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HIDDEN MARKOV MODEL FOR HEALTH ESTIMATION AND PROGNOSIS OF TURBOFAN ENGINES

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ABSTRACT

Determining the residual life time of systems is a determinant factor for machinery and environment safety. In this paper the problem of estimate the residual useful life (RUL) of turbofan engines is addressed. The adopted approach is especially suitable for situations in which a large amount of data is available offline, by allowing the processing of such data for the determination of RUL. The procedure allows to calculate the RUL through the following steps: features extraction by Artificial Neural Networks (ANN) and determination of remaining life time by prediction models based on a Hidden Markov Model (HMM). Simulations confirm the effectiveness of the proposed approach and the promising power of Bayesian methods.

INTRODUCTION

Systems, plants and machinery prognosis is the forecast of the remaining operational life, future condition, or probability of reliable operation, and it is based on an equipment that acquires condition monitoring data. This approach to modern maintenance practice promises to reduce downtime, spares inventory, maintenance costs and safety hazards [1]. The assumption under which the prognosis became effective is that failure mechanism of systems involve several degraded health-states, or systems are subjected to wear. Tracking and forecasting the evolution of health-states and impending failures, in the form of Remaining Useful Life (RUL), is a critical challenge and regarded one of the main topics of Condition Based Maintenance (CBM) [2]. CBM is a maintenance technology that employs such tasks as monitoring, classification, and forecasting to increase system readiness and safety while reducing costs attributed to reduced maintenance and inventory, increased capacity, and enhanced logistics and supply chain performance.

Many approaches exist to monitor the health state or to estimate the RUL of systems, they can be divided into physics-based prognostic models and data-driven prognostic models. Physics-based models typically involve building mathematical models to describe physics relations of the system, failure and wear propagation [1], [3] and [4]. Data-driven approaches attempt to derive models directly from collected Condition Monitoring (CM) data, they produce prediction output directly in terms of CM data. Conventional data-driven methods include simple projection model, such as exponential smoothing [5] and [6]. Most of these trend forecasting techniques assume that there is some drift in measured system signals that reflects the health degrada-

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tion. Artificial Neural Network (ANN) is one of the most commonly data-driven technique in the prognostic algorithms. In [7] a Recurrent Wavelet Neural Network (RWNN) is developed to predict rolling element bearing crack propagation. The network performes a tracking of enlarged crack. In [8] a Neuro-Fuzzy (NF) network is used to predict spur gear condition value one step ahead. Fuzzy interference structure is determined by experts, whereas fuzzy membership functions are trained by neural network. Adaptive training technique was proposed in [9] to improve the NF model. Multiple-step-ahead prediction is also performed in [10] for rolling element bearing condition monitoring and estimation, by feeding the predicted value back into the network input until desired prediction horizon is reached. Some rules are used to vary data sampling period taking into account the change ratio of consecutive condition index value. Particle filtering has also been implemented to provide non-linear projection in forecasting the growth of a crack on a turbine engine blade [11]. In [12] a recursive Bayesian technique is proposed to calculate failure probability based on the joint density function of many CM data features. The use of Hidden Markov Models (HMMs) in bearing fault prognosis is proposed in [13]. In an HMM a system is modeled to be a stochastic process in which the subsequent states have no causal connection with previous states. Typically the HMMs are trained to estimate health or fault states. Indeed HMMs are able to estimate unobservable health-states using observable sensor signals or defined features computed by other algorithms. Some approaches combine fault diagnosis and prognosis in a unified framework, or need to extract features from data, that are used by HMMs for estimate the health-state. In [14] and [13] the features are computed by Principal Component Analysis, where measured signals are vibrations. The features are extracted by amplitude demodulation as in [15]. Whether signals from sensors are used or that features are computed, the inputs of HMM need to be chosen as most reliable as possible. Indeed appropriate features are able to capture unique properties of fault conditions and health state. Another motivation that induces authors to generate features, is to reduce the computation complexity of HMMs algorithms.

