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Yang, Chunsheng; Létourneau, Sylvain; Zaluski, Marvin; Scarlett, Elizabeth

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APU FMEA VALIDATION AND ITS APPLICATION TO FAULT IDENTIFICATION

Chunsheng Yang
National Research Council Canada
Ottawa, ON, Canada

Sylvain Letourneau
National Research Council Canada
Ottawa, ON, Canada

Marvin Zaluski
National Research Council Canada
Ottawa, ON, Canada

Elizabeth Scarlett
National Research Council Canada
Ottawa, ON, Canada

ABSTRACT

FMEA (Failure Mode and Effects Analysis) is a systematic method to characterize product and process problems. As a standard document, an FMEA is produced during the design of a product or system. However, once a system is deployed, the corresponding FMEA is rarely validated and updated. This is mainly due to the lack of method to validate and update FMEA. This paper argues that historical maintenance and operational data could be used to help address this problem. Building on data mining and database techniques, the paper introduces a FMEA validation and update technique. The proposed technique derives statistics from real world historical operation and maintenance data and uses these statistics to update key FMEA parameters such as Failure Rate and Failure Mode Probability. The paper then shows how the validated FMEA can be used with data mining for fault detection and identification of root contributing component for a given failure mode or failure effect. The paper presents the developed methodology for FMEA validation and experimental results for fault identification. The results show that the updated FMEA can provide more reliable and accurate information that could benefit the decision-making process and improve maintenance efficiency.

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 [1]. 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 Class (SC), Failure Rate (FR), and Failure Mode Probability (FMP) for determining the effects of each failure mode on system performance. Most of the research related to FMEAs focus on the generation process. For examples, techniques have been introduced to automatically generate FMEA documents [4], model the manufacturing processes [5] and identify the failure modes [6]. These enhancements result in improved FMEA quality and cost reduction. The need to further improve maintenance practices lead to recent investigations on the use of FMEA information to help develop intelligent fault diagnostic systems [2, 3]. This paper suggests that prior to use FMEA information, one must try to confirm its validity.

Since FMEAs are produced at design time and then hardly validated after deployment of the corresponding system, there is a risk that the information provided is incomplete or no longer accurate. The likelihood for such inaccuracies is particularly high for complex systems such as aircraft engines that operate over a long period time. In such cases, using the initial FMEA information without adequate validation could result in the introduction of irrelevant maintenance actions. To avoid such issues, the initial FMEA information needs to be validated and then updated as required. In this paper, we propose to perform this task using real-world readily available maintenance and operational data. In particular, the paper investigates validation and updating of an FMEA for an APU (Auxiliary Power Unit engine). Our study relies on an “in-house” representation of an 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 in 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. This paper complements a previous study [7] which presented an initial investigation with preliminary results.

In addition to validate and update the FMEA information, this study investigates the use of the resulting information for data mining-based fault identification/isolation, a key in Prognostic Health Management (PHM). In analyzing failure modes/effects for a complex system, a fault or failure is usually associated with many potential components based on FMEA documents or the Trouble Shooting Manuals (TSM). To efficiently perform fault identification, it is important to identify the root component for a given failure effect. In maintenance practice, both TSM and FMEA could be used to help identify to root component. However, these documents often involve expensive and time-consuming processes. To address this issue, we propose a novel data mining-based approach. We start by developing a data mining-based model for each component related to a given failure mode. Then we use the validated FMEA to rank the models to help identify the root component contributing the specified failure mode. This paper presents the FMEA validation process and the application of the updated FMEA in fault identification for the APU system.

The next section describes the available APU FMEA documents and the data used for validation and for developing the data mining-based models for fault identification. Following that, we review the FMEA validation, present the data mining-based fault identification, discuss the results obtained by applying the validated FMEA for model ranking. The final section concludes the paper.

APU FMEA AND DATA

The APU engines on commercial aircraft are mostly used at the gates. They provide electrical power and air conditioning in the cabin prior to the starting of the main engines and also supply the compressed air required to start the main engines when the aircraft is ready to leave the gate. APU is highly reliable but they occasionally fail to start due to failures of the APU components such as the Starter Motor. When this happens, additional equipment such as generators and compressors must be used to deliver the functionalities that are otherwise provided by the APU. The uses of such external devices incur significant costs and may even lead to a delay or a flight cancellation. Accordingly, airlines are very much interested in monitoring the health of the APU and improving the maintenance with reliable failure-fixing guideline information such as the reliable and accurate FMEA to ensure the correct operation.

