PREDICTIVE MODELING AND INTERACTIVE ELECTRONIC TECHNICAL MANUAL SUPPORT FOR RELIABILITY CENTERED MAINTENANCE

A Thesis

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ABSTRACT

The effectiveness of Reliability-centered Maintenance relies on its maintenance framework that has been integrated into the system. The system can be mechanical equipment, production process or a combination of both. Predictive modeling is a concept in Predictive Maintenance within Reliability-centered Maintenance that enables the operator to predict the performance of the system and decide the maintenance schedule. This model provides a huge advantage when compared with other maintenance schemas as it tells when a component is going to fail in the future, thereby helping us plan the maintenance process and calculate the Remaining Useful Life of the components in the system. This research focuses on developing a predictive model for an aircraft system. This model will live capture the performance of the components in an aircraft by tapping on in-situ sensor data and runs through an algorithm to predict its future performance. The algorithm developed uses the concept of Multivariate regression from Machine Learning and Hidden Markov Model. Multivariate regression converts non-linear data into a lower dimensional linear one, which is then processed by Bayesian networks to establish dependencies. The results are compared to the data from the past and the future is predicted. The Hidden Markov model section of the algorithm considers individual component and determines the degradation level of it in terms of its performance. This may be due to wear, stress or other operating conditions, but the decrease in effectiveness of its performance is calculated. Combining these two parts of the algorithm creates an effective predictive modeling framework that can be employed on a system for Reliability-centered Maintenance. This also gives the advantages in terms of cost, labor and time to the system maintenance. Finally, a proposal to develop an interactive electronic technical manual with predictive modeling support is made and its effect has been discussed on par with virtual and live environments.

1. INTRODUCTION

Reliability-centered Maintenance (RCM) is defined as the process of maintaining a complex system in a cost-effective manner. Reliability is the probability that a system will perform its intended function for a given period of time under the stated conditions. RCM focuses on this probability and gives a maintenance schema that will increase the reliability of the system. With increased reliability comes more uptime and less cost for maintenance. The US Air Force first invested its resources to research on RCM when they had to maintain their aging aircrafts with less budget and time. The idea was to have an aircraft made with reliable components that have a longer time to fail. But most of the aircraft that needed maintenance were already manufactured and the only way to increase their life is to have an effective maintenance schema. Nowlan and Heap [1] published a report titled "Reliability-centered maintenance" after years of work and research on the topic and concluded that it is the way to achieve inherent safety and reliability capabilities at minimum cost. The report also states that it is a time consuming, resource intensive process that will give a level of reliability that is the maximum possible under the given conditions of system usage. This level is established by the design of each item and the manufacturing processes that produced it.

The above explanation from the report clearly states that any asset management program should address maintenance in all phases of development. The RCM cannot survive in a system that has been poorly designed with unreliable components and parts. Thus, it is important that we apply this schema right from the early stages of development of a system to cash out all the available life form the components. There are also many different maintenance schemas developed by the industry to tackle the reliability problem, but not all are classified as RCM. According to the SAE JA1011 standard, the following are the seven questions that a maintenance schema should answer to be qualified as RCM they are,

- What are the functions and associated standards of performance of the asset in its present operating context?
- In what ways it can fail?
- What causes each failure?
- What happens during each failure mode?
- What are the immediate and long time consequences of the failure?
- What should be done to predict/prevent the failure?
- What should be done if a proactive task cannot be found or determined?

The goal of the RCM is to answer the above questions for each sub system. In most cases, the answer is not straightforward and we need to perform some analysis to find it. RCM's primary procedure is to apply some analytical methods to find the answers for each step. The analytical methods involved are identifying failures, criticality analysis, failure mode effective analysis, maintenance task determination and maintenance packaging. These steps are common throughout the RCM schema but they are usually divided into three major categories depending on the approach of maintenance task.

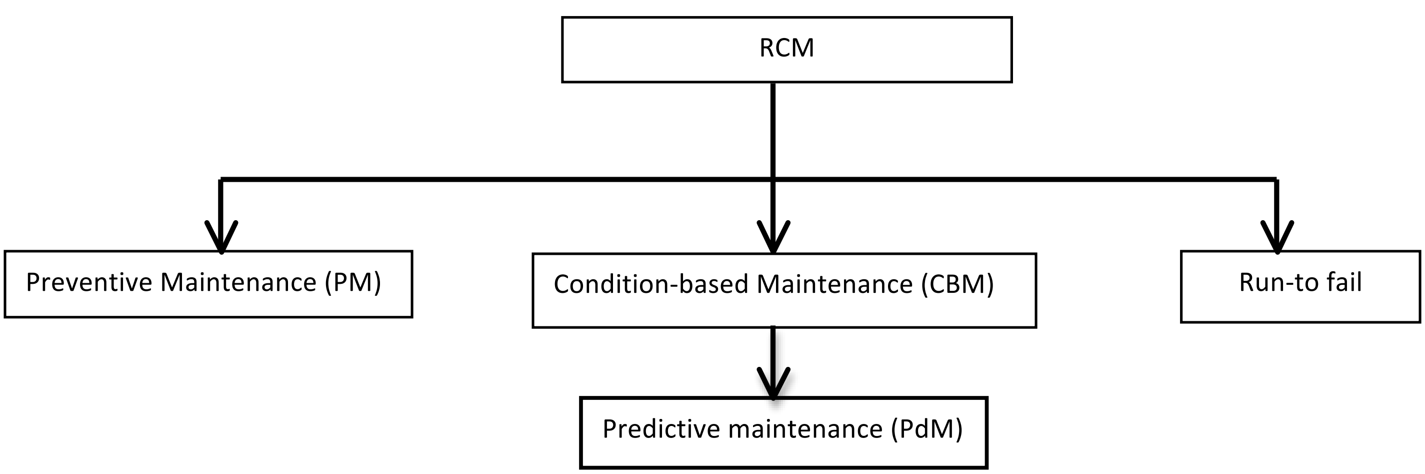

Fig.1 Components of Reliability-centered maintenance

Preventive Maintenance schema follows scheduled maintenance repair of the system as determined by the system manufacturer and it goes on even if the system is healthy. There are pre-defined intervals that have been calculated from the reliability calculation and repair is done at the end of those intervals. The disadvantage in this maintenance schema is the component may be repaired/replaced even before it is fully worn out resulting in loss of usage life of the component. Condition-based Maintenance, on the other hand, does not perform regular interval repair but instead monitors the health of the component and reacts according to the need. The con here is, the component may fail at any time and the maintenance crew may not be available to repair at the required moment. Predictive Maintenance is a type of this maintenance schema that aims to predict the condition of the system, i.e. when a component in a system is going to fail. This is advantageous because if we know when the component is going to fail, we can schedule maintenance accordingly. This brings the benefits of the entire maintenance schema in one place and establishes a cost effective solution.

For the advantage stated above, the current research focuses on Predictive Maintenance schema of the RCM. This thesis uses an aircraft as its system of application to apply the concepts of predictive maintenance and propose a method that would effectively put forward a maintenance step with less cost and more uptime. As explained earlier, RCM should be applied to all phases of development and in some cases its overall effectiveness depends even during the maintenance repair. The technician performing the repair should be adept with the working of the system and the troubleshooting methods. With recent advancements in complex technologies, it is hard for these technicians/repairmen to catch up with the manual updates. This thesis proposes a solution for that by innovating the way Interactive Electronic Technical Manuals are used. Interactive Electronic Technical Manuals (IETM) is the present generation of digital manual that has been evolved over the years from the conventional paper manual. Detailed explanation on how we can use these IETMs with predictive maintenance and gain an additional advantage is explained in the following chapters.

2. BACKGROUND

There are numerous journals that have published their findings on Predictive Maintenance (PdM) and how they can adapt this schema for their application. As defined, PdM is the method of having a maintenance schema that enables us to predict the life states of the components. We can apply this concept to all the systems that need a maintenance schema provided we have necessary tools and provisions to apply.

Cher Ming Tan and Nagarajan [2] proposed a framework for PdM for multi-state systems. They used a flow transmission system, which contained three elements of which two of them combined to give the output at the third one to illustrate their proof. The elements in the flow system had multi states of performance and they used this performance factors to determine the most impact causing terms. A PdM schema was developed based on those identified impacting parameters. So, they used Markov Model to quantify the states and obtained a degradation rate based on the decrease in performance for each operation cycle. The important take away from this journal is the performance factors that they introduced to measure the predictive model parameters. Restoration Factor (RF) was one of the parameters that were introduced by them, which is defined as the ratio of mean performance after each maintenance step. If the performance increased after each maintenance step then the RF will be higher and the system will be restored to its healthy status. They also went on to provide other parameters that are used to quantify the performance. These can be used to model a predictive model, but this follows a back tracing way of designing the system, which usually takes a lot of iterations. In the system under our consideration, aircraft, we cannot afford to do multiple iterations to develop a schema, as it might be expensive and diminish the resources.

Deterioration of a system was studied by Langeron, Grall, and Barros [3] by establishing a control system and checked its deterioration level. They used a mathematical formulation to quantify the deterioration level of the control system. They considered physical parameters such as wear and tear of the system, external factors such as environment, operator behavior, etc. All these parameters were numerically calculated and a degradation rate was established with a mathematical equation. This generalized mathematical equation was then used to obtain a curve between degradation of the control system and the loss of effectiveness of the system. While, it concluded with obvious fact that the more the control system undergoes physical degradation the more was the loss of effectiveness of its performance, it also gave a good understanding of the path of the effectiveness loss that the system undertakes. The same idea was applied to an actuator to calculate the degradation rate of that. With that information, the remaining useful life of the actuator is calculated. RUL can be used to apply a Conditional based Maintenance schema to the system. If the tolerance limit set by the operator is reached then the maintenance has to be performed on the system, which may include repairing or replacing a part or a system as a whole. This paper gave a numerical understanding of the deterioration level of components in a complex system.