In the present work a HMM is used to estimate the RUL of a turbofan, features are extracted by an ANN that is trained to identify faultless parameter of the turbofan in different flight conditions. Residuals are obtained at the end of each flight and a set of indexes are generated. The HMM uses these indexes and computes RUL estimation, as the number of remaining flights. These models give estimations on residual life and health-state by modeling observations (inputs) as probability density functions. Thus it is possible to define a model composed by a set of states that are described by a probability density function already. This permits the use of Bayesian inference algorithms for estimate health conditions. Data are generated by the model simulator C-MAPSS (Commercial Modular Aero-Propulsion System Simulation). Signals consist of time series of sensed measurements typically available from aircraft gas turbine engines. The data were used as challenge for the Prognostics and Health Management (PHM) data competition at PHM'08 [16].

The paper is organized as follows. Section 1 gives the problem description that is taken as the case study. In section 2 the HMM model and related algorithms are presented. Section 3 discusses the features extraction procedure and in section 4 the implementation and results are shown. Finally section 5 refers to some conclusions and comments about future works.

1 PROBLEM DEFINITION AND PROCESS MODEL

Turbofan engines constitute a complex system, requiring adequate monitoring to ensure flight safety and timely maintenance [17], [18] and [19]. Therefore it is essential to assess prognostic techniques, that can help to provide early detection and isolation of precursor and/or incipient fault condition to a component failure, and can also help manage as well as predict the progression of various faults to component failure. The prognostic module would also perform failure prognosis, which involves both forecasting of system degradation based on observed system condition (current diagnostic state and available operating data), and prediction of useful remaining life of the turbofan engine. Prognostics has taken centre stage in condition-based maintenance where it is desirable to estimate remaining useful life (RUL) of a system. Estimating the RUL of a component or system with uncertainty bounds that are narrow enough offers the prospect for increased system safety along with more cost-effective maintenance. Based on RUL estimation, the operation team can perform on-demand maintenance or CBM, otherwise from the traditional time-based practice in which components are managed to life limits based upon fleet-wide statistics and average expected usage. The traditional approach is necessarily conservative, requiring the replacement of parts irrespective of how much of their useful life is actually expended. For example, aircraft engine turbine discs are usually retired at the time when 1 out of every 1000 discs has initiated a short detectable fatigue crack. On a life-distribution plot, this is the "-3 sigma" life curve. This implies that over 99.9% of expensive turbine rotor discs are retired before their useful life has been consumed, a practice that is extremely wasteful [20], so conventional maintenance strategies (like corrective and preventive maintenance) are not adequate to fulfill the needs of expensive and high availability systems, such as the turbofan engine. In contrast, a condition-based predictive maintenance, that is needed to assess the future health of critical components of engines based on observed data and available knowledge about the system, results are therefore used for making proactive decisions about preventive and/or evasive actions with the objectives of maximizing the service life of replaceable/serviceable components, minimizing operational risks, and reducing costs, with the same safety margin, incurred during inefficient schedule-based preventive maintenance. To accomplish this demanding task, engine monitoring systems (EMS) have become increasingly standard in the last two decades, in step with advances in aircraft engines and computer technology. So the goal, to be asked, is to automate the procedures for monitoring and prognosis in order to reduce costs and maintain high system reliability. Moreover, in turbofan engines the control task is an essential part of the jet engine, that result in a mechatronic system. Turbofans are most effective when they can operate at or near their mechanical, thermal, flow or pressure limitations, such as rotor speeds, turbine temperatures, internal pressures, etc. Controlling at but not exceeding a limit is a very important aspect of engine control which must, therefore, provide both regulation and limit management. Minimum control requirements include a main fuel control to provide limit protection. More advanced controls schedule engine geometry and provide fan and booster stall protection, control variable parasitic engine flows, and need to monitor many engine parameters [19].

A common turbofan has as its "core" a compressor, combustor, and a turbine which drives the compressor. In addition it has a fan in front of the core compressor and a second power turbine behind the core turbine to drive the fan as shown in figure 1. The flow capacity of the fan is designed to be larger than the compressor so that the excess air can be bypassed around the core and exhausted through a separate nozzle. The bypass approach reduces engine specific thrust but increases propulsion efficiency thereby reducing fuel consumption and is the engine chosen for subsonic commercial airplanes [19]. Some of the particular features of turbofan engine are [21]:

1. single stage fan with high pressure ratio.
2. a low pressure compressor.
3. high stage pressure rise mixed-flow compressor.
4. double-annular combustor.
5. high pressure turbine.
6. low pressure turbines.
7. variable cycle capability with forward blocker doors and an aft variable area bypass injector.
8. advanced exhaust nozzle technology.