For this study, we considered the data produced by a fleet of over 100 commercial aircraft over a period of 10 years. Only ACARS (Aircraft Communications Addressing and Reporting System) APU starting reports were made available. The data consists of operational data (sensor data) and maintenance data. The maintenance data contains reports on the replacements of many components which contributed the different failure modes. Operational data are collected from sensors installed at strategic locations in the APU which collect data at various phases of operation (e.g., starting of the APU, enabling of the air-conditioning, and starting of the main engines).

APU FMEA documents are provided by an OEM. This FMEA were created following the standard procedure during design. It contains typical FMEA information: failure effect, failure mode (failure identification), failure cause, contributing component, symptoms, functions, corrective actions, Failure Rate (FR), Severity Class (SC), Mean Time between Failures (MTBF), FMP (Failure Mode Probability), etc. The some information is quantitative such as SC, FR, MTBF, and FMP. These quantitative parameters are very useful for maintenance operation. However, they are determined based on design requirements. We believe that these FMEA parameters may not confirm to reality but can be updated with operational data and maintenance data in practice. The updated FMEA will provide more reliable and accountable information for decision-making support on maintenance. The validated FMEA is also valuable resource for developing PHM systems for real-world applications like APU prognostics and fault identification. The following section introduces briefly APU FMEA validation using historic operation data.

APU FMEA VALIDATION

Using the historical operational and maintenance data, we validate APU FMEA before applying it to data mining-based fault identification. The objective is to update FMEA information and to make FMEA confirm to reality. We follow the procedure shown in Figure 1 to conduct FMEA validation. The details are referred to our previous work [7]. Here is a brief overview on FMEA validation.

As shown in Figure 1, the FMEA validation consists of three main steps:

1. *Obtain the failure events from maintenance database given a failure mode in FMEA*
2. *Gather the relevant data for the failure events and conduct the statistical analysis for APU usage time*
3. *Update the FMEA parameters using statistical information*

A. OBTAINING FAILURE EVENTS

Given a failure mode, the first task is to obtain the relevant failure events or component replacements from maintenance data by using database techniques. For instance, we need to retrieve occurrences of replacement of the components that caused "Inability to start" effect for APU with maintenance data based on part information (part name and part number). The components are identified in the FMEA as contributors to the failure effect "Inability to Start". 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

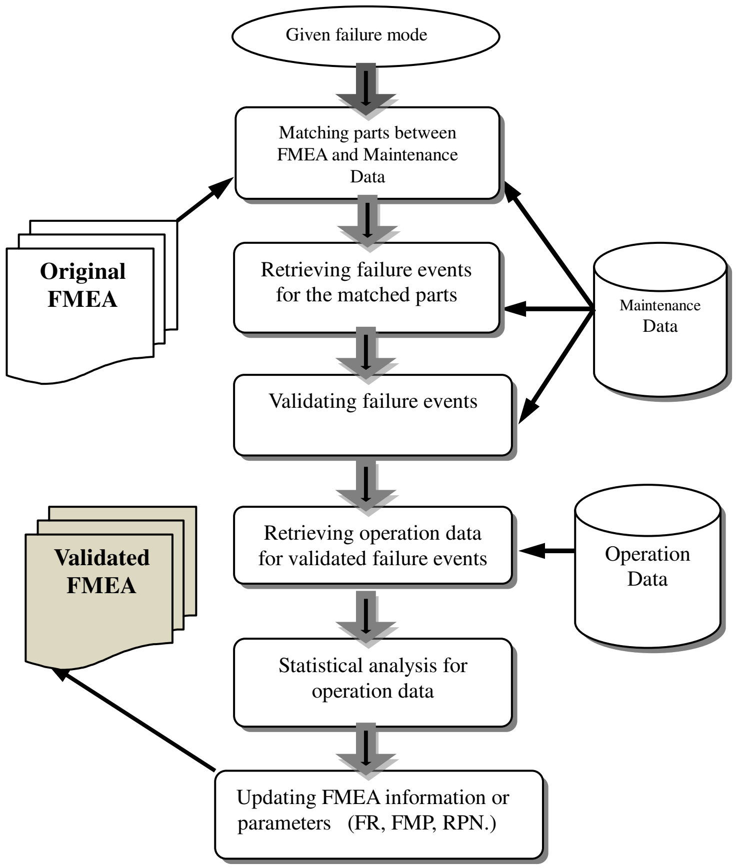

Figure 1, The procedure of FMEA validation

"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.