Yang Liu [4] gave a very good insight on how to apply Predictive Maintenance for a manufacturing process in an industry. The sample author chose was the semiconductor manufacturing and considered multivariable regression model and Hidden Markov Model to develop the schema. This paper innovated the idea of using regression tools to process the data obtained from different input places and process it. It also opened a new field of application of PdM, which was the optimization of the process. The inputs were the information from various stations of the manufacturing line and it is collected, processed and segregated according to the algorithm. This algorithm gives a state in which we can establish a Bayesian network that can predict the outcome of the system based on the input values. With that, the degradation of the silicon chips was also modeled by using Hidden Markov Models. HMM gives the path that the component goes through before it is degraded to a final state. Compared to the work of Langeron, this HMM model does not use a numerical rate to calculate the degradation but instead used an established constant parameter called lambda. This determines the rate at which the component is getting degraded. From that, a decision support tool is also integrated to the schema, which helps in making effective decisions regarding the failure of a particular line in a manufacturing plant. Much of the knowledge for this research was acquired from the readings of this work and the background research conducted by Liu.

PdM in smaller systems is achieved by having a dynamic system i.e. a dynamic sensor that is usually hand-held and is used to monitor the vibration of the system at times. This collects vibration data, stores it, processes it and predicts the health of the system. Advantage of this dynamic method is that we can apply PdM to even smaller systems and achieve cost benefits. On the other side the disadvantage of this method is that the user has to have a personnel go to the field in person to carry out the reading. This may be difficult if the system is operating in an inaccessible place like underwater or high above ground. To use this schema in those systems we may have to embed sensors on the system while it is built and have a provision to transmit it to the acquisition system.

Recently Internet of things (IOT) has taken all the electro-mechanical embedded software systems to a higher level of excellence by its features and capabilities. PdM has also gained some advantage by using this innovation. Commercial manufacturers of Predictive systems such as IBM [5], Windriver [6] has started to implement this methodology to their product. Since, IOT has no human-to-human or human-to- computer interaction its efficiency is very high to transfer data about the health of the component and predict its future. Transportation, Energy, and Buildings are the three major sectors where this type of PdM finds its application.

With these background understanding on the predictive modeling, degradation of components, and establishing a decision support system we were able to develop a model that we can use on our system with all the advantages of the PdM.

3. PREDICTIVE MODELING OF MULTIVARIATE SYSTEM

3.1 INTRODUCTION

Aircrafts are one of the most complex machines in existence. Maintaining these requires a lot of effort, time and money. Development of an efficient maintenance schema has been the topic of research in recent years among the HUMS community. Maintenance schemas can be of different types,

- Preventive Maintenance (PM)
- Predictive Maintenance (PdM)
- Condition based Maintenance (CBM)
- Corrective Maintenance (CM)

Out of these types, the current research is inclined to support the PdM schema, which is a way to predict in advance that maintenance is required for a particular component so that the user/operator/maintainer can be prepared. Knowing in advance will help in bringing down the cost and estimating the reliability of the component and the system. If the PdM schema predicts that a particular component is going to fail and if that component can be repaired without grounding the entire system then it is a huge advantage. It decreases the downtime.

Implementation of Predictive maintenance schema requires the following, [7]

- Top management understanding of the true cost of poor maintenance, which is several times initial estimate
- Sustained management leadership and absolute commitment
- Knowledge of equipment/process conditions required to yield quality, output, safety, and compliance standards
    - One cannot determine what problems exist until knowing what conditions are proper

- PdM and other programmed maintenance must be a normal part of schedule and capacity determination. Management must insure that PdM is never delayed.
    - PdM must be conducted as a Controlled Experiment
        - Plan
        - Do
        - Evaluate
        - Define
    - Weekly adherence to a balanced PdM schedule
- Dedicated staffing is preferable
- Operator should participate in daily machine checks
- Efficient PdM routes
- Effective PdM checklists defining program required limits of equipment condition
- Adequate Equipment Records and Equipment Histories
- Three phases
    - Detection—the key element
    - Analysis—defines the specific problem from which the symptom originates
    - Correction—the return of the PPM investment

The current research proposes a framework that helps in development of a PdM schema by explain the three phases involved in it.

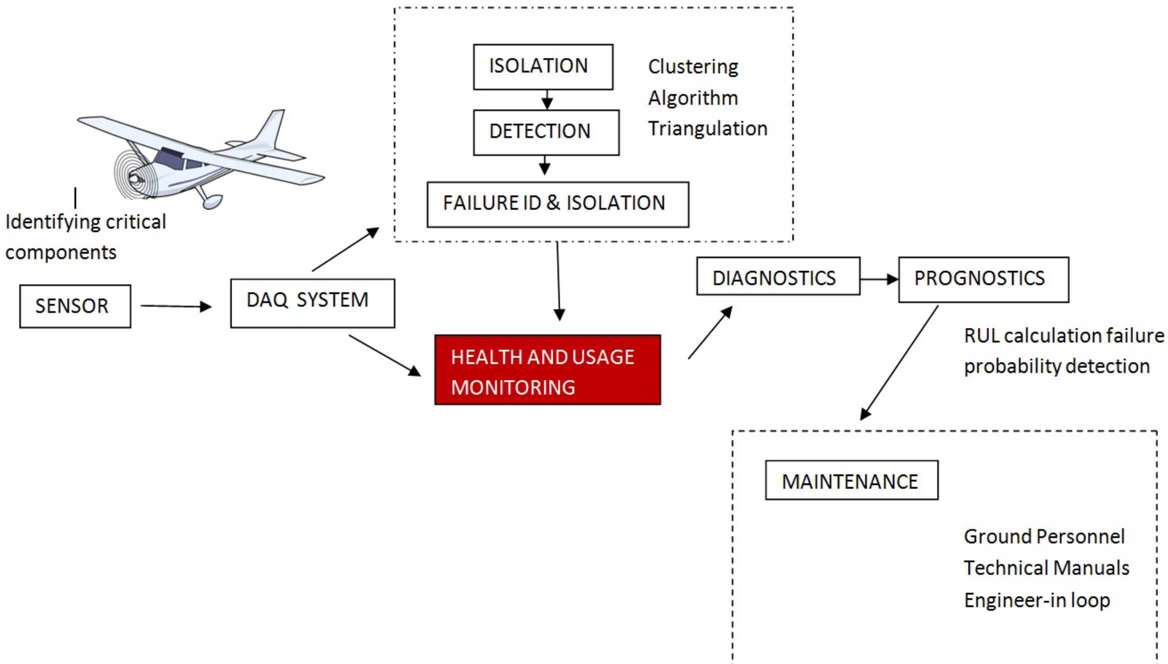

Fig. 2 Model of Health and Usage Monitoring system

Sensing of component health

The first step in achieving an effective PdM schema is to detect the health of components in a system. Sensors are placed on board to monitor the component parameters such as Temperature, Pressure, Loads, Deformation, etc. These data are then transmitted to a Data Acquisition System (DAQ System) as pictured above, which is either on board or in ground. Sensor type, position, and accuracy also decides the efficiency of the total system as a diverging data from sensors can make all the calculations down the line in the predictive model to be inaccurate. So, it is important to choose a sensor that is best suited for the system under study and the transmit/receive method we are going to implement. The components that need to be monitored in system with lot of sub systems are determined by conducting a Failure Mode Effective Criticality Analysis (FMECA) on the system. The analysis takes all the failure modes of the system components and allots an RPN number from the severity, Occurrence and detection of those failure modes. This number helps us determine the criticality of that failure mode and that component is given importance or monitored with more than one sensors.

The responses from the sensors should also take into effect the uncertainty with the positioning of the sensor. Sensors placed at different spots in a single component can give different readings on vibration. This must be taken into account while calculating the health of that component. From studies and experiments, it is accepted that sensors should be placed at point where it can capture maximum resonance from the vibration of the component. The same concept applies for sensors measuring other parameters.

Analysis of sensed data

Analysis of the sensor data is the next step in the predictive modeling process and it is the most important one. This research concentrates on this step of the process. Data from the sensors are collected in the Data Acquisition System and it is then sent in to the Health & Usage Monitoring System (HUMS). The system that we recommend to be designed has to collect data from individual components, which will then be used to calculate the degradation of the component and also the failure state of the subsystem. The analysis step consisting of two different parts can be structured as,

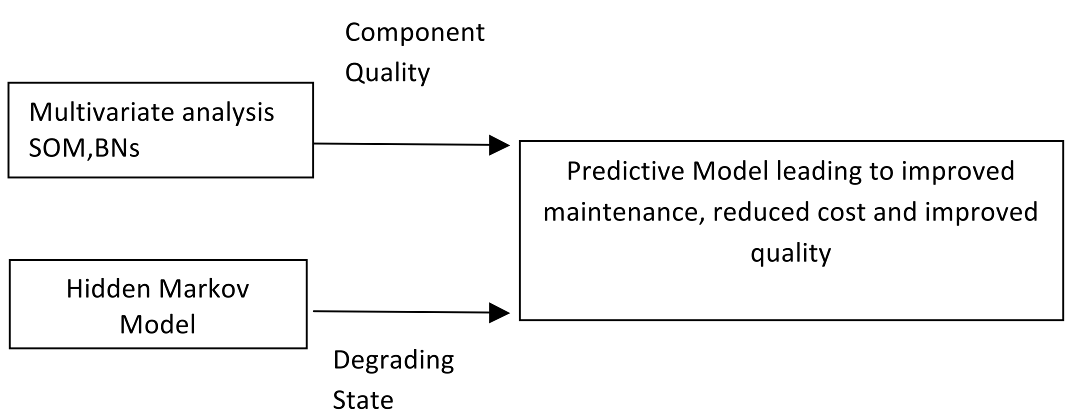

Fig.3 Illustration of Predictive model algorithm

3.2 MULTIVARIATE ANALYSIS

Sensor data from the system usually has many variables because of the different parameters that are being monitored. This is the reason the first part of the analysis step is called as Multivariate analysis. DAQ system collects data from the different parts of the aircraft. In order to calculate the overall probability of failure of the system it is important that we consider data from these systems,

- Operating conditions and associated parameters of Engine
- Outside structural condition of Wings, flaps and fuselage
- The interior cabin parameters such as temperature, pressure
- Avionics, that runs through the entire aircraft
- Landing gear and cargo compartment

These are not the only systems that might fail in an aircraft. But these are more important ones and require prime maintenance activity and we consider those in this research.

The sensors placed on each of these components collect the responses and send it to DAQ system as previously mentioned. Each part sends a data that is multi-dimensional. So, if p number of systems send in data with q dimensionality then the total variables that the DAQ system has to handle is $p*q$. In order to reduce the dimension of this data and to make the computing time of the probability model quicker, we use an algorithm called Self-organizing maps (SOM). The work of the SOM is to take all the input parameters of multi variables and integrate it into a lower or single dimension. Self-organizing maps are proven method to reduce dimension of a data. It is a machine-learning concept that is classified under unsupervised learning. In order to further explain the process by which we propose to use the SOM we need to explain the working concept of it.

