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DRES: Data recovery for condition monitoring to enhance system reliability

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A R T I C L E I N F O

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A B S T R A C T

The system reliability depends heavily on the sensed condition data which are mainly collected by various types of sensors. The missing or faulty condition data can result in wrong decision-making or lead to system fault. To realize data integrity for system condition monitoring, one data-driven framework for recovering condition data is proposed in this article. The proposed model is combined by mutual information and Multivariable Linear Regression (MLR). The correlations among condition monitoring data sets are firstly analysed by mutual information. Then, MLR is utilized to recover condition monitoring data. A case study of aircraft engine condition monitoring data sets which are offered by National Aeronautics and Space Administration Ames Research Center is carried out to evaluate the performance of the data-driven framework.

1. Introduction

In the area of modern industry, the system is becoming more and more complex. The requirement for enhancing the reliability of the system is getting much stronger. Many types of technologies have been realized to diagnose and predict the incoming faults of the complex system [1]. Among these technologies, Condition Monitoring (CM) can provide valuable information for diagnosis or prognosis and has been recognized as one of the most effective tools [2,3]. For years, a lot of methodologies for system CM have been developed. On the other hand, CM can provide valuable suggestions on maintenance schedule, reducing life-cycle cost, etc. [4].

To improve the availability of the system in further, many methodologies have been proposed and realized to increase the performance of system CM. The method of dynamic fault tree is applied for filtering false warning and identifying abnormal events, achieved by analysing the operational data [5]. The damage indicator constructed by several physical parameters (i.e., gate leak current, threshold voltage, etc.) is proposed to evaluate the condition of power device [6]. Gamma process [7] and Brownian motion [8] can be utilized to distinguish the degradation of the system. Markov process is suitable to describe the state evolution of the system [9]. Autoregressive Moving Average has been used to model degradation signals [10]. By establishing appropriate evaluation process, the sudden failures in system can also be monitored [11]. One important direction in this area is to enhance the accuracy and integrity CM data to enhance the system reliability. For example, the efforts in [12–14] focus on sensor anomaly detection and sensor fault diagnosis.

In this study, the objective is to enhance system reliability from the perspective of ensuring the integrity of CM data. A data-driven framework is proposed to recover the system CM data. The correlations among different CM data are analysed by mutual information. Mutual information belongs to the domain for probability theory and can be applied to weight the mutual dependency of different sensors data [15]. Then, Multivariable Linear Regression (MLR) is used to recover the CM data which are missed or lost due to the sensing element.

The rest of the article is organized as follows. The aircraft engine for case study is presented in Section 2. The overview of proposed data-driven framework is introduced in Section 3. The detailed evaluations experiments and analysis are illustrated in Section 4. The conclusions and the future works are depicted in Section 5.

2. Aircraft engine for case study

In this work, the aircraft engine is chosen as the system monitored for case study. The diagram of the engine is illustrated in Fig. 1. The aircraft engine is comprised by several typical subsystems, i.e., Fan, Nozzle, Combustor, two Compressor (i.e., Low-Pressure Compressor, LPC and High-Pressure Compressor, HPC), two turbines (High-Pressure Turbine, HPT and Low-Pressure Turbine, LPT), etc.

C-MAPSS (Commercial Modular Aero-Propulsion System Simulation) is employed to build the engine. C-MAPSS has been successfully employed to simulate the working conditions in many practical scenarios. C-MAPSS provides several graphical user interfaces (GUI) and makes the input and output control simple. C-MAPSS has the simulation setup of open loop or closed loop. By editing the input parameters and

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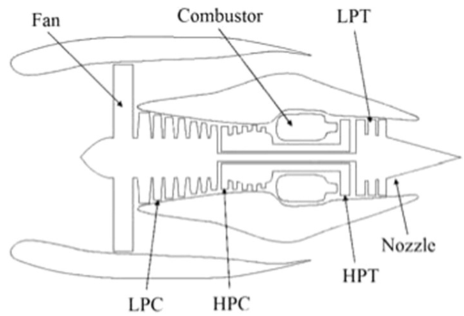

Fig. 1. Diagram of the aircraft engine [15].

simulation setup, many operational modes can be achieved. The various subsystems assembled in the simulation setup are shown in Fig. 2.

The build-in control system in the engine includes a fan-speed controller, several limiters and regulators. The limiters are consisted of three high-limit regulators which are used to operate the engine in normal condition. to prevent the engine from exceeding the operating limits (e.g., the engine-pressure ratio, the core speed, and the HPT exit temperature). These simulated working conditions are the same with the situations in the real engine. There are 21 sensors installed onside or inside the engine to sense and gather its various parameters of working status, as shown in Table 1.