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 and the part name only, 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 maintenance data. Since the FMEA APU and APU used in the study is 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.

Table 1, Instances of replacements for components

FMEA Part	***AMTAC data***		
	Identified Instances of Part Replacements (Failures)		
	by Part Number	**by Part Description**	**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

B. STATISTICAL ANALYSIS

We only focus on the contributing components which were replaced in practice. For those components which have never had any replacements in the historic maintenance data, we are not able to validate their FMEA information.

This task is to analyze the operation data to find out 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_OPERATIING_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***).

C. UPDATING FMEA PARAMETERS

As we mentioned before, we are interested in updating quantitative FMEA information, such as FR, FMP, SC, and MTBF. We also considered the "Risk Priority Number" (RPN) [8, 9], which is defined as the product of SC, FMP, and FR. The RPN is a measure used when assessing risk to help identify critical component associated with the failure effect. 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 retrieve examples of replacements from the maintenance data. Based on RPN, most occurrences of APU "Inability to Start" 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 original 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.

Table 2, Updated parameters for APU FMEA (for Failure Effect: "Inability to Start")

Component Name	**Original APU FMEA Information**						**Updated FMEA Information**			
	SC	**FMP (%)**	**FR**	**MTBF (hours)**	**RPN**	**Old Rank**	**FMP (%)**	**FR**	**RPN**	**New Rank**
Starter	4	1.96	9.75	500,000	0.76	7	41.4	47.61	78.84	1
Igniter	3	16.67	27.78	36,000	13.89	1	31.2	35.88	33.58	2
Fuel Control Assembly	3	16	20	50,000	9.60	3	13	14.95	5.83	3
Fuel Pump	3	0.02	2.0	500,000	0.00	9	5	5.75	0.86	4
Fuel Flow Divider	3	0.8	20	50,000	0.48	8	2.8	3.22	0.27	5
Low Oil Pressure Switch	4	4.44	22.22	45,000	3.95	4	2.2	2.53	0.22	6
Monopole Speed Sensor	3	20.0	20.0	50,000	12.00	2	0.8	0.92	0.02	7
Oil Pump Assembly	3	4.25	17.0	58,824	2.17	5	0.8	0.92	0.02	8
EGT Thermocouple	2	5.0	20.0	50,000	2.00	6	0.2	0.23	0.001	9

Note: (1) Risk Priority Number = SC · FMP · Rate; (2) Failure Rate (FR) is failures in million hours;
(3) The shaded columns show the updated parameters.

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.

To update the FR and FMP parameters based on real practice, we introduce the following Equations

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

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

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 four columns in Table 2 show the revised information. FMP and FR are computed from Equation 1 and 2 using *NFc* from Table 1 and *UT* obtained in statistical analysis. RPN is recomputed using the revised parameters. The revised RPN results closely reflect the real maintenance practice. We also add ranking information based on RPN. The ranking parameter is useful for model ranking in the fault identification described in next section. 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.

DATA MINING-BASED FAULT IDENTIFICATION WITH FMEA RANK

This section presents the application of the validated FMEA to the data mining-based fault identification. The objective is to evaluate the usefuleness of the validated FMEA. We start with a framework, which uses data mining-based models to detect the failure for individual components and the updated FMEA to rank models. Then we present the development of the data mining-based models and experimental results.

A. DATA MINING-BASED FAULT IDENTIFICATION FRAMEWORK

Fault identification for a given failure effect or mode is a reactive process. Usually, a failure has occurred and it needs to identify which component is the root cause or to isolate the fault to a specific contributing component. Traditionally, the process is conducted following TSM, FMEA, or human experiences. In practice, the suggested procedures from the TSM or FMEA are complicated, expensive, and time-consuming. The TSM outlines list of possible causes, but these lists are not ranked. The work in [20] used maintenance and operational data to provide maintenance technicians with a ranked list of possible causes along with the standard TSM list. To further enhance the troubleshooting procedures, we proposed a data mining-based fault identification framework, which applies the updated FMEA to rank models and uses the operation data prior to failures as input to identify the root contributing component for a given failure mode. The main idea is to build a diagnostic model for each individual component using readily available historic operation and maintenance data. The model assesses the likelihood of a failure of the corresponding component based on the given data. When a failure effect is contributed by ***n*** components, ***n*** models are developed. All outcomes from the ***n*** models are ordered following the FMEA ranking. The final result is a ranked list of the contributing components for a given failure mode or a given observation ($\vec{X}_{t=i}$). Figure 2 shows the proposed framework.