Self-organizing maps

SOM uses the approach of using ‘neurons’ to organize itself. It is hence also a type of neural network algorithm. For each input data set, there will be neurons associated with it that has weigh vector of dimension *I,* where I is the dimension of the input parameters. Hence the weight vector associated with neuron is W = $\{G_1, G_2, \dots, G_n\}$. With this set, the SOM takes each individual input value and calculates the Euclidean distance between that data and the neuron. It satisfies the condition,

$\|a(t) - m_c(t)\| < \|a(t) - m_i(t)\|$ for any i, provided m is the weight vectors and c is the WINNER data.

Once, the distance is calculated for all input data, the closest input value (WINNER DATA) is selected and the neuron is now placed at the mean distance of that. The process is then repeated iteratively until we get an organized order. Another important thing the SOMs do to achieve efficiency in organizing is Normalization. [8] It converts data of different range value into a single distribution with a common mean and variance. If the input variables are $a = \{a_1, a_2, \dots, a_n\}$ then

$$a' = \frac{a - \min(a)}{\max(a) - \min(a)}$$

All this might be similar to k-means algorithm but this SOM also does organize all the neurons in a way that similar weights are placed near [9]. Similar neighborhoods are grouped together using the algorithm,

$$T_{j,I(a)} = \exp\left(-S^2{}_{j,I(a)}/2\sigma^2\right)$$

where, T is the topological neighborhood distance. S is lateral distance between two neurons i and j, I(a) is the winning neuron, σ is the variance of the input data after normalization.

Bayesian Networks

The data from the SOM are now discretized and normalized. This is not the end and we need to establish dependencies between these values to get the effect of each individual part of the airplane to its overall health probability. Using Bayesian Networks does this. A Bayesian Network (BN) is a type of representation that establishes parts as different nodes and the dependency between these nodes are indicated by an arrow that leads to another node, which is the result of previous nodes coming together.

If nodes A, B and C are connected to a common node D then it means that the action of A, B and C affects the outcome of node D. It is also possible that the nodes A, B and C are also interconnected.

Here, the outcome from each SOMs are represented as a node in a Bayesian Network (BN) and the dependency between these states are calculated by running the BN. It is a two-step process, learning and inference. Learning is the step in which the dependencies between the nodes are calculated and inference is the step in which certain hidden steps that are unobserved are calculated.

The entire analysis step with SOMs and BNs can be diagrammatically represented as shown in the next section.

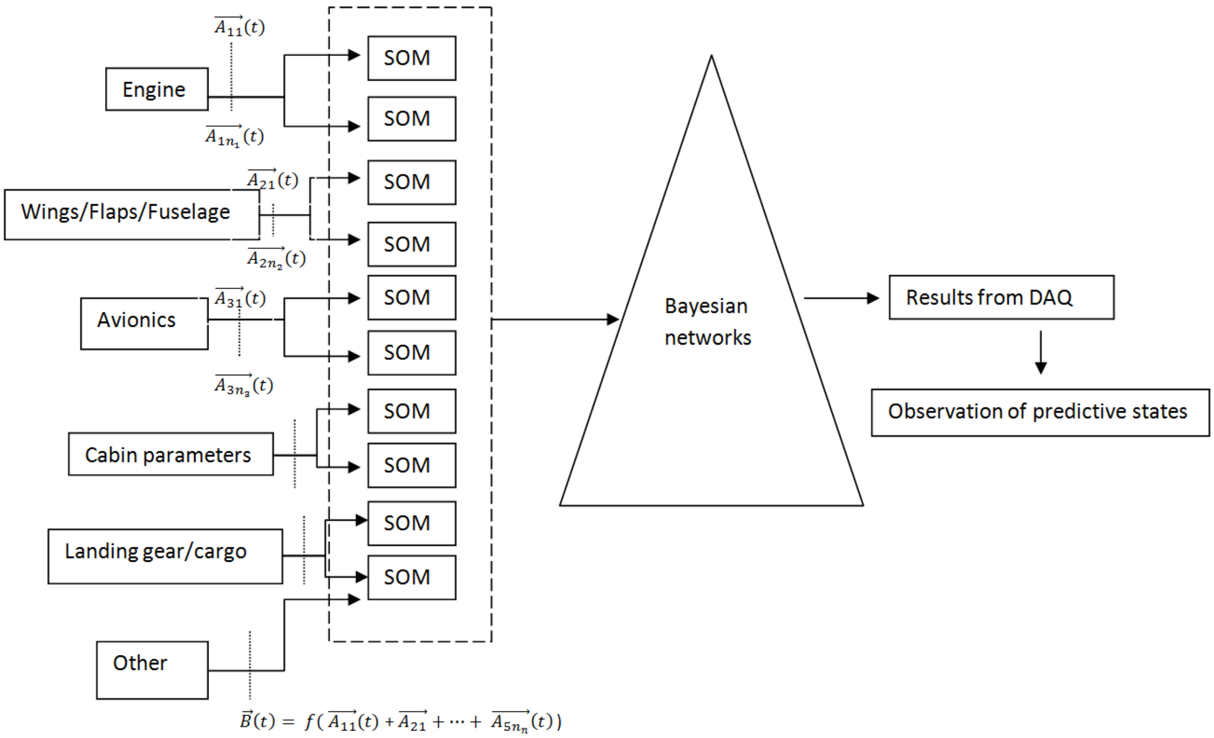

Fig. 4 Multivariate analysis step with parameters

3.3 SIMULATION STUDY

The aim of this simulation study is to check the validity of the proposed method to establish dependencies between the parameters in the system. But before that we need to discretize and normalize the input data from the sub systems by using Self-organizing maps. Let us assume the above mentioned diagram representation with 5 stations and each having 5 feature variables. The stations are Engine, Wings/Flaps, Avionics, Cabin parameters, and Landing gear. Though there may be many other stations in a real aircraft we have considered only 5 here because of the simplicity in explaining the concept. If this schema is to be applied to an aircraft with more than 5 stations then appropriate number of feature vectors may be considered and added to the matrix. The reason we are calling the variables of continuous data from the sensor as feature vectors is because we are going to represent them in vector form. By this way we can do, vector quantization of those values (reducing the dimensionality) and feed it to Bayesian Networks.

Here, the feature vectors are represented as, for Engine = { $\overrightarrow{A_{11}}, \overrightarrow{A_{12}}, \dots, \overrightarrow{A_{1n_1}}$ }, for Wings/Flaps = { $\overrightarrow{A_{21}}, \overrightarrow{A_{22}}, \dots, \overrightarrow{A_{2n_2}}$ }, for Avionics = { $\overrightarrow{A_{31}}, \overrightarrow{A_{32}}, \dots, \overrightarrow{A_{3n_3}}$ }, for cabin parameters = { $\overrightarrow{A_{41}}, \overrightarrow{A_{42}}, \dots, \overrightarrow{A_{4n_4}}$ }, and for landing gear = { $\overrightarrow{A_{51}}, \overrightarrow{A_{52}}, \dots, \overrightarrow{A_{5n_5}}$ }. All these vectors can be represented in matrix form and be subjected to clustering algorithms of SOM. The magnitude of the vectors in each station is in a different range and should be normalized with a common mean and variance. To explain how the Self-organizing maps convert the continuous data to discrete lower dimension values, we use SOM toolbox from MATLAB. [10] The input for that toolbox will be the matrix containing all the feature vectors of our system. Each row represents a station with its feature vectors. The concatenated matrix is,

$$\text{A\_input} = \begin{bmatrix} A11 & A12 & A13 & A14 & A15 \\ A21 & A22 & A23 & A24 & A25 \\ A31 & A32 & A33 & A34 & A35 \\ A41 & A42 & A43 & A44 & A45 \\ A51 & A52 & A53 & A54 & A55 \end{bmatrix}$$

where all the entries of the matrix are vectors denoting their respective station and variable. The numerical value equivalent of the above matrix is obtained through random initialization and it is used to explain the method. In the case of experimental validation, this may be used as a starting guess and the algorithm should be trained to be accurate. Then the matrix A_input is,

$$\text{A\_input} = \begin{bmatrix} 0.9352 & 0.1795 & 0.2073 & 0.2296 & 0.3729 \\ 0.0773 & 0.5621 & 0.6184 & 0.9927 & 0.4172 \\ 0.7672 & 0.8314 & 0.5273 & 0.2787 & 0.0837 \\ 0.1493 & 0.9529 & 0.9548 & 0.0245 & 0.7424 \\ 0.6306 & 0.5419 & 0.5321 & 0.0840 & 0.5013 \end{bmatrix}$$

Using the above matrix in the SOM toolbox, using *selforgmap* function to solve the input matrix. It is then trained using *trainbu*. As explained in the previous section, SOM clusters the given input continuous data by using neurons. Here, we specify to use 10 neurons, which in turn gives us,