The diagram in Figure 1 shows the main elements of the turbofan engine model [16]. The simulated turbofan has equipped with 21 sensors that describe the engine state and has 5 input that are considered as external conditions. Table 1 and 2 resume the signals acquired with their descriptions.

2 HIDDEN MARKOV MODELS AND PROGNOSIS PROCEDURE

HMMs are a class of Markov models composed by a set of states that map observations in a probability density function of each one. The resulting model consists of two stochastic processes, one of which is not directly observable but can be estimated through the other one, that produces the sequence of observations. These models have many applications in speech

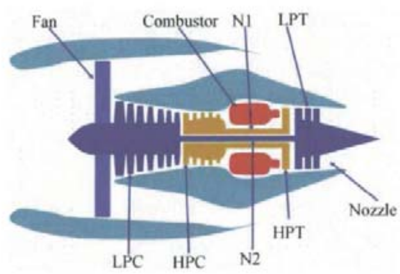

FIGURE 1. Simplified diagram of turbofan engine

Variable name	Description
T2	Total temperature at fan inlet
T24	Total temperature at LPC outlet
T30	Total temperature at HPC outlet
T50	Total temperature at LPT outlet
P2	Pressure at fan inlet
P15	Total pressure in bypass-duct
P30	Total pressure at HPC outlet
Nf	Physical fan speed
Nc	Physical core speed
epr	Engine pressure ratio (P50/P2)
Ps30	Static pressure at HPC outlet
phi	Ratio of fuel flow to Ps30
NRf	Corrected fan speed
NRc	Corrected core speed
BPR	Bypass Ratio
farB	Burner fuel-air ratio
htBleed	Bleed Enthalpy
Nf_dmd	Demanded fan speed
PCNfR_dmd	Demanded corrected fan speed
W31	HPT coolant bleed
W32	LPT coolant bleed

TABLE 1. C-MAPSS outputs

Variable name	Description
alt	Altitude
MN	Mach number
TRA	Throttle resolver angle
Wf	Fuel flow
Fn	Net thrust

TABLE 2. C-MAPSS inputs

recognition where they were studied [22]. Define the states as $S = \{S_1, S_2, \ldots, S_N\}$, with N the state number, the state at time t as q_t and the observations $\mathbf{O} = \mathbf{o_1 o_2} \ldots \mathbf{o_T}$, the HMM is defined as $\lambda = (\mathbf{A}, \mathbf{B}, \boldsymbol{\pi})$ where:

- $\mathbf{A} = \{a_{ij}\}$ is the state transition probability distribution, $a_{ij} = P[q_{t+1} = S_j | q_t = S_i]$;
- $\boldsymbol{\pi} = \{\pi_i\}$ is the initial state distribution, $\pi_i = P[q_1 = S_i]$;
- $\mathbf{B} = \{\mathbf{b_j}(\mathbf{O})\}$ is the continuous observations probability distribution, $\mathbf{b_j}(\mathbf{O}) = \sum_{m=1}^{K} c_{jm} \mathbf{N}(\mathbf{O}|\boldsymbol{\mu}_{jm}, \boldsymbol{\sigma}_{jm})$.

$1 \leq i, j \leq N$, $1 \leq t \leq T$, c_{jm} are the mix factors, $\mathbf{N}(\mathbf{O}|\boldsymbol{\mu}_{jm}, \boldsymbol{\sigma}_{jm})$ are the gaussian distributions of a Gaussian Mixture Model (GMM) and K is the number of mix factors [23] and [24]. The probability of being in state S_i at time t, and state S_j, at time $t+1$, given the model and the observation sequence is:

$$\xi_t(i,j) = P[q_t = S_i, q_{t+1} = S_j | \mathbf{O}, \lambda], \tag{1}$$

so the expected number of transitions from S_i to S_j is:

$$\boldsymbol{\varepsilon}(i,j) = \sum_{t=1}^{T-1} \xi_t(i,j). \tag{2}$$

The three basic problems [22] in Hidden Markov Model are:

- given the observation sequence $\mathbf{O} = \mathbf{o_1 o_2} \ldots \mathbf{o_T}$, and a model $\lambda = (\mathbf{A}, \mathbf{B}, \boldsymbol{\pi})$, compute $P(\mathbf{O}|\lambda)$, the probability of the observation sequence given the model;
- given the observation sequence $\mathbf{O} = \mathbf{o_1 o_2} \ldots \mathbf{o_T}$, and the model $\lambda = (\mathbf{A}, \mathbf{B}, \boldsymbol{\pi})$, choose a corresponding state sequence $S_1, S_2, \ldots, S_N$ which best explains the observations;
- fix the model parameters $\lambda = (\mathbf{A}, \mathbf{B}, \boldsymbol{\pi})$ to maximize $P(\mathbf{O}|\lambda)$.