By analysing the gathered physical information (e.g., pressure, temperature, fan speed, core speed, etc.), the status of the engine can be concluded. Those sensors in Table 1 can collect the related physical parameters of the aircraft engine. In this study, the focus is to recover the missing or lost condition data to enhance the system reliability.

3. Overview of methodology

The related theories adopted in our study are introduced in this section, which include mutual information and Multivariable Linear Regression.

3.1. Mutual information

Mutual information belongs to the domain of information theory. Its definition is related to the definition of entropy which belongs to the information theory and can weigh the information embodied in the random variable. For discrete variable, entropy is defined by [17]

$$H = -\sum_{i=1}^{N} p_i(x) \log p_i(x), \quad (1)$$

where $p(x_i)$ is the variable probability, and N refers to all the states of the process X_{x_i}.

If the random variable x is continuous, its distribution can be depicted by the probability density function, denoted by $f(x)$. Its entropy

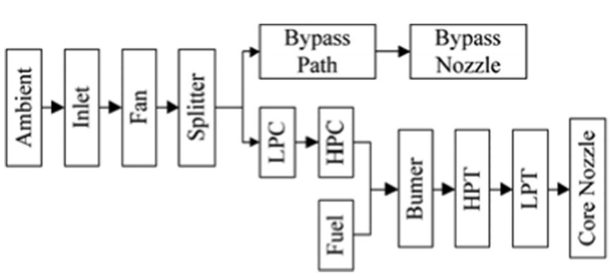

Fig. 2. Layout of various modules [16].

Table 1
Description of sensors signals [16].

Index	Symbol	Description	Units
1	T2	Total temperature at fan inlet	°*R*
2	T24	Total temperature at LPC	°*R*
3	T30	Total temperature at HPC	°*R*
4	T50	Total temperature at LPT	°*R*
5	P2	Pressure at fan inlet	psia
6	P15	Total pressure in bypass-duct	psia
7	P30	Total pressure HPC outlet	psia
8	Nf	Physical fan speed	rpm
9	Nc	Physical core speed	rpm
10	Epr	Engine pressure ratio	–
11	Ps30	Static pressure at HPC outlet	psia
12	Phi	Ratio of fuel flow to Ps30	pps/psi
13	NRf	Corrected fan speed	rpm
14	NRc	Corrected core speed	rpm
15	BPR	Bypass ratio	–
16	farB	Burn fuel-air ratio	–
17	htBleed	Bleed enthalpy	–
18	Nf_dmd	Demanded fan speed	rpm
19	PCNfR	Demanded corrected fan speed	rpm
20	W31	HPT coolant bleed	lbm/s
21	W32	LPT coolant bleed	lbm/s

°*R* The Rankine temperature scale.
psia Pounds per square inch absolute.
rpm Revolutions per minute.
pps Pulse per second.
psi Pounds per inch.
lbm/s Pound mass per second.

can be calculated by

$$H = -\int_S f(x) \log f(x) dx, \quad (2)$$

where S refers to all the random variable.

The unit of entropy can be different according to the different bases of the logarithm. The base of the logarithm can be 2, and the unit of entropy is *bits*. If the logarithm is based on *e*, the value of entropy is measured in *nats*. In addition, the base can be other values, the unit of entropy will be changed accordingly. In this study, the base is fixed to be 2 and is omitted in the following content of this article.

In order to define the mutual information, the conditional entropy needs also to be defined, which is about the expected value of the entropy of one random variable at the factor of the other variable. The conditional entropy $H(X|Y)$ is defined by.

$$\begin{aligned} H(X|Y) &= \sum_{j=1}^{m} p\left(y_j\right) H\left(X|Y = y_j\right) \\ &= -\sum_{j=1}^{m} \sum_{i=1}^{n} p\left(y_j, x_i\right) \log p\left(x_i|y_j\right). \end{aligned} \quad (3)$$

Similar to the definition of $H(X|Y)$, the $H(Y|X)$ is defined by.

$$\begin{aligned} H(Y|X) &= \sum_{i=1}^{n} p(x_i) H(Y|X = x_i) \\ &= -\sum_{i=1}^{n} \sum_{j=1}^{m} p\left(x_i, y_j\right) \log p\left(y_j|x_i\right). \end{aligned} \quad (4)$$

The mutual information denoted by $I(X;Y)$ refers to the reduction between two variables X and Y. The definition of mutual information