Research on Selection Methods for Aircraft Landing Gear System Health Feature Parameters

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Abstract

This paper proposes a new approach for the health feature parameters selection of the Aircraft Landing Gear (LG) system. Firstly, the health feature parameters selection is summarized in three approaches. Second, the working principle of the LG system is analyzed, and the model-based method combining with the theoretical knowledge of the control system is applied to establishing the physical-mathematical model of the LG system. Third, the LG retraction/extension (R/E) time is determined as the feature parameters of health monitoring. An analysis based on the model simulation is conducted to investigate the relationship between the health feature parameters and the main hydraulic pressure and the inherent characteristics of the LG system. The response characteristics of the second-order system verify the feature parameters' validity. Finally, the Statistical Process Control (SPC) criterion utilizes the factual flight data for LG health monitoring. The Shewhart charts and the Nelson rules are adopted to estimate the LG performance. The research approach that the control system theoretical to parameter selection can be utilized for the other aerospace applications.

Keywords: health feature parameters; Aircraft LG system; LG R/E time; SPC criterion; LG health monitoring

1. Introduction

Latest military and civil aircraft programs have substantively advanced Diagnostics, Prognostics, and Health Management (DPHM) technology concepts into an integrated system approach that can enhance aircraft reliability and passenger safety. Paul Phillips points out that within the aerospace industry there is the desired paradigm shift within aircraft maintenance towards offering maintenance systems with predictive capabilities [1]. The effective work about the LG extension/retraction system plays a leading part in the safety during the aircraft take-off and landing phases. The DPHM about aircraft LG system attracts many researchers to further investigate. Paul Phillips reviews such a framework and design methodology being used for the development of knowledge-based condition monitoring systems for aircraft LG actuators [2]. Qian Kun proposed Multiple-Models Adaptive Estimation (MMAE) for failure detection and identification (FDI) of aircraft LGs [3]. Jie Chen proposed health monitoring of LG retraction/extension system based on optimized fuzzy C-means algorithm [4].

The development of health monitoring technologies for aerospace systems creates many challenges for the community of engineers and technical specialists as they seek to integrate the technology into well-defined working practices [1]. Andrés Jiménez designed a Weight on the Wheel system which detects whether the aircraft airborne is on the ground. Based on CESA experience in this field, a new approach oriented to fatigue health monitoring of LGs is presented [5]. S Sivakumar built a mathematical model of aircraft with active LGs. Vibration analysis indicates that the active LG system increases the fatigue life of the aircraft structure and landing system [6]. Syed Haider overviewed the shock absorber PHM system by using multiple sensors to monitors different parameters to perform RUL calculations. Its output would allow planning and scheduling of any required component replacement and preventing disruption to flight schedules [7]. Wenwen Liu carried out fault analysis of the abnormal opening of the main LG door of civil aircraft and improved the understanding of the LG door extension/retraction system [8]. However, the sensors installed are limited due to the high requirement of operating safety in aerospace applications. Thus, many degradation estimation methods restricted by sensors measurement are not feasible for the diagnosis of GL performance degradation. The feature parameters are the health indicators (HIs) that are linked to aircraft system functional and operational failures. The health monitoring and prediction based on feature parameters are an effective way to solve the problem in GL's degradation estimation. Many researchers devote themselves to the study of feature parameters' extraction and identification, the approaches of which at home and abroad are summarized in this paper.

The contributions of this paper are that the LG retraction/extension time is determined as the feature parameters for the system health monitoring by using a new model-based identification method. The main ideas of this paper are organized as follows. Three selection methods of the feature parameters for DPHM are summarized in Section 2. Section 3 constructs the aircraft LG retraction system model. The simulation results analysis and experiments validation by using the factual flight recorder data are shown in Section 4. Section 5 concludes this study and presents our future work.