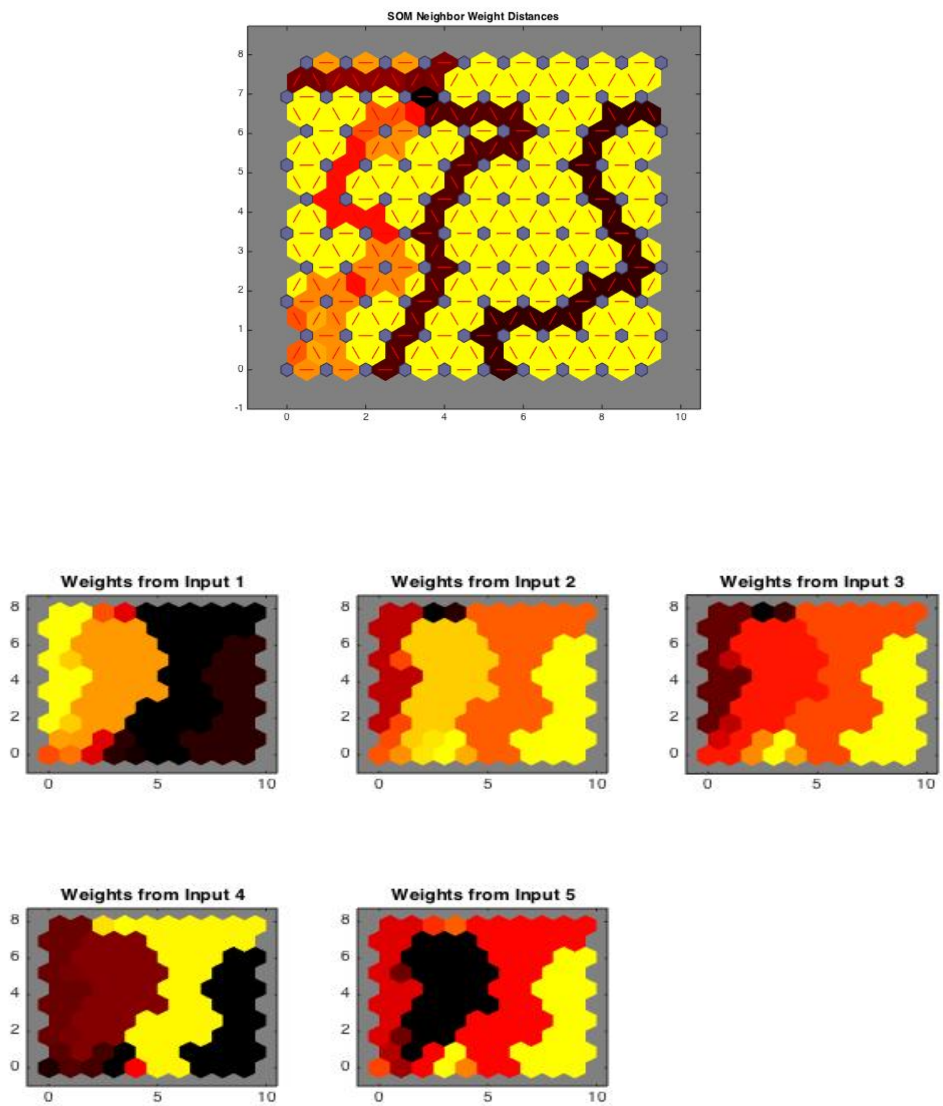

Fig. 5 Results from SOM Toolbox - Clustering

In the plots above, we see the inputs from different stations being organized by using SOM. The one below gives the neighborhood distance between the nodes of the input parameters. One thing to notice is that all the input parameters have been normalized to a common mean and variance. This will make it mathematically logical to juxtapose the weight functions of all inputs. By doing this, it will present lower dimensional input of discretized values to the Bayesian Network. BN takes the input and it is not dependent on the values of the variables that these systems give out. It takes the states of the system to establish a conditional probability of the entire system and how individual state probability affects the overall system's probability. For the description of Bayesian Network, let us consider the graphical representation of BN with their probabilities as,

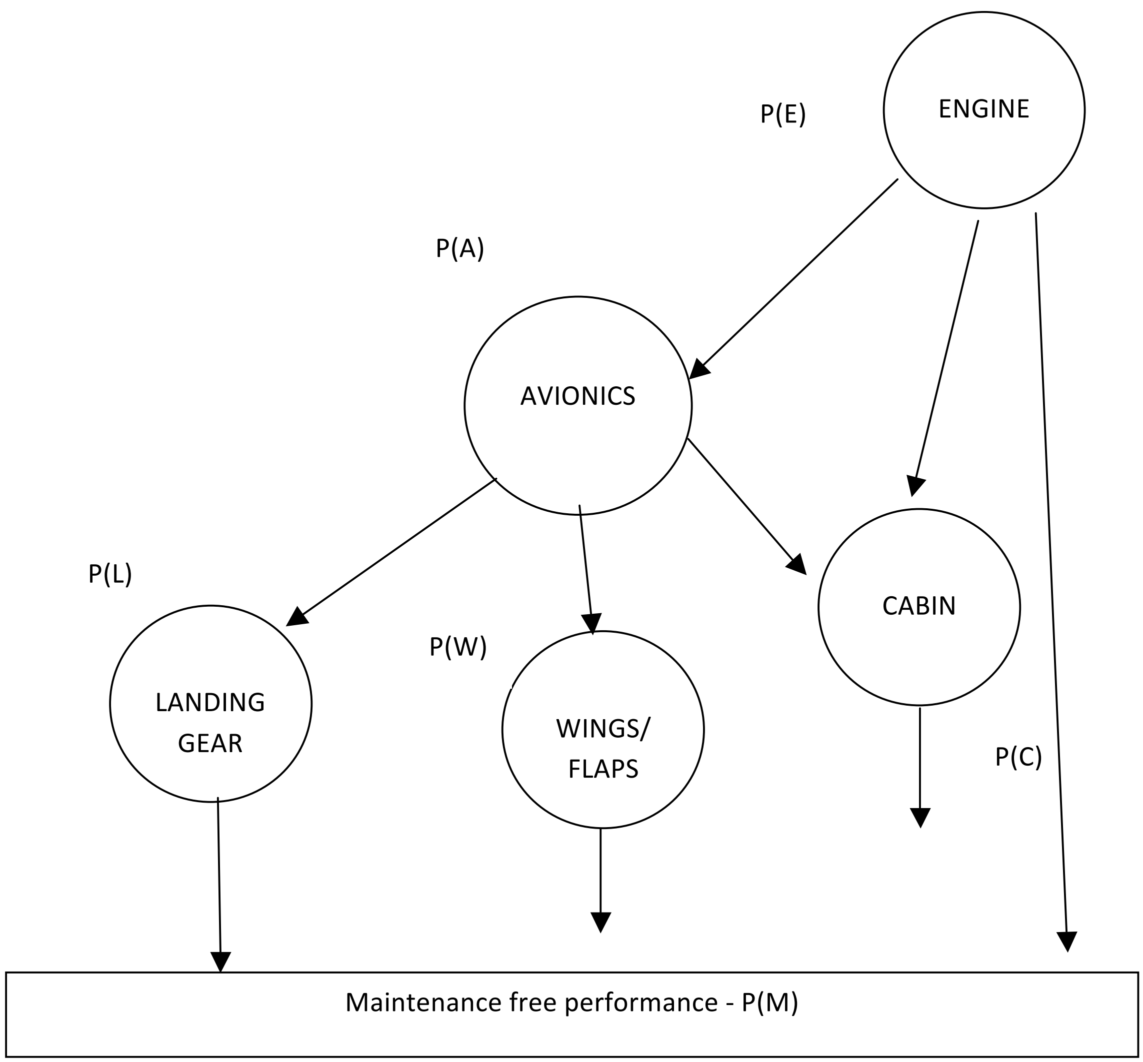

Fig. 6 Bayesian Network representation of the system

The given network has 5 nodes and it states the probability of failure of the system performance as P. The Avionics sub system drives the Wings/Flaps and landing gear, and cabin parameters, while it is dependent on the engine condition. The cabin parameters on the other hand also depend on the state of the engine as engine powers the pressure system that maintains the air quality inside. This interconnectivity is not entirely the same as found in a common aircraft, but it is similar. More complex dependencies are possible, where a tiny decrease in performance of a single sub-system can affect more dependent systems that are on board leading to ripple effect of failure. For simplification and explanation purposes, we will stick to this network to describe the working of Bayesian Network.

P(A = Healthy)	P(A = Fail)
0.98	0.02

A	P(L= Healthy|A)	P(L = Fail|A)
Healthy	0.9	0.1
Fail	0.01	0.99

P(E = Healthy)	P(E = Fail)
0.75	0.25

A	P(W= Healthy|A)	P(W = Fail|A)
Healthy	0.7	0.3
Fail	0.1	0.9

E	A	P(C= Healthy|E,A)	P(L = Fail|E, A)
Healthy	Healthy	0.9	0.1
Healthy	Fail	0.2	0.8
Fail	Healthy	0.9	0.1
Fail	Fail	0.01	0.99

Fig 7 Probability values of nodes in the Bayesian network

The probabilities P(E), P(A), P(W), P(L), and P(C) denoted on the flowchart in previous page has values as defined above.

Inference from BN

With the probabilities of individual states given we can infer the predictive support for the system based on the nodes connected to it. The nodes that are dependent on some other are called child nodes and the one that influences other are called as parent nodes. We now establish the conditional probability of each node based on their parent-child dependencies. Now, to establish the conditional probability that the system will need maintenance is given as,

P(M)	**L**	**W**	**C**	**E**
State 1	+	+	+	+
State 2	+	+	+	-
State 3	+	+	-	+
State 4	+	+	-	-
State 5	+	-	+	+
State 6	+	-	+	-
State 7	+	-	-	+
State 8	+	-	-	-
State 9	-	+	+	+
State 10	-	+	+	-
State 11	-	+	-	+
State 12	-	+	-	-
State 13	-	-	+	+
State 14	-	-	+	-
State 15	-	-	-	+
State 16	-	-	-	-

Fig.8 Conditional probability states for maintenance of the system

here, the healthy states of individual probabilities are given as (+) and failed ones are given as (-). These are the 16 different probabilities that are possible for the overall outcome of the system P(M). The need for maintenance at each state is decided by the overall probability that we get from the state response.

$$P(\text{need maintenance}) = P(\ M = \text{fail} \mid L, W, C, E)$$

Furthermore, it also helps us to decide if we need to maintenance immediately or schedule one later. Some system failures are not severe that they need the aircraft to be grounded down. It can be done on-site or while transit. The severity of the failure is determined by an entirely different parameter, which much is established prior to this predictive maintenance schema being applied. This schema will enable us to tell which state of the system will be the output if the sub-systems respond in a particular way. For example, let us assume we get responses from the SOM of individual stations as '+' from Landing Gear, '-' from Wings/Flaps, '-' from Cabin, and '+' from Engine then we can conclude that the aircraft will behave in a way to output State 7. This enables us to prepare to respond for the state 7, which may be a severe maintenance schema.

On other hand, we can also monitor the states of output of the system and conclude which of the subsystems is going to fail and which among them will stay healthy. This schema serves its purpose two-way, bottom-up and also top-down. Both of which will enable us to predict the behavior of the system. One important thing to consider here is the fact that we established the connection dependencies between the nodes of the Bayesian Network but in most cases we may never know that and we need to train the network. This is called as BN Learning Problem [11].

Case	**BN Structure**	**Observation**	**Proposed Learning method**
1	Known	Full	Maximum-likelihood estimation
2	Known	Partial	Expectation Maximization/Markov Monte Carlo
3	Unknown	Full	Search model
4	Unknown	Partial	EM + search model

Fig.9 Types of BN Learning process

Learning BN structure is much harder than BN parameter learning. Another big obstacle in BN structure learning is when the nodes have hidden dependency states that are unobservable. The BN Learning process is of four types from literature and can be tackled by using appropriate methods that have been tested. It is listed as a table above.