These problems are solved by three efficient and well defined procedures: forward-backward algorithm [25], Viterbi algorithm [26] and Baum-Welch algorithm [27]. The computational complexity is related to forward-backward inference algorithm that is $N^2 T$.

The HMM can be used to describe the fault progression process of physical systems. In figure 2 the HMM model is shown, it represents the fault progression where each state is an health-state, this model is called left-right model.

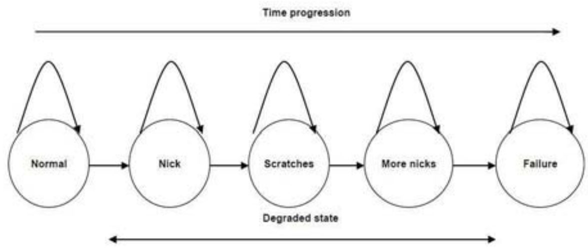

FIGURE 2. Fault progression process described by a HMM

The HMM based scheme is useful for prognostic because by monitoring the progression of the state sequence it is possible to have a qualitative information of the current degradation state and the wear progression, a quantitative information of the RUL, and it is possible to predict the system life evolution. To obtain these informations, the following algorithms are used:

1. the progression of states and the current state is calculated by Viterbi algorithm [26], [28];
2. the RUL is estimated using transition matrix that defines the evolution of failure progression in terms of quantity.
   The mean time $steps^*$ to failure state, given the current state, is calculate with Monte Carlo simulation [2]: considering n simulations, during each of the n simulation runs, next health-state is estimated based on the transition probabilities by generating an uniformly distributed random number between 0 and 1. This process is repeated considering the calculated next state as the current state until the failure-state is reached. Then, the number of transitions is counted as the RUL value. This is repeated for all samples yielding n RUL$_i$ values and $steps^*$ is the mean of the n RUL$_i$ value:

$$steps^* = \frac{1}{n} \sum_{i=1}^{n} RUL_i. \tag{3}$$

The advantage of this method is that requires no assumptions about the knowledge of the HMM model.

The prognosis algorithm consists of two procedures: the training and the prognosis. The training consists of:

- the initial parameters of HMM model are chosen to better perform the HMM training:
  1. the initial state distribution $\boldsymbol{\pi} = \{\pi_i\}$ is uniformly distributed;
  2. the initial state transition probability distribution $\mathbf{A} = \{a_{ij}\}$ is set based on the structure of the HMM model chosen;
  3. the dataset is clustered with Gaussian Mixture Model (GMM) algorithm. The outputs are $c_{jm}, \boldsymbol{\mu}_{jm}$ and $\boldsymbol{\sigma}_{jm}$ to obtain $\mathbf{B} = \{\mathbf{b_j}(\mathbf{O})\}$, the continuous observations probability distribution;
- the number of HMM states is determined computing the Bayesian Information Criterion (BIC) [29]:

$$BIC = L * \ln T - 2 \ln P(\mathbf{O}|\lambda), \tag{4}$$

  where L is the number of parameters. The minimum of this index gives the information of the states number of HMM;
- to avoid over fitting, during the training step, add a constant called σ_{min}, to the diagonal of $\boldsymbol{\sigma}_{jm}$ matrix. This entity prevent the possibility of matrix $\boldsymbol{\sigma}_{jm}$ to became singular and the following expression of GMM covariance matrix update is used:

$$\boldsymbol{\sigma}_{jm} = \frac{\sum_{j=1}^{T} \gamma_t(j,m) * (\mathbf{o_t} - \boldsymbol{\mu}_{jm}) * (\mathbf{o_t} - \boldsymbol{\mu}_{jm})'}{\sum_{j=1}^{T} \gamma_t(j,m)} + \sigma_{min} I, \tag{5}$$

  where $\gamma_t(j,m)$ is the probability of being in state j a time t with the mth mixture component accounting for $\mathbf{o_t}$;
- the HMM is trained by Baum-Welch algorithm [27].

