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Introductory invited paper

Quantitative selection of sensor data based on improved permutation entropy for system remaining useful life prediction☆

Liansheng Liu, Shaojun Wang, Datong Liu *, Yu Peng

School of Electrical Engineering and Automation, Harbin Institute of Technology, Harbin, China

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ABSTRACT

Condition monitoring is an effective tool for diagnosing and predicting the system fault or failure. One class of method in system condition monitoring is based on the condition data (i.e., data-driven methodology). However, not all the collected condition data can be utilized for the data-driven methodology. Hence, the selection of reasonable condition data is crucial for the application of the data-driven methodology. This is especially useful for the system which has the characteristics of degradation. In such system, the condition data that have the increasing or decreasing trend are desirable. This article proposes the quantitative selection of sensor data for system remaining useful life prediction. The main advantage of the proposed metric to select sensors is that the information theory is adopted. Hence, the selection of sensors can be determined by the proposed quantitative metric. Two case studies which include one simulation data set and one practical data set are carried out to evaluate the effectiveness of the proposed metric. The detailed experiments prove the advantage of the proposed approach.

1. Introduction

The system reliability directly determines its safety and life-cycle cost, especially for the complex system [1]. Among the available approaches to enhance system reliability, one effective technique is Prognostics and Health Management (PHM) [2–4]. For example, PHM-oriented method for the aircraft engine can provide the premonitory warning of failure and help prolong the system life [5] and predict the system Remaining Useful Life (RUL) [6,7]. In many different practical areas, PHM has been recognized as one significant technology to improve the system performance, optimize maintenance schedule, etc.

Generally, PHM technique is grouped into three main varieties: experience-based approach, model-based approach, and data-driven approach [8]. For experience-based approach, it needs to build stochastic model to represent the system, which is infeasible for some complex systems [9]. The model-based method needs to formulate a model to describe the system, which is not applicable for the most applications [10]. Compared with the above two approaches, the data-driven approach is based on the collected system condition data which is easy to be implemented by sensors [11]. Therefore, how to select the appropriate sensors for system RUL prediction is studied in this article.

The data-driven approach depends heavily on the collected condition data of the system. In theory, if more condition data are available, the system condition can be more accurately identified. However, too large volume of condition data will increase computing resource utilization and system cost [12]. Therefore, the desired strategy is to select some directly correlated condition data for the final objective. The appropriate selection of condition data can help improve the ultimate result and cut down system cost. In many systems, the degradation is the most widespread phenomenon and is necessary to be monitored. In this article, we focus on predicting the degradation of the system. To be specific, how to select the appropriate condition data to monitor the degradation will be studied.

The existing works in this category mainly utilize the observing strategy to select the condition data which have the monotonous trend [13,14]. In their studies, the focus is to propose high-powered PHM approaches to enhance the ultimate result. However, the original data which can provide valuable information for RUL prediction are often neglected. The condition monitoring data that have the feature of monotony contain the system degradation information. By utilizing such kind of data, more precise RUL prediction value can be expected. There are some related works which focus on data monotonic feature selection [15–18]. The mainly utilized rank mutual information indeed has good performance on monotonic feature selection. However, for RUL prediction application, the realized process is based on the constructed system health indicator which is one kind of indirectly data analysis. For machine processing, the method which can analyze data

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* Corresponding author.
E-mail address: liudatong@hit.edu.cn (D. Liu).

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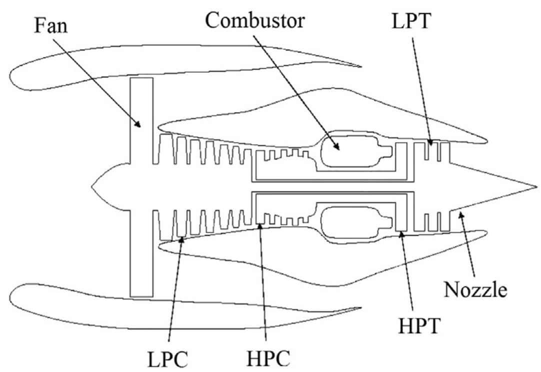

Fig. 1. Illustration of the aircraft engine [21].

directly is much easier to be carried out. The reason is that analysing data directly will not require the RUL prediction method to evaluate the performance of data selection.