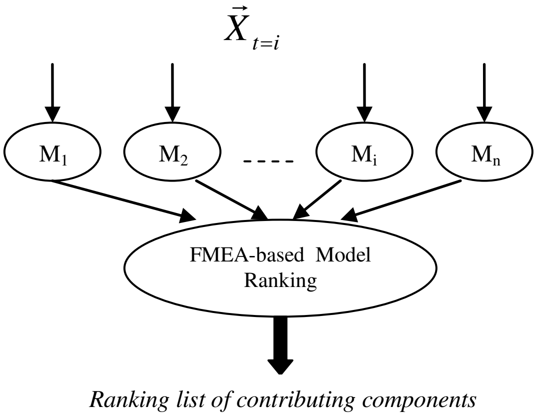

Figure 2, Data Mining-Based Fault Identification Framework

Models, $M_1, M_2 ... M_i, M_n$, in Figure 2 are the binary classifiers. These models classify the given observation ($\vec{X}_{t=i}$) as a positive ("1") or a negative ("0"). The results from all models will be ranked using the FMEA rank parameter in Table 2. For example, for a given observation ($\vec{X}_{t=i}$), if the outcomes are positives from Starter model and Igniter model but negatives from other models, the result will be a ranked list in which Starter is ranked as No.1 priority component; and Igniter as No. 2 priority component for "Inability to Start" failure effect.

B. DEVELOPING DATA MINING-BASED MODELS

Models, $M_1, M_2 ... M_i, M_n$, in Figure 2 are developed using the data mining methodology documented in [10, 11, 12]. This methodology consists of several steps: data gathering, data labeling, data transformation and feature selection, model building, and model evaluation. The following is the succinct description of these steps. For additional information, please refer to the publications listed above.

The first step is to get the relevant data from the operational data. The dataset created from these reports consists of 18 original attributes (5 symbolic, 11 numeric, and 2 for date and time of the event). More than 161,000 observations are available for this task. Only a subset of these observations is relevant for learning the detective models. These are the ones collected around each occurrence of component failures. In this particular task, we use engine operating hours as the time unit. We based our analysis on data generated up to 250 operating hours prior to the failure. Each occurrence of component replacement is associated with a time series. Moreover, each time series is distinguished with a unique *pbmID* and has the varied numbers of instances. We request each time series contains at least 20 instances prior to failures when we create data for modeling. A comprehensive search in the maintenance database revealed information on 68 time series (problems/replacements) for Starter, 80 for Igniter, 41 for Fuel Control Assembly, 10 for Fuel Pump, 9 for Fuel Flow Divider, and 6 for Low Oil Pressure Switch. Because of the limitation of time series length, we did not get the relevant operation data for three components: Monopole Speed Sensor, Oil Pump Assembly, and EGT Thermocouple. For those components, we cannot build the data mining-based models.

The second step is to label data. In order to use classification learning, we need to add a class attribute to the sensor data. We proceed with an automated approach. This approach labels as positive ("1") all instances that fall in a pre-determined target window before the occurrence of a starter motor failure and as negative ("0") all other instances. This labeling scheme allows us to build a classifier that generates an positive detection whenever the patterns in the data are similar to the ones observed near a failure. In practice, we define the length of the target window by taking into account the balance between positive and negative instances. As a rule of thumb, we try to keep a minimum of 30% as positive instances to simplify the learning.

The third step is to transform data to enhancing the data representation. We systematically try to improve the initial representation by augmenting it with new informative features. We construct these features using methods from signal processing, time-series analysis, and constructive induction. Feature selection is also applied on the augmented data representation to automatically remove correlated or irrelevant features [13, 14].

The fourth step builds the models. After updating the initial dataset with the class attribute and incorporating data representation enhancements, we build the required classifier. We use data from a subset of all failures for learning the models and keep the remaining data for testing. Any classifier learning algorithm can be used. In early experiments, we tended to prefer simple algorithms such as decision trees, and Naive-Bayes over more complex ones because of their efficiency and because they produce models that we can easily explain to the end users. We apply the same algorithm several times with varying attribute subsets and cost information.