2. The identification methods for the health state feature parameters

The health state feature parameters are also called health indicators, which are the monitoring signal applied for reflecting the health state of object systems. Various expressions denote the same meaning, such as failure precursor parameters usually appearing in Remaining Useful Life (RUL) prediction of electronic systems, physically meaningful parameters which refer to the health monitoring indicators in the physical system model, identification parameters which represent the model parameters changing with the system degradation. The health state feature parameters selection approaches can be grouped into three main categories: Failure Modes, Mechanisms, and Effects Analysis (FMMEA), Model-Based approaches, and Data-Driven approaches.

2.1 Failure Modes, Mechanisms, and Effects Analysis

FMMEA focus on failure parameters. These parameters provide information about the system's performance, its current health, its usage, and the environmental conditions in which it is operating. A failure precursor is an event or a series of events that can be used to directly or indirectly indicate impending failure [9]. The Center for Advanced Life Cycle Engineering (CALCE) devotes many research efforts to the study of failure precursor parameters selection for electronic systems. Born, Boenning and Pecht et al. [10] firstly proposed several measurable parameters that can be used as failure precursors for electronic systems by FMMEA [11]. A guideline for the selection of failure precursor parameters about electronic subsystems is shown in [1]. Table 1 lists failure precursor parameters of electronic products which are obtained from several other researchers. Accelerated aging based on FMMEA is in-situ monitoring of failure precursor parameters selection, which places aging of electronics in a controlled environment with the purpose to monitor degradation parameters and capture damage propagation characteristics. For instance, Prasanna Tamilselvanet al. [12] carried out the identification of IGBT failure precursor parameters, such as collector-emitter current, transistor case temperature, transient and steady-state gate voltages, and collector-emitter voltages, through accelerated aging.

Table 1 Failure precursor parameters about electronic systems

Researchers	electronic systems	Failure precursor parameters	
Sachin Kumar et al. [11]	a computers system	fan speed, CPU temperature, motherboard temperature, video card temperature, %C2 state, %C3 state, %CPU usage, and %CPU throttle	
B Shunfeng Cheng and Michael H. Azarian[13]	PME-MLCC under THB conditions	performance parameters	insulation resistance, capacitance, and dissipation factor
		environmental parameters	temperature and humidity
		operational parameters	bias voltage
Shunfeng Cheng[14]	PPTC Resettable Fuses	Trip time	
		Resistance	Resistance after reset

			Resistance during trip
		Surface temperature	
		Current	Current through the devices at normal condition, Trickle current, Actual hold current
		The voltage across the device	
S. Mathew et al. [15]	the voltage regulation unit of the SMPS	the power MOSFET	temperature
		the IC chip	temperature
		the output voltage, the output ripple voltage, and the output current	
Hyunseok Oh et al.[16]	cooling fans	fan bearings	acoustic noise, vibration, and lubricant temperature
		the aerodynamic point of view	rotational speed
		motor wiring	current consumption
Renxiao Xu et al. [17]	The compressor of a Refrigeration Device	inlet pressure, outlet pressure, compressor current, compressor voltage, condenser current, internal temperature, controller current, and temperature of the environment.	
M. H. Chang et al. [18]	LED Devices (Packages)	[19]	