The prognosis steps consist of:

- when a new data is collected the inference is calculated to obtain $\boldsymbol{\varepsilon}_{data}(i,j)$;
- subtract the model HMM matrix $\boldsymbol{\varepsilon}_{model}(i,j)$ with the new data matrix $\varepsilon_{data}(i,j)$

$$\boldsymbol{\varepsilon}_{new}(i,j) = \boldsymbol{\varepsilon}_{model}(i,j) - \boldsymbol{\varepsilon}_{data}(i,j), \tag{6}$$

  to obtain the $\boldsymbol{\varepsilon}_{new}(i,j)$ and so the new transition matrix is:

$$\mathbf{A}_{new} = \{a_{ij}\} = \frac{\boldsymbol{\varepsilon}_{new}(i,j)}{\sum_{j=1}^{N} \boldsymbol{\varepsilon}_{new}(i,j)}, 1 \le i,j \le N; \tag{7}$$

- apply the Viterbi algorithm to evaluate the current state;
- by current state and new transition matrix, calculate RUL (3).

3 FEATURES EXTRACTION

The HMM inference algorithm has a computational complexity of N^2T using the forward-backward procedure, however it is not possible to use the simulator signals directly because it generates 21 turbofan variables sampled at 1Hz for a flight of about 1 hour, and a variable number of flights depends on the degradation rate of the turbofan. The result is that a feature extraction is needed to reduce the number of variables and samples. Reduction of computational complexity is made by an Artificial Neural Network (ANN), considering that what matters is to estimate the number of remaining flights as a measure of the RUL, then the ANN is used to extract a scalar set of indexes that describe the situation of all sensors for the whole flight. Another objective is to estimate the engines faultless RUL using some faultless simulations for training the prognostic procedure.

The ANN model is trained to fit engine parameters given the flight condition inputs. Then for each flight the following error indexes are evaluated from all parameters residuals of entire flight:

MSE, Mean Square Error;
Std, Standard Deviation of the error;
Ave, Average error.

The ANN used is a 3 layer Multi Layer Perceptron (MLP) network with 5 input neurons and 21 hidden layer neurons and output neurons. The ANN inputs and outputs are those described in the Section 1, reported in tables 2 and 1 respectively.

The ANN training step is performed using a set of faultless turbofan simulations. Then a clustering technique is applied in order to reduce the sample number. For each cluster the sample number is reduced and the ANN is trained with the obtained dataset. Once the ANN is trained the procedure that calculate the features is applied, this procedure is summarized in the following algorithm:

1. **For** *each flight* **do:**
2. collect data sample of the current flight simulation;
3. simulate the turbofan parameters behavior through ANN;
4. compute residuals of ANN parameters identification;
5. compute features of the current flight as MSE, Std and Ave of residuals.

4 IMPLEMENTATION AND RESULTS

Data are collected from the C-MAPSS simulator from data competition at PHM'08. Data are referred to a turbofan engine that simulates parameters values from flight conditions. Each flight is recorded at sampling frequency of 1Hz and consists of 7 flight conditions repeated for every flight. Then an engine is simulated until its wear index reaches zero, this means that the turbofan ended its remaining operational life. These simulations are repeated for several engines in different conditions, faultless cases, fault Fan, fault High Pressure Turbine (HPT), fault High Pressure Compressor (HPC) and fault Low Pressure Turbine (LPT).

The HMM training step is performed using the dataset generated by the neural network in its training step, this mean that the training dataset is the same for both algorithms and it is a faultless dataset. HMM training steps are summarized below:

1. using GMM algorithm, cluster the degradation curves previously extracted by the neural network, which represent the faultless operation of turbofan;
2. evaluate BIC index to choice the N number of states for HMM;
3. set the lower bound of the covariance matrix σ_{min} to 10^{-16} and train the HMM with the data and GMM;

Once the training is done, it is possible to run the prognosis steps on the fault data, summarized in the following steps:

1. obtained new data sample from ANN, calculate the current health-state by Viterbi algorithm;
2. update the state transition matrix with the new observations (7) and calculate the RUL with Monte Carlo technique (3).