The final step is to evaluate modes for selecting a good one for individual component. To compare the classifiers developed, we apply a score-based approach that we have developed to evaluate classifiers [10]. The one with the maximal score on testing data is selected as the best classifier for the component.

C. EXPERIMENTS AND RESULTS

Using obtained dataset, we conduct the experiments for data mining-based fault identification. Basically, the dataset for each component is divided into two parts: training dataset and testing dataset. The training dataset is used for building models, and the testing dataset is used for evaluation. The experiment setting for each component is shown in Table 3. Each time series in Table 3 contains at least 20 instances prior to failures. Using these data, we perform two experiments.

Table 3, Experiment setting for each component

	# of time series	**# of time series for training**	**# of time series for testing**	**Data mining –based model**
Starter	68	44	24	M_1
Igniter	80	53	27	M_2
Fuel Control Assembly	41	30	11	M_3
Fuel Pump	10	6	4	M_4
Fuel Flow Divider	9	6	3	M_5
Low Oil Pressure Switch	6	4	2	M_6

The first experiment is to develop the binary classifier for each individual component. We use the training dataset of each component to build models following the steps described above. This involved a large-scale computational effort that we have automated using an in-house tool named EBM3[1] [19]. In Table 3, the models M_1, M_2, M_4, M_5, M_6 are selected from a bunch of the models in the experiment corresponding to each component in the left column. For example, we name M_1 as the model for Starter, M_2 for Igniter, etc

The second experiment is to perform fault identification in order to evaluate the usefulness of the validated FMEA for model ranking. As shown in Table 3, there are 71 times series (replacements/failures) in all testing datasets. From them, we select some interesting instances/observations which are prior to replacements (t = 0) to create a testing dataset for fault identification. In other words, we select 20 instances with t = [-19, 0] from each time series. For a given time (t) prior to failure, there are 71 instances. In total, the dataset has 1420 instances. We run all six models M_1, M_2, M_4, M_5, M_6 on this dataset. For every given instance, $\vec{X}_{t=i}$, we obtain 6 outcomes, noted $y_x^1, y_x^2, \ldots y_x^6$. We also add the FMEA ranking (noted R_k, R_k=1, 2, 3, 4, 5, 6) to each instance based on the FMEA rank in Table 2. This ranking information indicates component that the instance should belong to. For example, if an instance,

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[1] EBM3 (Environment for Building Models for Machinery Maintenance) is an automated data mining system. It provides a simple user interface that the researchers use to define the overall data mining experiment that needs to be executed to build the desired data mining-based models.

$\vec{X}_{t=i}$, from the testing dataset of Fuel Pump, its FMEA ranking R_k will be assigned to “4”.

To evaluate the effectiveness of the validated FMEA for model ranking, we proposed a “cost”-based method. We assume that the cost (noted ***C***) for replacing a component is the same for all APU components and that the failure will be fixed when a root component is replaced in practice. We also assume that the fault will be isolated given a specific time prior to a failure. Given an observation ($\vec{X}_i$), if we note its cost as c_i, then we can compute c_i using Equation 3 and the notations above.

$$c_i = \begin{cases} \sum_{j=1}^{R_k} y_{x_i}^{j} \bullet C & \text{if } y_{x_i}^{R_k} \neq 0 \\ 6C & \text{if } y_{x_i}^{R_k} = 0 \end{cases} \quad \ldots\ldots(3)$$

In Equation 3, $y_{x}^{R_k}$=0 means the outcome of the own model is negative. In other words, the root component is not successfully identified. Therefore, the cost will be assigned a maximal value (6C) in this experiment, regardless of the outcome from other models. Table 4 shows some examples for computing the cost for 4 observations at different given time.

The first row shows an example for an instance for which positive outcomes come from equally ranked models. In this case, the root component is identified using its own model (R_k = 2). The outcomes from the other models (M_4, M_5, and M_6) are ignored. Therefore, there is only one replacement, and the cost is assigned 1C. The second example shows that there are two positive outcomes from higher ranked models (M_1, M_2). Thus, it takes 3 replacements to work out the root component. The cost is assigned to 3C. The last two examples show that no positive outcomes are generated by its model (***M_1***). The cost is assigned to 6C based on Equation 3.