4. PREDICTION OF COMPONENT DEGRADATION BY USING HIDDEN MARKOV MODELS

4.1 INTRODUCTION

Component degradation is a major source of system failure in an aircraft. There are more than thousand components in each subsystem and each undergoes degradation at its own rate. This degradation has a significant impact on the overall health of that subsystem. Health of the subsystem decides the total health of the HUMS system in the system under study. So, we can safely conclude that the degradation of individual components decides the health of the aircraft. Now the most important question arises, how do we monitor the degradation of components in an aircraft? The most common and effective solution is to use on-board sensors that continuous collect and transmit data about the health of the component. Marquez and Perez [29] did research on various types of in-situ sensors for wind turbine to monitor its health. Literature also reveals that the effective methods include Transmittance Functions (TF), Operational Deflection Shapes (ODS), resonant comparison (RC), and Wave propagation (WP). All these methods are based on exciting the structure with piezoceramic patch actuators and measuring the vibration response using piezoceramic patch sensors. Though the response of the vibration depends on various factors such as placement of sensors, precision of the readings, external factors we may conveniently use that with a degree of uncertainty to calculate the health of the component. The uncertainty sometimes seems large that most systems these days still use preventive maintenance, which causes system to be "over-maintained" or "under-maintained". Over maintaining of a component occurs when we waste the remaining useful life of the component and repair it before it breaks down. Under maintaining occurs when an unexpected failure occurs between the two repairs or when the component is not scheduled for repair. This is the main reason for increased cost of the maintenance in any system and it calls for effective HUMS to be integrated with it. The current research will help to address this problem by predicting the component health and letting the user know when maintenance is required, effectively cancelling out over-maintenance and under-maintenance.

According to the above explanation, a predictive modeling approach will give us,

- Accurate health of the components that form the subsystem
- Start maintenance schema based on the response from the in-site sensors, advantage to prepare us for a downtime and time to bring the repair components on site (or) arrangements to transport the part to OEM

This clearly tells us about the immense benefits for aircraft owners, maintainers, and manufacturers ensuring them of less downtime and less maintenance cost, while extending the remaining useful life of components.

The above-mentioned advantages have some impediments before its effect can be fully utilized. Those impediments are the reason for the uncertainty of sensor data and use of preventive maintenance. They are,

- Observing a component for degradation is a complex problem due to the inaccessibility of various components in a sophisticated design component like jet engine. There are many places where it is intrinsically difficult to place a sensor and measure response. This may also be due to the extreme operating conditions where the sensors are not equipped to operate.
- The data from the in-situ sensors of component conditions such as temperature, pressure, and vibration are highly stochastic and are dependent on the particular operation. Like if the aircraft is operated on a desert condition, the data may be of a kind, which is completely different from the data during normal civilian use.

- Since a particular system can perform multiple operations and the data obtained for each operation, it is difficult to establish a dependency among the data. This in turn increases the dimension of the data that needs to be analyzed for potential health hazard.

Due to the above said reasons, the best way to approach predictive modeling is by proposing a component degradation analysis method by having different discretized states rather than try to extract an analytical relation between the data of various operating conditions. These discretized states are then used in a Hidden Markov Model (HMM) to determine the relations between the observable component information and the unobservable discretized state that each component undergoes. This HMM will develop a model from the dependencies, which will enable us to predict the degradation level at a component on which the sensor is placed.

Since we are dealing with information from hundreds of sensors, the response from one may be related to another. The model developed will capture this connectivity and consider the effect of other's performance on its own when calculating the probability of the component. The advantage of this is, when we need to monitor only a particular subsystem of the aircraft, the model will rebuild itself to capture only the response from sensors that it needs for that particular predictive maintenance task and calculates the solution. Thus using less energy and computation to achieve the same efficient solution we are able to maximize the available resources.

4.2 HIDDEN MARKOV MODEL

To understand what a Hidden Markov Model is we need to first explain the definition of Markov process. A process is termed as Markov process if the future is dependent only on current state and independent of past states. i.e. the past states of the process does not affect the future condition. A sequence in a process that follows the above definition fits as Markov Chain.

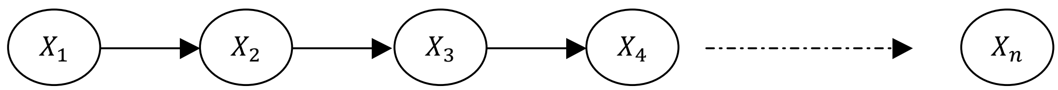

Fig. 10 Markov Chain

$$p\big(X_n\big|(X_1, X_2, .., X_{n-1})\big) = p(X_n|X_{n-1})$$

where $X_1, X_{2,...}\ X_n$ are discrete random variables that represent the various states of degradation of a component. Then from Markov model we have the joint distribution function as,

$$p\big(X_1, X_{2,...,}X_n\big) = p(X_1)p(X_2|X_1)p(X_3|X_2) \dots \dots .\, p(X_n|X_{n-1})$$

The discrete states of the component are difficult to completely observe that they might give incomplete data, which may affect the outcome of the joint distribution effectively miscalculating the degradation of the component. This can be solved by assuming that each state in the chain hides some information. We try to extract this information by creating more states to represent this hidden information. These are called hidden or unobserved states. When a Markov model has hidden states then it is called as Hidden Markov Model, provided that it follows the definition of Markov process. The structure of Hidden Markov Model is given as,

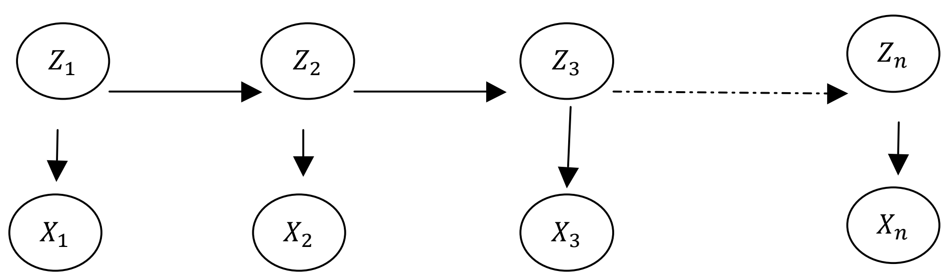

Fig. 11 Hidden Markov Chain

where $X_1, X_{2,\dots}\ X_n$ are discrete random variables that represent the various states of degradation of a component and $Z_1, Z_{2,\dots}\ Z_n$ are discrete random variables that represent the various hidden states of degradation of a component.

The joint distribution of the Hidden Markov Model is,

$$p(X_1, \dots, X_n, Z_{1,\dots,}Z_n) = p(Z_1)p(X_1|Z_1)\prod_{k=2}^{n} p(Z_k|Z_{k-1})p(X_k|Z_k)$$

Given a particular type of Hidden Markov Model (HMM) we can use parameters such as emission probability distribution, transition probabilities, and initial state probability distribution. The parameters are defined as follows

- *N* is the number of states in the model. The states are interconnected and can be related from any other state. The states are X = $\{X_1, X_2, \dots, X_n\}$
- *M* is the different observations per state. This is related to the output of the model. x = $\{x_{1,}x_2, \dots, x_m\}$
- **Emission Probability Distribution:** The emission probability for the model considered is given in density form as,

  $$\varepsilon_i\,(x) = p(x|Z_k = i)\text{ , where i } \epsilon \{1,2, \dots . m\}$$

  The above equation in probability mass function form is represented as,

  $$\varepsilon_i\,(x) = p(X_k = x|Z_k = i)\text{, Where i } \epsilon \{1,2 \dots m\}$$

- **Transition Probability:** The transition probability can be written as an *mxm* matrix, also called a stochastic matrix. It is represented as,

$$T(i,j) = p(X_{k+1} = j | Z_k = 1) \text{ , where i, j } \epsilon \, \{1,2, \ldots . m\}$$

- **Initial state distribution:** The initial state distribution for the hidden markov model is given as,

$$\pi(i) = p(Z_1 = i) \text{, where i } \epsilon \, \{1,2, \ldots . m\}$$

Therefore, the joint distribution of the Hidden markov model can be written in terms of these parameters as,

$$p\big(X_1, .., X_n, Z_1, .., Z_n\big) = \pi(Z_1)\varepsilon_{Z_1}(X_1) \prod_{k=2}^{n} T(Z_{k-1}, Z_k)\varepsilon_{Z_k}(X_k)$$

In most cases, the form of the distribution is independent for the above probability. Therefore, the distribution of the state values from the sensor response need not be treated as Gaussian distribution for simplification purposes.

For complete specification of HMM we need values for two model parameters (*N and M*) . There are problems in using this model. From Yang Liu [4],

- Learning problem: Given the underlying model λ = (A, B, π) adjust the model parameters A, B and π to maximize the probability of the observation sequence P[O | λ].
- Decoding problem: Given the underlying model λ = (A,B,π) and observation sequence O = $\{O_1 O_{2 \ldots} O_T\}$ find the most likely state sequence Q = $\{Q_1 Q_{2 \ldots} Q_T\}$
- Evaluation problem: Given a model λ = (A,B,π) and observation sequence O = $\{O_1 O_{2 \ldots} O_T\}$, the solution to evaluation problem is to calculate the probability of the occurrence of the observation sequence P[O| λ].

The dynamic programming algorithms known as the Viterbi algorithm and the Forward-Backward algorithm, respectively, can solve the first and the second problem. An iterative Expectation-Maximization (EM) algorithm, known as the Baum-Welch algorithm, can solve the last one.

4.3 APPLICATION OF HMM

The research proposes to use the Hidden Markov Model developed in the previous section to be used in the framework of the system of the aircraft under study.