2.2 A Model-Based Approach

The model-based approach provides the observations of unmeasurable system state variables or the identifications of feature parameters which can be adapted to represent the status system performance degradation [20]. The central idea of the Model-Based approach for failure precursor parameters identification is to build a physics-based mathematical model. And this model must be configured specifically for the system being monitored and should accurately simulate the response of the system when given command signals. The multiple, specific parameters that reflect the actual physical characteristics of the system are selected by this approach. Carl S. Byington, P.E. proposed and summarized the implementation of this model in detail [21]. He demonstrated a physical model of an electromechanical actuator (EMA) and changed the single underlying physical parameter to simulating the system degradation. Thus, several physical parameters (friction-damping coefficient) were identified as indicators of faults within the model. Jie Chen [22] modeled an aircraft flap control system based on the bond graph (BG). Based on the system diagnostic BG model, the monitoring parameters are selected. Moreover, the parameter uncertainty intervals are estimated and a new adaptive threshold is constructed by linear fraction transformation. The model parameters and failure models have an apparent correspondence, which is the most significant advantage of model-based methods. The adaptive observers are designed to estimate the unmeasurable state variables which indicate the health state of the system. C. Martínez-García designed the interval observer scheme, which is experimentally evaluated by estimating the upper and lower bounds of a torque load perturbation, a friction parameter, and a fault in the input voltage of a permanent magnet DC motor [23]. Jinquan Huang described a new aircraft engine gas-path health monitoring architecture using a sliding mode observer (SMO), which possesses better feature parameter observing performance. As we all know, the occurrence of a fault will cause changes in the physical process parameters of the system model. Another basic idea behind the model-based approach is that using parameter identification algorithms to identify the process parameters. Md Ashiqur Rahman et al. [24] investigated a gradient-free optimization technique, namely particle swarm optimization (PSO) algorithm. And this method is utilized to identify specific parameters of the electrochemical model of a Lithium-Ion battery. Four electrochemical model parameters which exhibit significant variations under severe operating conditions have been successfully identified. Saikumar Reddy Yeratapally [25] investigated the fatigue crack initiation in polycrystalline materials. Global Sensitivity Analysis (GSA) was used to identify the set of most influential parameters in the microstructure-based fatigue life prediction model. Shintemirov et al [26] proposed a novel model-based approach for parameter identification. This method established a transformer core model using the duality principle between magnetic and electrical circuits for parameter identification with genetic algorithms (GA). The model-based parameter identification with GA is based on searching for the optimal model parameters by minimizing the difference, i.e., fitness, between reference and simulated model frequency responses.

2.3 A Data-Driven approach

With the improvements of user demands for applications veracity and automation, the system complexity increases, which distracts the system's accurate modeling. Hence, it is impractical to apply the model-based method to develop degradation simulation. However, many sensors are deployed on or in the aircraft to monitor various physical parameters. By analyzing these sensors' data, the relationship between the feature parameters and the failure/degradation can be evaluated and determined in advance. The feature parameters can be selected by quantitatively measuring the valuable information. Liansheng Liu et al. [27] proposed an entropy-based sensor selection method for condition monitoring and prognostics of the aircraft engine. Compared to the observing method, the proposed method can provide the quantitative metric to measure the valuable information contained in the sensor data sets. The experimental results showed that the sensors selected by their method were more suitable for aircraft engine condition monitoring and prognostics. Zeli Lin et al. [28] used the method of information fusion to get a set of information entropy to the characterization of hydraulic pump health status parameters, the selection of aircraft hydraulic pump inlet pressure, hydraulic pump outlet pressure, hydraulic pump outlet flow, and hydraulic pump power as feature parameters of aircraft hydraulic pump health status.

3. The Aircraft LG system modeling

Aircraft LG takes an important mission in preventing aircraft structure damage, slowing aircraft flutter, improving occupant comfort, and ensuring aircraft flight safety. The health status of the LG R/E system directly affects the take-off and landing performance of the aircraft. The LG R/E system is divided into a mechanical part and a hydraulic part. The gear actuator is the vital component for connecting the mechanical part to the hydraulic part. It converts the hydraulic energy provided by the hydraulic system into the mechanical energy of the LG. Modeling the entire landing R/E gear system and simulating the overall R/E performance have attracted many researchers' interest. However, the actuator is simplified into a simple actuator model containing a piston rod. There is no specific analysis of the key device actuators. However, this paper focus on the LG actuator modeling which contains the association between the main hydraulic and the displacement of LG.