Figure 3 shows a sample of features extracted by ANN from flight data, that are used for training step. These features are taken to train the HMM model. In figure 4 the BIC index, computed by 4 is shows, its optimum is the minimum value reached. In this case the HMM states number is 30, in other words there are 30 health-states from the normal operation condition to the failure condition state. In figure 5 is shown the data clustering of the training step by means of GMM in the scatter plot of dataset.

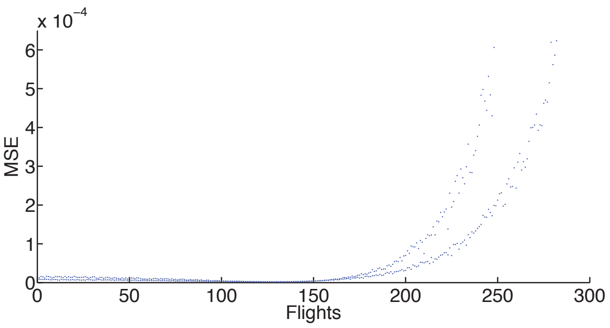

FIGURE 3. Faultless features extracted from ANN training data

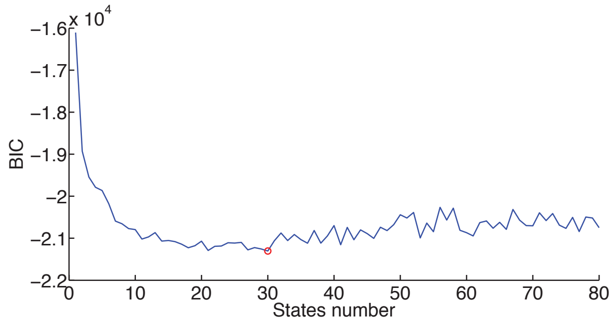

FIGURE 4. Bayesian information criterion of fan engine 1

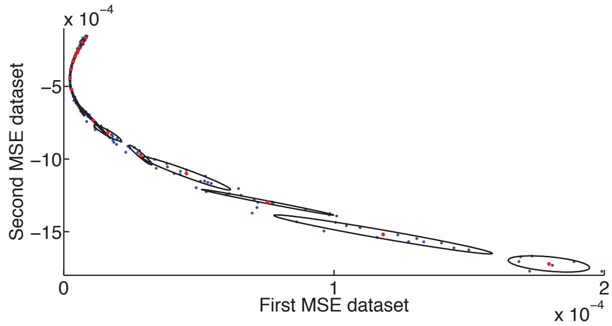

FIGURE 5. Cluster of training data

Once the ANN and HMM are trained the simulations on prognosis can be made on test datasets. In particular a fault arises at unknown flight in the simulated turbofan to generate a test bench for the integrated procedure. The simulated faults are non safety critical for obviously reasons and they decrease the turbofan life. This difference can be seen by comparing the number of flights of faultless dataset in figure 3 and of test datasets in figures 6, 7, 8 and 9.

The following simulations report how the developed procedure is able to track the true RUL even if perturbations occur. Figures 6 show the prognostic results of the turbofan life when a fault occurs in the fan. In particular figure 6(a) shows the RUL tracking and the figure 6(b) shows the health-state progress. The fault on fan is visible at flight 60 when the RUL has a jump.

Next simulation is performed in the case of a fault in HPT. In this case the jump in the RUL estimation is better highlighted as shown in figure 7(a). Again the state sequence, shown in figure 7(b) quickly track degradation evolution when the fault occurs.

The last two simulations start with an initial error on the estimate because the algorithm doesn't know the initial RUL value and cannot takes into account the degradation induced by the fault. The prognosis of the turbofan affected by the HPC fault is shown in figures 8. The RUL shown in figure 8(a) converges to the real RUL after the fault occurrence. The health-state se-