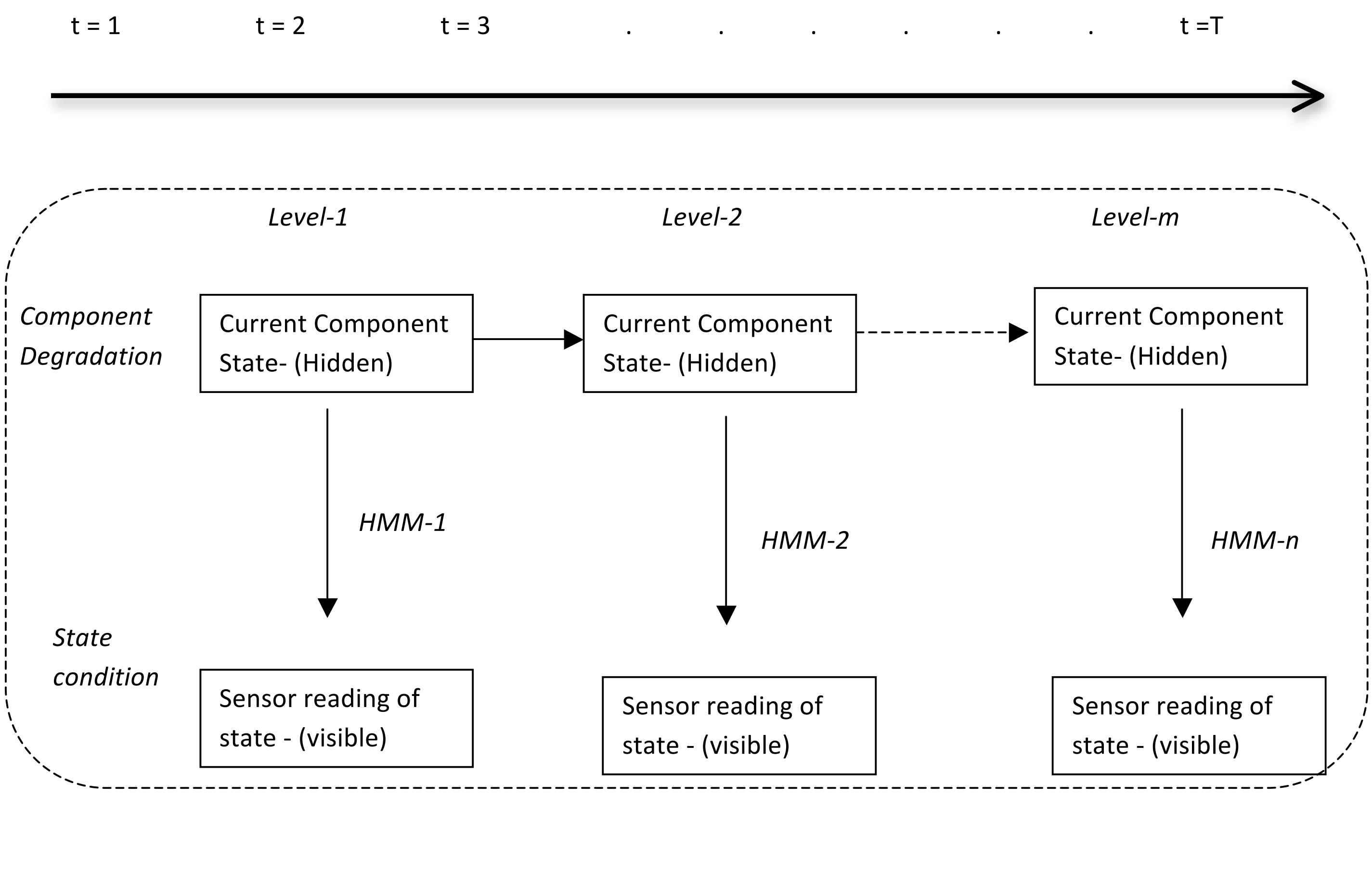

Fig. 12 Hidden Markov Model representation of the system

In the proposed HMM model, the directly unobservable degradation of components is calculated by using responses from the in-situ sensors that are placed on the component. Since, these sensors collect and transmit different data it is necessary to have a HMM model of multi dimension. The original baum-welch algorithm is designed for 1D systems and we need to modify it to suit our needs.

From literature, one way to modify the algorithm to suit multi-dimensionality is to assume the data from the sensors are independent of each other and then the emission probability can be calculated by multiplying emission probabilities of individual dimension. In summary, we have

Predictive Model Step	HMM algorithm to use
To find the probability of particular output sequence (here particular degradation state)	Forward and Backward Algorithm
To find the most likely sequence of hidden states that has generated the obtained output	Viterbi Algorithm
Given a particular output, to find the most likely set of state transition and output probabilities	Baum-Welch Algorithm

Fig 13 HMM Algorithms

4.4 SIMULATION STUDY

With the model proposed, we conduct simulation study to test the predictive algorithm schema. To validate the model we consider the degradation states of components as a one-dimensional Hidden Markov chain. Much of the conceptual equations described and applied to the model considered is similar to the ones described in a seminal paper by Cholette and Djurdjanovic [27]

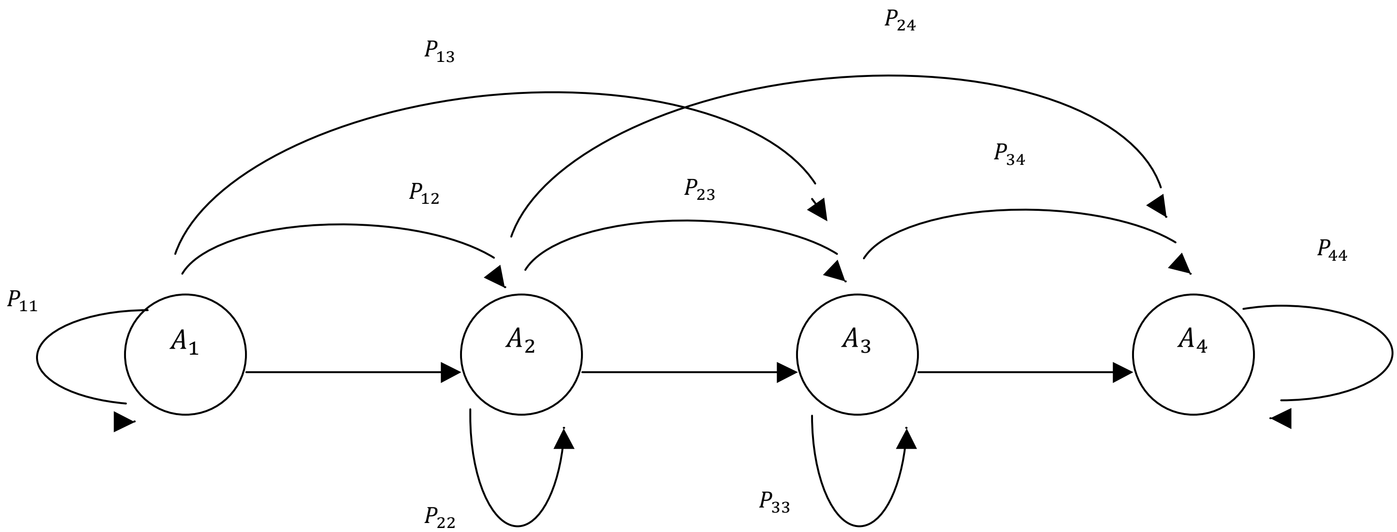

Fig. 14 One-dimensional HMM with probability states

Here, we consider 4 states and 2 observations from each states. From the above-mentioned theory, we can obtain the transition probability and emission probability matrices from random initialization as,

$$\text{Transition probability, A } = \begin{bmatrix} 0.6013 & 0.9038 & 0 & 0 \\ 0 & 0.9251 & 0.2843 & 0 \\ 0 & 0 & 0.5749 & 0.4677 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\text{Emission Probability, B} = \begin{bmatrix} 0.9240 & 0.1514 \\ 0.5314 & 0.1496 \\ 0.3668 & 0.3508 \\ 0.3639 & 0.3360 \end{bmatrix}$$

The above obtained matrices are the random initialized states of the given degradation markov chain. By using the Statistics and machine Learning Toolbox functions in MATLAB that are related to hidden markov models we get,

The sequence of states and emissions for the model by using *hmmgenerate* command for 10 steps is,

seq = [1 1 1 1 2 1 1 2 2 1]

States = [1 1 2 2 3 3 3 4 4 4]

Given the sequence of states and matrices we can estimate the most likely sequence of states the model would go through to generate a given sequence of emissions. Using hmmviterbi command in the MATLAB toolbox does this. For the given sequence of emissions the likely states are,

likely_states = [1 1 1 1 2 2 2 2 2 2]

For the given sequence of output we can estimate the true transition and emission probability matrices by using another in-built MATLAB toolbox, *hmmestimate* which then gives the final estimate as,

$$\text{Estimated Transition probability, } A' = \begin{bmatrix} 0.5 & 0.5 & 0 & 0 \\ 0 & 0.5 & 0.5 & 0 \\ 0 & 0 & 0.667 & 0.333 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\text{Estimated Emission Probability, } B' = \begin{bmatrix} 1 & 0 \\ 1 & 0 \\ 0.667 & 0.333 \\ 0.333 & 0.667 \end{bmatrix}$$

The above estimated transition and emission probabilities are obtained from the initial random initialization that we started with. Most of the paper sin the literature use a random guess to start the algorithm and they train it by using the maximum tolerance and iterations. Tolerance is the value that sets the limit for the varying states and the algorithm halts when it is reached.

Output State Probabilities: It is the probability for the obtained emission sequence *seq* that the model is in particular state when it generates a symbol in that *seq*, given that *seq* is emiited. For our model we get,

The output state probabilities, OP as

$$OP = \begin{bmatrix} 0.8373 & 0.6678 & 0.4980 & 0.3388 & 0.2093 & 0.1371 & 0.0758 & 0.0374 & 0.0202 & 0.0108 \\ 0.1627 & 0.3202 & 0.4553 & 0.5386 & 0.5194 & 0.5126 & 0.4484 & 0.2875 & 0.2143 & 0.1864 \\ 0 & 0.0120 & 0.0417 & 0.1003 & 0.2078 & 0.1998 & 0.2419 & 0.3406 & 0.2857 & 0.1954 \\ 0 & 0 & 0.0050 & 0.0223 & 0.0635 & 0.1506 & 0.2340 & 0.3345 & 0.4798 & 0.6074 \end{bmatrix}$$

It is an ixj matrix, where i =4 (Number of states) and j = 10(Length of sequence). Each element of the matrix gives the probability that the component's degradation is in particular state and sequence.

Inference from the Simulation Study

From the simulation study we did, we can conclude the degradation level of a component from the output probability matrix. The state that has the highest probability has the most likely chance to occur. Also, from the different algorithms mentioned above we can track the progress of degradation from the sequence obtained. We can also trace back to the path that the degradation took by analyzing the sequence of states.