3.1 The working principle analysis of the LG retraction system

The LG R/E system is the pressure application system. The hydraulic energy provided by the hydraulic source is applied to realize the normal R/E tasks of the LG. Firstly, the hydraulic pump transmits pressure and flow to the LG system by maintaining outlet pressure stability. The hydraulic oil flows from the outlet of the hydraulic pump, through the hydraulic oil filter, the check valve, the accumulator, and the pressure relief valve, to the inlet of the LG selector valve. A return oil filter and a check valve are arranged downstream of the selector valve return port. The oil flows to the R/E pipeline of the LG R/E system through the R/E passage of the selector valve. And the movement of the retracting cylinder is driven by the differential pressure thrust F on both sides of the actuator piston, which completes the retracting movement of the LG. The schematic diagram of the aircraft's LG hydraulic R/E system is shown in Figure 2. The LG retraction system and the LG extension system are two similar action processes, so the LG retraction process is only selected for modeling.

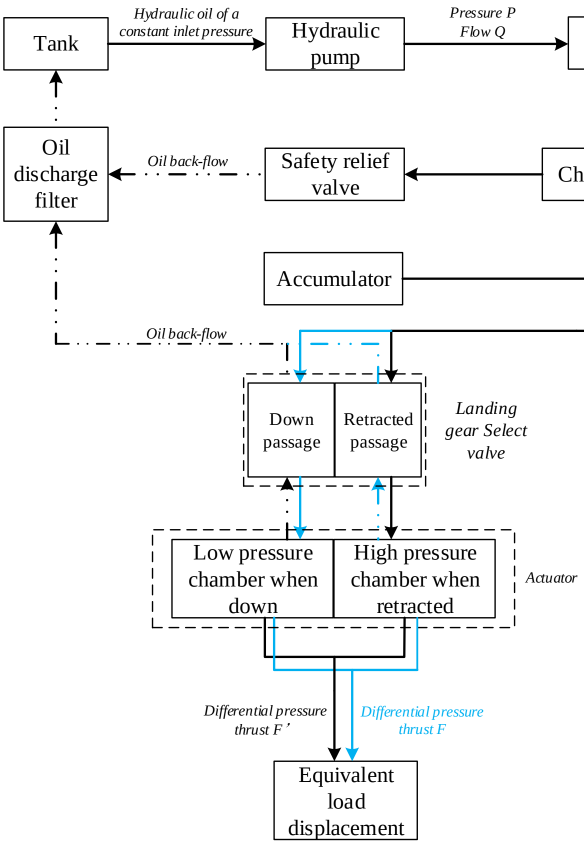

Figure 1 – Schematic diagram of working principle analysis of LG retraction system.

3.2 The nose gear actuator modeling

During the retracting of the LG as shown in Figure 2. Firstly, the actuator moves inward under the differential pressure thrust F and drives the wheels and the LG strut to move upwards. The force analysis of the whole moving process is shown in Fig.3, where o_1 is the fixed end of the actuator, o_2 is the fixed end of the LG strut, o_3 is the moving end of the piston of the actuating cylinder. It is defined that the center of wheel gravity and the fixed end of the LG strut is equivalent to $\Delta o_1 o_3 M$ during the LG is extending, where a represents the distance between o_1 and o_2, b represents the distance between o_2 and o_3, r represents the distance between o_2 and M, F is the differential pressure thrust, mg denotes the equivalent load of LG wheel and strut, α denotes the angle between a and horizontal plane, θ denotes the angle between r and horizontal plane, φ denotes the angle between b and a, which decreases with the LG retracting, γ denotes the angle between b and actuators, which increases with the LG retracting, β denotes the angle between r and b.

The motion physical equations for the LG actuator based on this retraction process are shown in Table 1, associated with Laplace linear transformation by Equation (1). The transfer function is shown in Fig. 4, which describes the relationship between the displacement of the actuator and the main hydraulic pressure.