The work in [19] provides one type of entropy-based strategy to quantitatively describe the monotonous trend of condition data directly. However, the insufficiency is that the work does not consider to search the optimized number of sensors for RUL prediction. In other words, how to select the quantitative number of sensors is not carried out. The motivation of this work is to study what the quantitative metric of improved permutation entropy is for the different system RUL prediction. In this way, the better RUL prediction result can be expected.

The first step in the proposed approach is to calculate the improved 2! permutation entropy to judge monotonous trend contained in the sensor data. Then, the appropriate number of sensors is selected for the RUL prediction. Finally, the effectiveness is evaluated by Gaussian Process Regression (GPR). The utilized simulation data set of the aircraft engine was offered by NASA Ames Research Center, which was adopted as the PHM challenge data in 2008 [20]. This data set has been adopted by many researchers to evaluate the performance and effectiveness of related methodologies. The utilized practical data set was also provided by NASA Ames Research Center, which was collected from the practical working progress of the electromechanical actuator.

The remaining of this paper is arranged as follows. Section 2 shows the details of the simulation data set and the practical data set for the following evaluation. Section 3 presents the related theories adopted for this study. Section 4 illustrates the detailed evaluation experiments and analyses the validation results. Section 5 draws the conclusion and provides the future works.

2. Data sets for case study

Two data sets utilized in this study are introduced in this section, including one simulation data set and one practical data set.

2.1. Simulation data set

The simulation data set is about the turbofan aircraft engine, which can represent the modern complex system at some degree. The typical structure chart of the aircraft engine is provided in Fig. 1 [21], which is consisted of several subsystems.

The working process of the engine is simulated by C-MAPSS, which has been employed to emulate many practical scenarios of working conditions of the aircraft engine. C-MAPSS offers several classes of graphical user interfaces which make the input setup simple. The open loop and closed loop of working condition can easily be realized by configuring related parameters. The other operational modes can also be easily achieved. The subsystems assembled in the simulation are shown in Fig. 2.

The build-in control system in the engine involves a fan-speed controller, a few limiters and regulators. The limiters are comprised by three types of high-limit regulators to keep the aircraft engine working under operational limits (e.g., the engine-pressure ratio, the core speed, and the exit temperature). These simulated settings and the working process are the same with the real conditions of the engine. In the simulation, there are 21 sensors which are placed on or inside the engine to gather the condition information of the engine during the simulation, as shown in Table 1.

Table 1
Sensor suit of the aircraft engine [21].

Index	Symbol	Description	Units
1	T2	Total temperature at fan inlet	°*R*
2	T24	Total temperature at LPC outlet	°*R*
3	T30	Total temperature at HPC outlet	°*R*
4	T50	Total temperature at LPT outlet	°*R*
5	P2	Pressure at fan inlet	psia
6	P15	Total pressure in bypass-duct	psia
7	P30	Total pressure at 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	Burner fuel-air ratio	–
17	htBleed	Bleed enthalpy	–
18	Nf_dmd	Demanded fan speed	rpm
19	PCNfR_dmd	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 square inch

lbm/s Pound mass per second

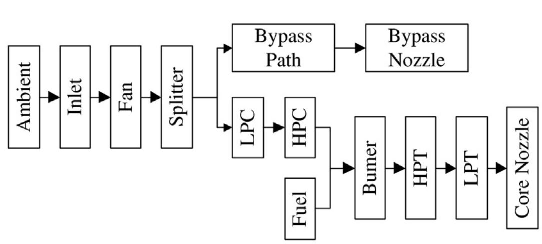

Fig. 2. Connection of various modules [21].

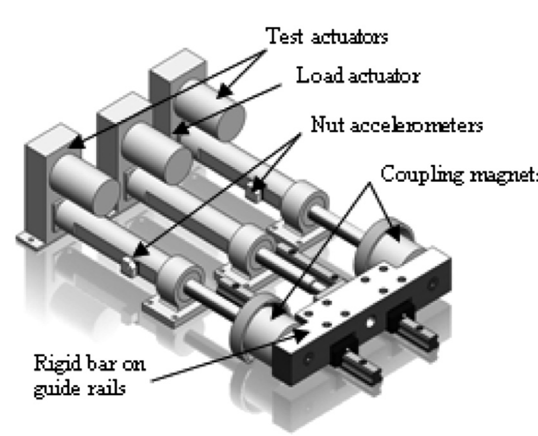

Fig. 3. Connection of various modules in FLEA [22].

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