This example is to explain the concept of using Hidden markov model to predict the degradation of a component. Of course, in real world application the markov chains have more than 4 states and more observations on each state. With increasing number of states and observations the computational cost and time goes higher. The system must be equipped to handle those. In some cases, the markov chains may be coupled, i. e two or more chains may be dependent on each other and the transition state of one may affect the other. This adds an extra dimension to the markov chain and those are called multi-dimensional markov chains. The above algorithms can be successfully applied to those coupled markov chains as well to get the output conditional probabilities.

5. INTERACTIVE ELECTRONIC TECHNICAL MANUALS

5.1 INTRODUCTION

Regardless of type of maintenance schema employed for a system, the efficiency of repair depends on the abilities of technician that performs the troubleshooting task. While most OEMS train their technicians on troubleshooting and system overhaul there are still cases in which the mechanical system fails in a way that they have not experienced before. In that case, the technician has no prior knowledge of how to treat the failure and what is the procedure to restore. To aid the technicians, all manufacturers and component builders started providing manuals. That manual, a paperback book has all the instructions on how to repair a component. This was the beginning of the manual history and over the course of evolution it started to evolve as,

Technical Manuals (TM) - these are paper documents that had instructions about troubleshooting and often 2D drawing of components. **Cons**: Too long, not easy to carry, takes longer time to navigate, not enough insight on component.

Electronic Technical Manuals (ETM) **-** with the advent of digital technology and software capabilities, the paper documents were converted to digital form, usually pdfs that had all the information from the technical manuals and with little added advantages like easy to navigate, quick search and more images with exact visual appearance.

Interactive Electronic Technical Manuals (IETM) - This is the latest advancement in the world of technical manuals and it adds the interactive capability to the already electronic technical manual. The interaction is an intelligent way of finding the resources that are needed to troubleshoot a problem. It also has 3D views, assembly animation, blow-up view, and videos of previous repair and often times the history of performance of the part in the system.

IETMs were first developed by US Army to help them in maintaining the complex war machines they had. This was how IETMs evolved into existence and this evolutionary development has been termed by classes of IETM in the industry, which are given as, [24]

5.2 CLASSES OF IETM

These classes of IETM were introduced during the later part of 1990s to give a structured level of advancement to be achieved during the process of IETM development. They are given here only to give an idea of how the IETMs have evolved over the years and not to classify the existing IETMs. Recent developments in IETM has been discussed in detail in section 5.4

Class I - Electronically Indexed Page Images

This is the first class of IETMs, which has the paper manuals scanned into images and put together with page numbers. The document can be accessed to a particular topic by using the index page. The document can also be printed and used as a reference manual while on the repair floor, without losing any information due to printing format changes.

Class II - Electronic Scrolling Documents

This class of IETMs has similar kind of scanned images with links to the index page but usually carries images, tables and other external links. They also have a word search option, which enables us to get particular information easily. It can also be printed for reference. The most usual type of class II IETMs are made in Standard Generalized Markup Language (SGML) and the second type is Abode pdf form.

Class III - Linearly Structured IETMs

This class of IETMs is advancement over previous two copies. It has a linearly structured pattern that has all the topic and information regarding it arranged according to this linearity. It is convenient when you are in need to print a hardcopy of Technical Manuals. Since they are arranged in a linear structure all the information concerned with a type of sub-system is placed close and can be easily accessed and taken out. This linearity also tells the technician which part to be repaired first and what order to follow in case of multiple component failure.

Class IV - Hierarchically Structured IETMs

Taking the hierarchal concept to next level, class IV IETMs totally redefine the way they are structured. It follows a pyramid hierarchal pattern with parent-child relations established depending on the dependency in the real mechanical system. The most important factor in this type of arrangement is the ability to eliminate the redundancy. This class is usually built upon the previous IETMs, which are first taken out, and re-authored to give the structured database that it needs using Logistic Support Analysis (LSA). This enables the IETM to break paragraphs of instructions into simple statements. The application (view) program then provides the necessary context and transition. The transition follows the hierarchy and gives us easy, correct, and only wanted information. This is a huge advantage over the previous 3 classes in which we had to scroll down all through the document to find the component information we needed. This can also be said as an advantage of having parent-child hierarchy structure.

Class V - Integrated Database IETMs

Class V IETMs are the integration of the technical database with an expert system with training. This class also follows the hierarchal structure and it has in addition, an expert links on all the leaves of the tree. This gives an extra knowledge support for the technician who can consult the expert in case of some problem that he/she couldn't solve. This system is close to being autonomous in the way that it can talk to the technician, take the problem question and give answers and instruction on how to act. The system can also be trained to be intelligent. This means that when the technician faces a new case of failure and troubleshoots, the database updates that with the information and provides it when this similar case occurs again.

This class is multi level accessible and it has links to all the possible resources that a technician might require. He can also access the data sheets from the OEMs and send information from this system. The more data that they collect the more expert the IETM becomes. This enables a quicker maintenance repair schedule that means less downtime. While more industry manufacturers and system installers push for this class of IETM available for their system, it had to be built over the previous classes and it is important to customize based on the system and also on the customer that user the system.

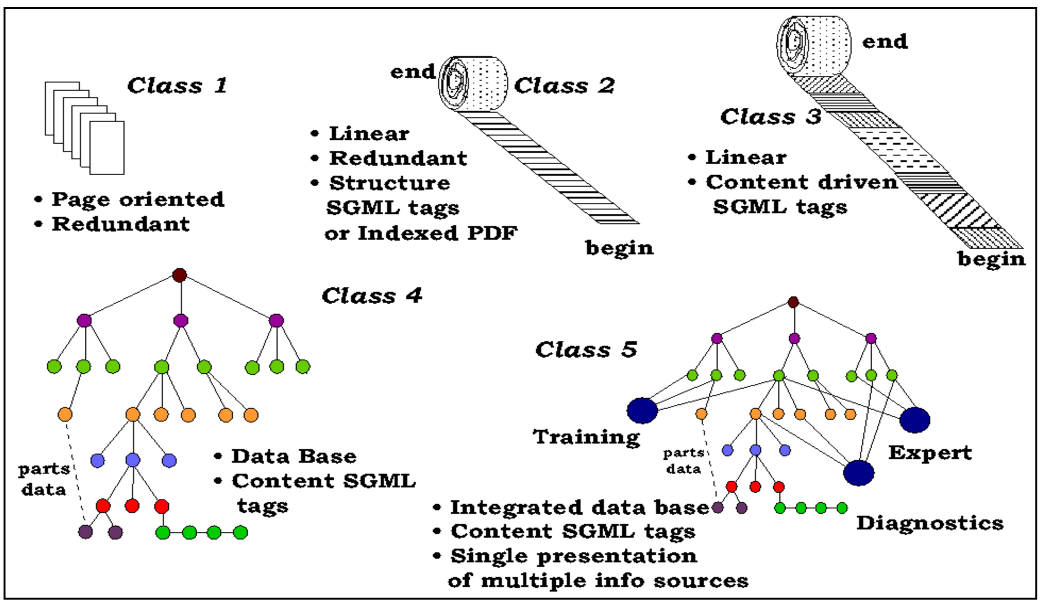

Fig. 15 Classes of Interactive Electronic Technical Manuals

5.3 BENEFITS OF IETM

We had already summed the importance of IETM for a system, which has to be maintained over a long period of time and in regular intervals. Here, we highlight those benefits and quantify the advantages that these type of manuals carry with them when compared to conventional manuals.

Problem	Traditional manual	IETM
Weight	Paper is heavy, manual for an Oliver Hazard Perry class frigate is 21 tons approx.	A standard CD can hold 3400 pages, recently all are placed in flash drive that is less than 10ounces
Volume	Paper takes a large volume and it also deteriorates as more people use	Less or nearly no volume, even with a backup copy. It is virtually fresh always and no information is lost
Information Access	They are complex and has multiple booklets for a single system which takes time to access information.	Access is easy as it is searchable, and it follows an hierarchal structure
Up-to date information	Changes and updates to the manuals takes time and work to be done	Database is interconnected and can be updated as soon as an update is ready

Fig 16 Conventional Manuals vs IETMS

The above table summarizes the benefits of the IETM over the paper based conventional manuals. There are also other benefits that are exclusive to the use of IETM. They are,

Maintenance Improvements

All system maintenance begins in finding the system malfunction, then goes to isolate it, and then repair it before its back up running. There are numerous stages in between that are hidden and are carried out by technicians. The work in those stages is prone to failures even with a troubleshooting manual. The instructions may be misleading a technician or he might not have the understanding of the technical jargon used in creating those manuals. But if the whole process uses Interactive Electronic Technical Manuals (IETM) then the process might be more efficient as many studies, including the one by DoD, find this true. The key maintenance improvements are,

- Reduced False alarms
- Better fault Isolation and diagnostics
- Improved personnel and equipment safety
- Less down-time

Fault isolation improvement

Fault isolation is an important step in the troubleshoot process. This step decides the rest of the process by setting a tone. By using IETM, the technician can isolate the fault by backtracking the fault component in the hierarchal structure. This way technician can identify the sub system that is under fault and he can concentrate on that part alone leaving the rest of the system untouched. This saves time and energy. By using IETM the fault isolation success rate can also be improved, as the database is up to date with the information and dependency relation between components in the system.

5.4 RECENT PRACTICES IN IETM

IETMs recently have undergone a massive overhaul in terms of the development and implementation. The classes of ITEMs explained above did early researchers make the classifications and they set this track of evolution for it. But recently development of IETM could not reach Class V for various reasons including collection of resources, building an effective hierarchal system, retrieval of information, etc. So, in order to compensate for the loss in evolution, they took a radical new approach of having virtual sources in addition to real sources and call it virtual environment. This was clearly stated by John Lacontora in his dissertation [22], where he developed the concept of having three environments: Live, Virtual and Constructive for the maintenance personnel to access resources and get trained.

Live environment is a space where real people collect live information from real systems. Personnel that have been assigned to manage the system by the original equipment manufacturer usually do this. Virtual environment is a simulated environment where real people learn maintenance by simulating failures in computer-aided system. This helps to train personnel in issues that are usually expensive to create for training. Constructive environment is a simulated experience of having component failure that is created by computer-aided systems to create combinations of failures that are possible to occur in a system. This gives a wide variety of failure modes that are then used to train the personnel.

