	17.0	58,824	2.17	0.8	0.92	0.022

Table 2, Updated Parameters for APU FMEA (for failure effect: inability of starting)
Note: (1) Risk Priority Number = severity · FMP · Rate; (2) Failure Rate is failures in million hours;
(3) The shaded columns show the updated parameters.

maintenance data. Since the FMEA APU and APU used in the study are not the same model, it is also possible that some of the contributing components mentioned in the FMEA do not exist in the APU used in the study.

3. FMEA INFORMATION VALIDATION

Focusing on the components for which we were able to retrieve occurrences of replacements, we decided to try to assess the accuracy of the information provided by the FMEA. This includes information such as "Severity Class", "FMP" (Failure Mode Probability), "Failure Rate", and "MTBF" (Mean Time between Failures). We also considered the "Risk Priority Number" (RPN) (N. Sellappan, et al. 2008, ASENT FMEA Software 2009), which is defined as the product of Severity, FMP, and Failure Rate. The RPN is a measure used when assessing risk to help identify critical failure modes associated with the process. The larger RPN is associated to a higher priority for a component to be replaced. The left hand side of Table 2 presents the values for these parameters for each components for which we have been able to retrieved examples of replacements from the maintenance database.

Based on RPN, most occurrences of APU inability to starter problems should be resolved by replacing either the "Igniter" or the "Monopole Speed Sensor". However, when considering the number of actual replacements (*NFc* in Table 1), we notice that the "Starter motor" comes first, followed by the "Igniter" and the "Fuel Control Assembly". Moreover, the "Monopole Speed Sensor" which was one of the first components to be suspected based on FMEA is almost never replaced by the maintenance crew (only 4 replacements as reported in Table 1). Such discrepancies between the original FMEA information and real maintenance practice clearly show the need for regular updates of the FMEA information.

We propose to update the FMEA information by relying on data acquired as part of normal operation. First, to update the probabilities, we need to determine the total number of hours of APU operation for the entire duration of the period covered by the maintenance data. This is done by retrieving the most recent value of the *APU_OPERATHING_HOUR* parameter, which is automatically reported as part of the APU starting report, for each APU and then adding all values. For the dataset considered, we obtained a total APU usage of 4,328,083 operating hours (noted as UT).

To update the Failure Rate and FMP parameters based on real practice, we introduce the following equations

$$FailureRate = \frac{NFc}{UT} \qquad \text{--- (1)}$$

$$FMP = \frac{NFc}{RN} \qquad \text{--- (2)}$$

where:

NFc: The number of replacements of a given component (Table 1);

UT: The total APU usage (in hours) for the entire fleet; it is 4,328,083 hours in this study;

RN: The total number of APU parts replaced during the investigation. It is a sum of *NFc* in Table 1. In this study, *RN* = 487.

The last three columns in Table 2 show the revised information. FMP and Failure Rate are computed from Equation 1 and 2 using *NFc* from Table 1. RPN is recomputed using the revised parameters. The revised RPN results closely reflect the real maintenance practice. We believe that the revised information, although quite different from the original number, are more representative of real world practice and therefore potentially more appropriate for decision-based support system to assist the operator in the maintenance of the APUs.

4. DISCUSSION AND REMARKS

In this brief report, we presented preliminary results from an investigation of FMEA information for PHM. These results are very limited due to the lack of domain knowledge, noise in maintenance data, and difference between FMEA and APU systems. However, some remarks we would like to make are as follows:

1. As most FMEAs are created during the design phase of a system or product, the information may not be accurate enough for practical maintenance decision support system. FMEA should be regularly updated and validated in order to accurately reflect the fleet operation. This updated and validated FMEA would constitute a more appropriate source of information for PHM systems.
2. Using operation and maintenance data, we can effectively validate and revise FMEA information. The revised FMEA provides more reliable and useful information for practitioners to perform an efficient maintenance.
3. This initial investigation only considered a limited number of failure modes. Repeating the same process for an entire complex system may turn out to be quite challenging due to large amount of FMEA documents and supporting data.

The proposed method only addresses the updating of the Failure Rate and FMP parameters. Many other parameters such as Severity Class and MTBF would also benefit from validation based on maintenance data. However, this would most likely require additional data. For example, most APU systems considered in this study either never suffered from the inability to start effect or did but only once. Therefore, we do not have enough data to conduct the statistical analysis required for the MTBF parameter. Another interesting issue is that there exists much redundant or conflicting information for a single component contributing to the same failure effect in FMEA. To correct such conflict information, domain knowledge and more operational data are required. Future work will focus on the application of the validated FMEA for fault identification and prognostics in PHM systems.

ACKNOWLEDGMENT

Many people at the National Research Council Canada have contributed to this work. Special thanks go to Xijia Wu for providing the FMEA documents and to Jeff Bird and Ken McRae for their support and valuable insights.

NOMENCLATURE

FailureRate failure rate
FMP failure mode probability
MTBF mean time between failures
NFc number of replacements of a component
RN total number of APU unit replaced
RPN risk priority number
UT total APU usage time

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