If the nonlinear function $y = f(x_1, x_2, \cdots x_n)$ has continuous partial derivatives and derivatives near the operating points $(x_{10}, x_{20}, \cdots x_{n0})$, then

$$Y(s) = (\frac{\delta f}{\delta x_1})_0 X_1(s) + (\frac{\delta f}{\delta x_2})_0 X_2(s) + \cdots + (\frac{\delta f}{\delta x_n})_0 X_n(s) \,. \tag{1}$$

According to Figure 4, the transfer function of the system is transformed into,

$$\frac{Y(s)}{P_s(s)} = \frac{K_g}{s^2 + T_m s + T_k} \,, \tag{2}$$

where $T_m = \frac{a_3 a_4 a_5}{a_1}$, $T_k = \frac{a_4 a_5 a_6}{a_1}$, $K_g = \frac{a_2 a_4 a_5}{a_1}$. The transfer function typical form of second-order system is expressed as,

$$\frac{C(s)}{R(s)} = \frac{\omega_n^2}{s^2 + 2\xi\omega_n s + \omega_n^2}\,. \tag{3}$$

Equation (2) of the nose LG retraction process can be transformed into the format of equation (3), shown as,

$$\frac{Y(s)}{P_s(s)} = \left(\frac{K_g}{T_k}\right) \cdot \frac{(\sqrt{T_k})^2}{s^2 + 2\xi\sqrt{T_k}s + (\sqrt{T_k})^2}\,. \tag{4}$$

The over-damping ratio $\xi = \frac{T_m}{2\sqrt{T_k}}$ of the LG model is obtained. It can be seen that the damping coefficient is determined by the inherent characteristics of the system.

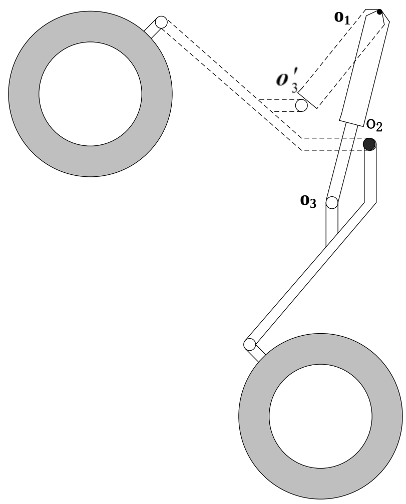

Figure 2 – Schematic diagram of the front LG retracting process.

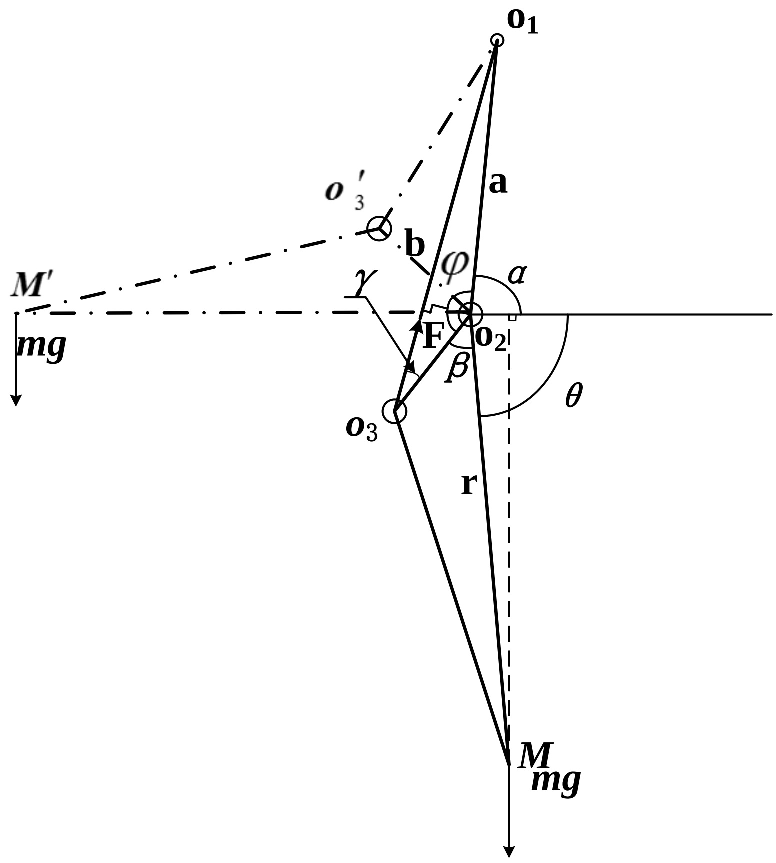

Figure 3 – Force analysis of nose LG.