Table 4, Examples of cost computation

	M_1	M_2	M_3	M_4	M_5	M_6	R_k	***Cost (C)***
$X_{t=-1}$	0	1	0	1	1	1	2	1
$X_{t=-5}$	1	1	0	1	1	1	4	3
$X_{t=-10}$	0	1	1	0	1	0	1	6
$X_{t=-15}$	0	0	0	0	0	0	1	6

After computing the cost for the 71 instances, we sum all costs and obtain a total cost given a specific time prior to failures. In this experiment, we compute a total cost for three cases: the original FMEA rank, the validated FMEA rank, and without ranking. The results are shown in Table 5. Each row represents the total cost of three different rankings for a given time prior to failure. The given time (‘***t***’) is a normalized time unit. In this work, it is a unit of APU starting times.

Table 5, The evaluation results for given testing data

Given time (t)	**Cost without ranking (in C)**	**Cost with original FMEA rank (in C)**	**Cost with validated FMEA rank (in C)**
-19	353	104	86
-18	318	97	85
-17	340	96	78
-16	324	101	92
-15	339	103	94
-14	324	93	92
-13	320	103	95
-12	326	98	93
-11	322	102	95
-10	329	97	86
-9	312	96	90
-8	325	94	92
-7	327	89	85
-6	329	89	81
-5	327	92	89
-4	323	87	81
-3	343	97	89
-2	336	97	87
-1	353	99	91
0	326	101	90
Average	329.8	96.75	88.55

DISCUSSIONS

The results in Table 5 demonstrated that the validated FMEA rank in data mining-based fault identification is better than the original FMEA rank. The cost is reduced for each given time prior to replacements. This also demonstrated the usefulness of the validated FMEA for model ranking.

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 reality. This updated and validated FMEA would constitute a more appropriate source of information for PHM systems. 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.

In this work, we only updated the FR and FMP parameters. Many other parameters such as SC and MTBF would also benefit from validation based on maintenance data. Our FEMA rank is determined based on a derived parameter RPN which is computed as a product of SC, FR and FMP. If we can update SC, the precision of RPN will be much higher than the current one. 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 SC and 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.

The FMEA validation 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.

Current fault identification approach looks into the 20 instances prior to failures. This number is empirically determined. For other applications, it may be different. We investigated the health status instance by instance. It could be better to find out a way to combine all results of the 20 instances to determine the root contributing component.

It is worth to note that even though the FMEA help rank models for data mining-based fault identification, there are many other factors affecting the performance of models. The key factor in fault identification is the robustness and accuracy of data mining-based models. Ideally, for a given instance, it should be detected solely by the model which belongs to its component, and the outcomes from other models should be negative. Additionally, we would like all models to be perfectly accurate. In practice, it is impossible to develop such ideal models. However, there are many techniques available to improve the preliminary results presented in this paper. An obvious approach is to develop classifier ensemble for combining multiple classifiers into a high performance system, including Bagging Boosting [15], Voting [16], Stacking [11, 17], and two stage classifications [18]. These techniques are developed purely based on machine leaning techniques. We believe that there is a way to integrate these techniques with engineering knowledge such as FMEA. We will continue working on the performance improvement for data mining-based fault identification by integrating machine leaning techniques and the validated FMEA.

CONCLUSIONS

In this paper, we proposed to validate APU FMEA using historical operational and maintenance data. We argue that this as a key requirement to successfully incorporate FMEA in intelligent decision support systems. The experimental results obtained suggest that the validated FMEA provides more reliable and accurate information for maintenance decisions by providing an overall reduction in cost by comparison to using the original FMEA information. In particular, the experiments performed suggest that the updated FMEA provide better ranking that the initial FMEA ant therefore help with the fault identification task. In order to further validate the usefulness of the proposed method, additional experiments with more systems and components need to be performed. As discussed, we will also investigate potential enhancements by integrating classifier ensemble techniques during model building.

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NOMENCLATURE

C_i	the cost of the component replacement
FR	failure rate
FMP	failure mode probability
M_i	the data mining-based model
$MTBF$	mean time between failures
NFc	number of replacements of a Component
R_k	the component rank in FMEA
RN	total number of APU unit replaced
RPN	risk priority number
SC	severity class of a failure mode
UT	total APU usage time
$\vec{X}_{t=i}(\vec{X}_i)$	the given instance/observation in a time series
$y_{x_i}^{j}$	the outcome of M_j for a given instance ($\vec{X}_i$)

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