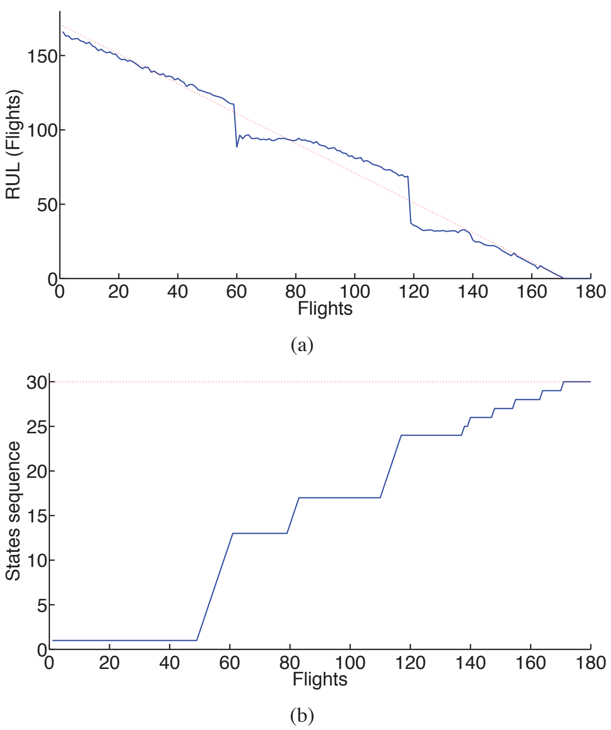

FIGURE 6. (a) Turbofan estimated RUL in presence of FAN fault, solid blue line denoted the estimated RUL, dashed red line denoted true RUL; (b) Turbofan health states sequence in presence of FAN fault, solid blue line denoted the states health sequence, dash red line denoted the failure state

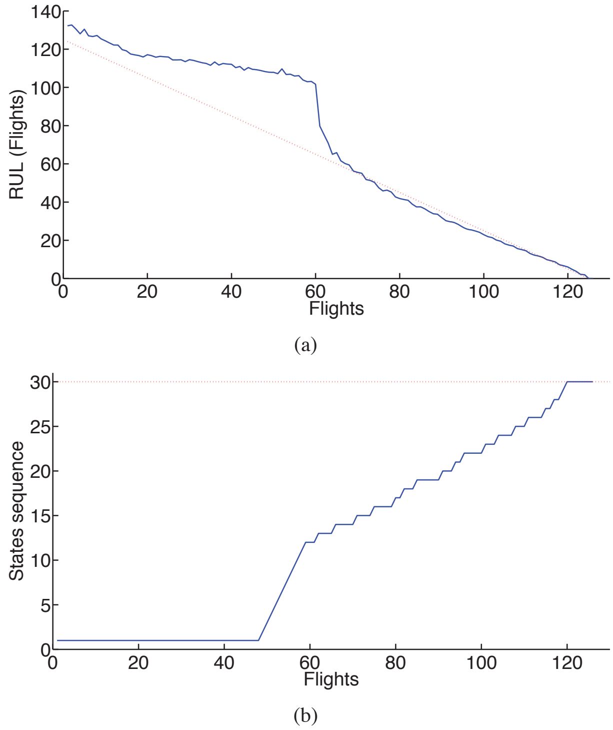

FIGURE 7. (a) Turbofan estimated RUL in presence of HPT fault, solid blue line denoted the estimated RUL, dashed red line denoted true RUL; (b) Turbofan health states sequence in presence of HPT fault, solid blue line denoted the states health sequence, dash red line denoted the failure state

quence is reported in figure 8(b).

The last simulation involve the turbofan with a fault on the LPT and is shown in figures 9. Figure 9(a) shows the initial RUL overestimate and the correct tracking reached after the fault occurrence. At the same time the health-state sequence shown in figure 9(b) follow the degradation of the turbofan engine.

These simulations highlight important considerations, first the initial error of the RUL is derived from the different working point of the new data from the trained model. Second once the fault occurs, the RUL suddenly falls down, it shows the algorithm robustness and its ability to correct the predicted RUL in presence of faults. Third, the RUL converges, in all types of fault.

5 CONCLUSIONS AND FUTURE WORKS

Prognosis is a topic of growing interest because it allows to determine the residual useful life time and the health-state of systems and machinery. This approach promises to reduce downtime, spares inventory, maintenance costs and safety hazards.