Table 2 – The modeling of the nose LG actuator

Force Analysis	Relational Expression	Laplace linear transformation
Geometric Relations	$\theta = 2\pi - \alpha - \beta - \varphi$ $\cos\varphi = \frac{b^2 + a^2 - (m+y)^2}{2ab}$ $\frac{a}{sin\gamma} = \frac{m+y}{sin\varphi}$	$\varphi(s) = a_1 Y(s)$
The net force acting on the actuator	$F_a = (S_1 p_s - S_2 p_0) - F_f$	$F_a(s) = a_2 P(s) - F_f(s)$
Damping force	$F_f = K_f \dot{y}$	$F_f(s) = a_3 s Y(s)$
Load motion	$\dot{\varphi} = \frac{1}{J}\int M_a dt + \varphi_a(0)$	$s\varphi(s) = \frac{1}{s} a_4 M_a(s)$
Net moment	$M_a = F_a bsin\gamma - Gr\cos\theta$	$M_a(s) = a_5 F_a(s) - a_6 Y(s)$
Load inertia	$J = mr^2$	——

Note: p_s, p_0 represent main hydraulic pressure and return oil pressure, respectively. S_1, S_2 are the area on both sides of the actuator piston p_s and p_0. K_f is the damping coefficient. a_1, a_2, $\cdots$, a_6 is the constant term merged after Laplace transform; y is the actuator displacement.

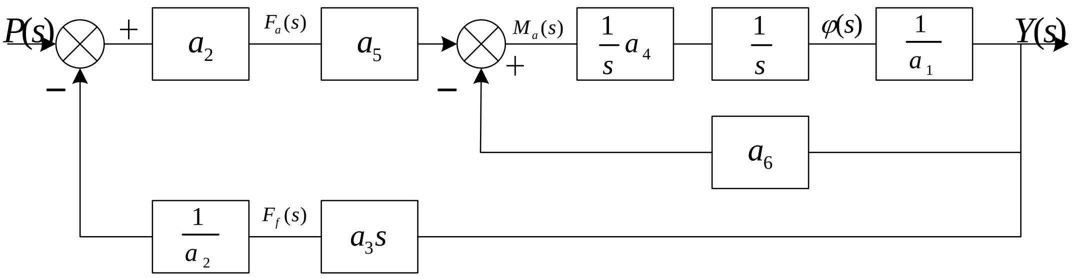

Figure 4 –Transfer function of the LG actuator displacement and main hydraulic pressure.

4. Analysis of simulation results and data validation of flight records

4.1 Parameter selection of the LG Retraction System

As shown in Fig. 5, when the second-order system is in the over-damped state ($\xi > 1$), its second-order system response curve is an increasing curve, and finally tends to a stable value. This means that when the LG is in the retracting process if the main hydraulic system provides continuous pressure to the actuator, the LG piston rod will drive its equivalent load mg to continuously shift along the direction of the retraction of the actuator. Finally finishing the entire working stroke of the LG actuator. This analysis is consistent with the actual motion effect. The movement of the LG with time is determined only by its transfer function. That is, each time corresponds to the unique displacement state. The LG retraction time as health feature parameters of the LG system can directly reflect the health state of the whole LG displacement. Thus, the validity of the LG R/E time is verified.