IETMs can tap these three environments and learn information from them. Recent studies have suggested that using these environments can give the advantages that are comparable to highest level of IETMs that can be developed with the technology available. One major deciding factor before implementing this type of IETM is deciding how much of each of the environment should be considered while deciding to develop an IETM system. Frank and Helms [17] proposed a technology-based methodology that makes necessary trade-offs between these environments while making an effective IETM schema. We can adapt their FAPV model (Familiarization, Acquiring the skills, practicing the skills, and validating the skills) to decide which part should carry more weight in deciding the outcome of the IETM system.

5.5 IETM in Predictive Maintenance:

Predictive Maintenance helps us predict the health of the component and lets the operator know when it is going to fail. This enables the operator to have a time frame to schedule maintenance and carry out the repair. While carryout repair, it would be an additional advantage to have Interactive Electronic Technical Manual (IETM). The IETMs are custom developed for a particular system and it serves its purpose of linking all the required resources to the technician at the time of need. There are numerous IETM providers in the market now that they do as a consulting work and they all follow the same standards to establish the best working aid.

The current research proposes the following: integrate the predictive maintenance schema with the IETM database for seamless working and resource mining.

The Health and Usage Monitoring System (HUMS) that is integrated on a airplane has on-board sensors that collects health information and sends it to a DAQ system as explained earlier. This is then passed through a Predictive maintenance schema, like the one suggested in this research, to predict the failure of a component in that system. The proposal adds to this in integrating the IETM with the predictive maintenance schema. This takes the outcome of the predictive maintenance taken to the IETM database, which evaluates it and presents the operator/technician with the required instruction to repair the component that has been predicted to fail. In other words, the IETM makes sure it is ready with the resources a technician might need even before the actual failure occurs, provided the predictive schema is trained enough and is accurate to its best. The proposal can be put in a flowchart as,

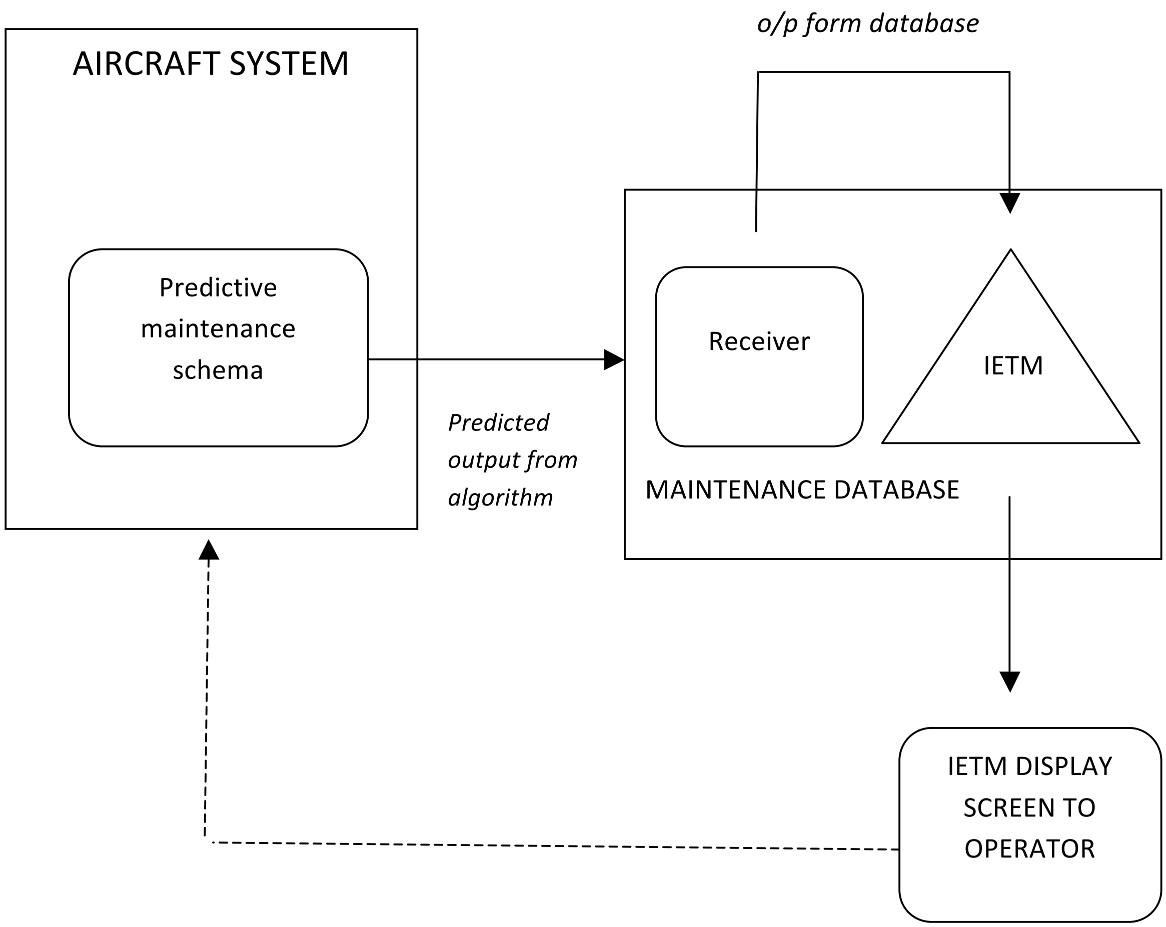

Fig. 17 Interactive Electronic Technical Manual in Predictive Maintenance

The flowchart explains the proposal in which the predictive maintenance schema integrated with the system executes the algorithm which then gives the output to the maintenance database as whether a particular component is going to fail or not. If it predicts it is going to fail, then the IETM is sent a signal that pulls out all the resources it has for that component that is predicted to fail. This is then sent to the operator if it is needed. The advantage of this method is it takes the response of the repair system a step closer to autonomy. This also saves time; money and technician training required navigating the IETMs.

6. CONCLUSIONS

This thesis has proposed a method of developing a predictive maintenance schema for a complex system like aircraft. Predictive maintenance was explained in general with some background on the advancements that have happened over the years in this field. The advantage of choosing a predictive maintenance schema over other types of maintenance schema was explained with reasons to prove the need for this research. In the system considered, the algorithm developed has used the multivariate regression analysis to process the incoming data from the sensor and use a Bayesian network to establish a relation between the different sectors of the system. Extraction of data from in-situ sensors and collecting it at the data acquisition system was assumed to be effective task in this model. But in reality, one might have to consider multiple factors while designing a data collection and processing system. As explained in the literature and in this thesis, the data collection can be dynamic as well as static. In dynamic collection the model is installed in a computer system that is placed in a location away from the system. The data is collected and brought to the computer to be analyzed by the maintenance schema. By comparing the data from past and learning from the new one, we can predict when a particular component is going to fail and when maintenance action is required. The schema also proposed a method to determine the degradation rate of components by using Hidden Markov Models. The current work used in-built MATLAB toolboxes to explain the concept of the proposal and presented examples. The data used in these examples are random initialized from the numerical system. The results from these samples are analyzed to find the health status of the component. This HMM coupled with the multivariate regression model that we used before makes the schema predict the failure of a component in a system. This whole maintenance schema can be applied to a static system as well, where the data acquisition system is integrated within the system while it is manufactured. This does the job of predicting the health of components without any human interface or loss of transmission. Hence, it is deemed as the effective method and is usually favored. The results from the predictive maintenance can be used to improve the capabilities of the decision support tools that the operator uses to conduct maintenance action. The maintenance action can be to repair or overhaul the component in a system or to replace a component or to shut down a production line based on the system under consideration. In any case, the operator needs to have a plan of action to decrease the downtime. If one of the production lines is predicted to fail then it is suggested to ramp up the production in other lines to compensate the loss in production. Even in this case, a probability model should be implemented to decide which other lines should be chosen to increase the production and at what level. In case of replacing a component, the required tools and new component should be made available before the component really fails. In many cases, it is required to transport the system to the original equipment manufacturers factory, and then logistic arrangements should be made. With the maintenance schedule totally defined from healthy performance to failure we then state the significance of the Interactive Electronic Technical Manuals in predictive maintenance. Combining the resources from live, virtual, and constructive environments a holistic manual is put together that has all the resources needed to perform a repair in a component. This also educates the personnel to have knowledge of the system and its maintenance, which is important with the recent advancements as the gap between the worker knowledge and system development is significant. This class of IETM is then integrated with the predictive maintenance schema to predict the resources that an operator might need. This will give a significant saving in time. As constructive environment is also attached to the IETM we have all the possible failures of the system simulated and ready with instructions to repair. If a new error occurs, the live environment captures it and records the set of actions. This then is updated into the database for future references. The IETM gets smarter as time progresses and becomes more effective resulting in more savings down the road.

7. FUTURE WORK

Suggested future work on this thesis includes implementing this algorithm in a real environment for test and validation of the model. The Health and Usage Monitoring System can be designed and built on an airplane and the algorithm can be installed on the system. Data should be collected from the critical components of that system. Data collection strategies should be studied as dynamic and static modes can give different values. Also, the location of sensor on the component affects the reading from the component. A complete study of data collection mode can be made. This data should then be discretized and analyzed by using SOM toolboxes and then set into Bayesian networks to give a result of dependencies among the components of the system. The sensor data can also be sent into the HMM model to determine the degradation level of individual component. A record should be made of all the results and a database is created. More experiments should be done and more reports are added to the database.

Future work may also include applying other kind of maintenance schemas such as preventive and condition-based to the same system that is under test and comparing the results obtained from these schemas to decide which one suits the need of the operator and matches the availability.

A database should be built or should be created bespoke for the system with all the available resources available to put Interactive Electronic Technical Manual together for the system. The usage of live, virtual, and constructive environments can be varied depending on their availability and ease of integration to the system. Then the proposed method of using IETM with predictive maintenance can be used to perform maintenance work. It can be compared to a normal usage of IETM without the predictive maintenance and visualize the exact quantity of advantage one might achieve in using this. Another recommendation is the implementation of a recommender system within the IETM database that would recommend the operator to use the related resources when it gets to know that the current resources that it is providing is not sufficient enough for the operator to repair.

Finally, Reliability-centered maintenance II methodology can be incorporated with this algorithm. This would produce a grand reliability centered maintenance schema that provides an efficient usage of the system, personnel efficiency and also the maintenance operation execution.

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