In this paper an integrated prognosis procedure is developed for estimate RUL and health-state of an aircraft turbofan engine. The algorithm is based on HMM and ANN. The Artificial Neural Network is trained and used to identify the faultless parameters and to generate features for each flight. Then HMM is used to compute RUL and health-state from these features. The RUL is calculated as the number of remaining safety flights and the health-state describes the turbofan degradation from normal to failure state. Observations are modeled as probability density functions, thus it is possible to define a model composed by a set of states that are described by a probability density function already. This permits the use of Bayesian inference algorithms for estimate health conditions. Data from C-MAPSS are used and simulations are performed to show the effectiveness an generalization power of this method. Obviously, the accuracy of the prognostics method depends on the sample size used to construct the HMM. Future research will attempt to introduce a Bayesian approach to update the parameters of such a prognostics model, as new data becomes available, to better estimate the RUL.

The hidden Markov models represent simple dynamic Bayesian networks, so it is possible to deal with prognosis problems by increasing the complexity of the degradation model. Fu-

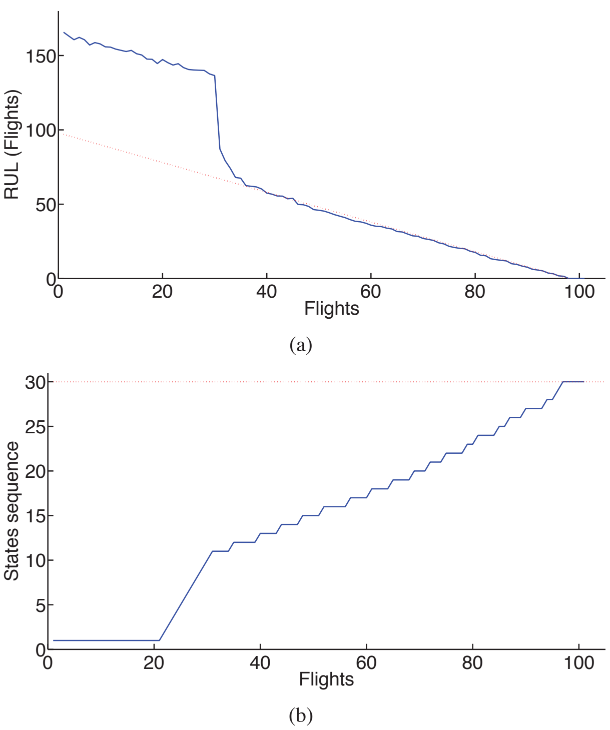

FIGURE 8. (a) Turbofan estimated RUL in presence of HPC fault, solid blue line denoted the estimated RUL, dashed red line denoted true RUL; (b) Turbofan health states sequence in presence of HPC fault, solid blue line denoted the states health sequence, dash red line denoted the failure state

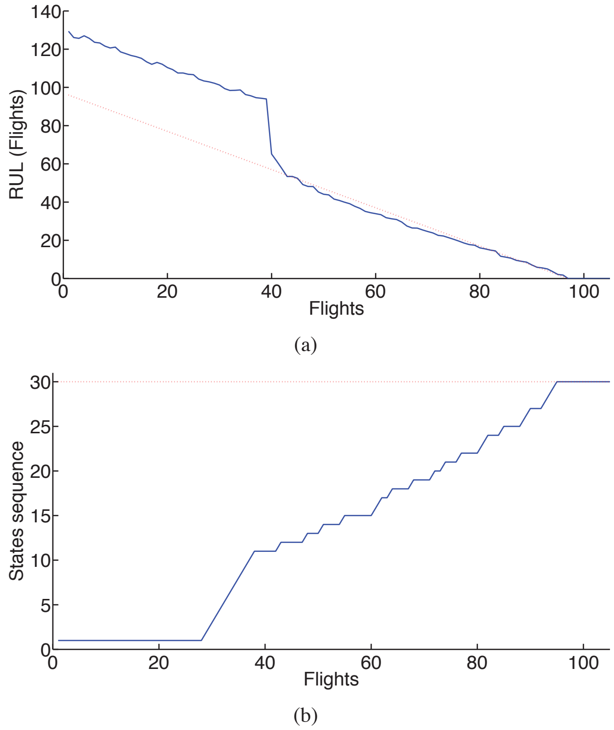

FIGURE 9. (a) Turbofan estimated RUL in presence of LPT fault, solid blue line denoted the estimated RUL, dashed red line denoted true RUL; (b) Turbofan health states sequence in presence of LPT fault, solid blue line denoted the states health sequence, dash red line denoted the failure state

ture work will explore the possibility to use dynamic Bayesian networks for better modeling the prognosis problem.

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