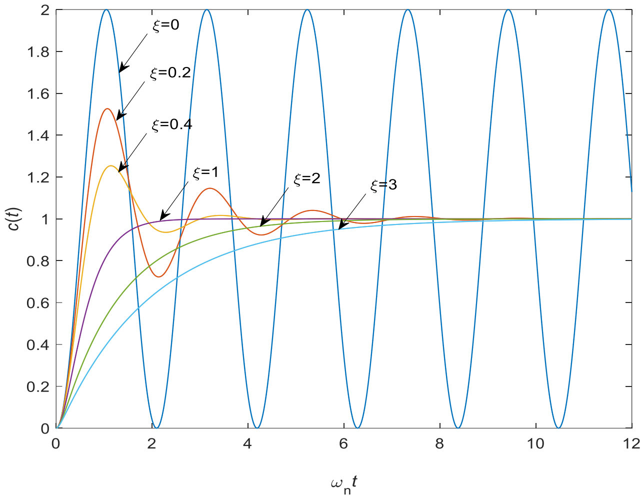

Figure 5 –The unit step response curve of the second-order system.

4.2 Simulation verification and result analysis

According to table 1 and the structure parameters of the factual LG system, the coefficients of equation (3) are calculated, shown in Table 2.

Table 3 – The coefficient of the second-order system response of the nose LG.

T_k	T_m	K_g
1.84	29.3	1.6×10^{-7}

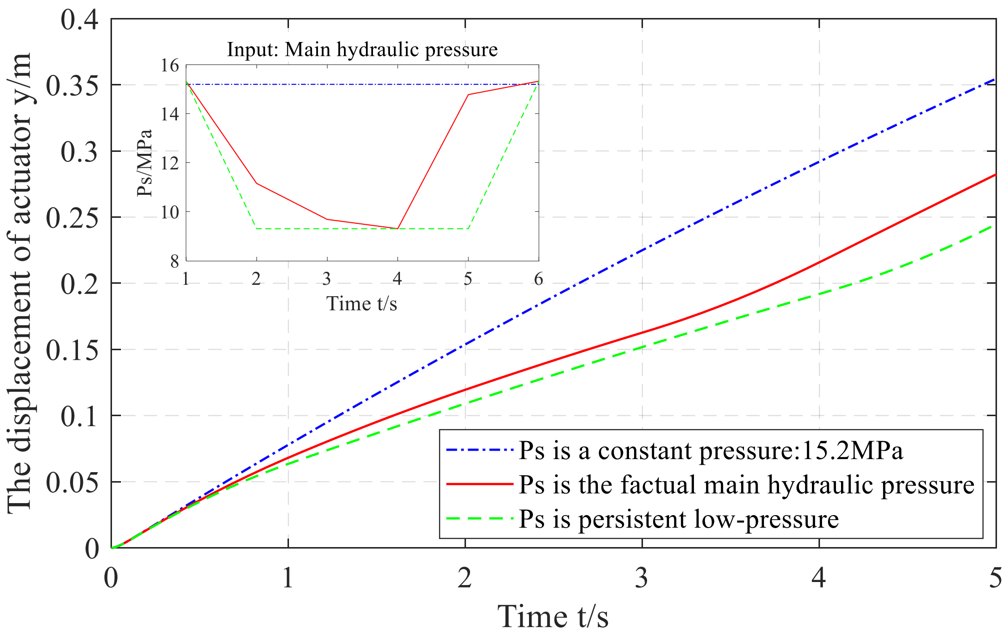

Figure 6 –The variation of retracting time response of LG with main hydraulic pressure.

According to equation (3), the response curve of the actuator displacement with the main hydraulic pressure is simulated. In Fig. 6, the blue curve represents the actuator displacement with a constant main hydraulic pressure. The red curve shows the actuator displacement with a real operating main hydraulic pressure during the LG retraction. One can notice that the main hydraulic pressure affects the LG retraction time. The longer the main hydraulic low pressure lasts, the longer the LG retracts. Moreover, the response curve of the actuator displacement with the variation of the damping ratio is simulated, which is based on equation (4). The simulation results are shown in Figure 7. One can notice that the LG retraction time is related to the system's inherent characteristics T_k, T_m, K_g . The retraction time increases with the over-damping ratio rise. It can be concluded that the LG retraction time is a health feature parameter of the LG retraction system. As the same as, the LG extension time is a health feature parameter of the LG extension system.

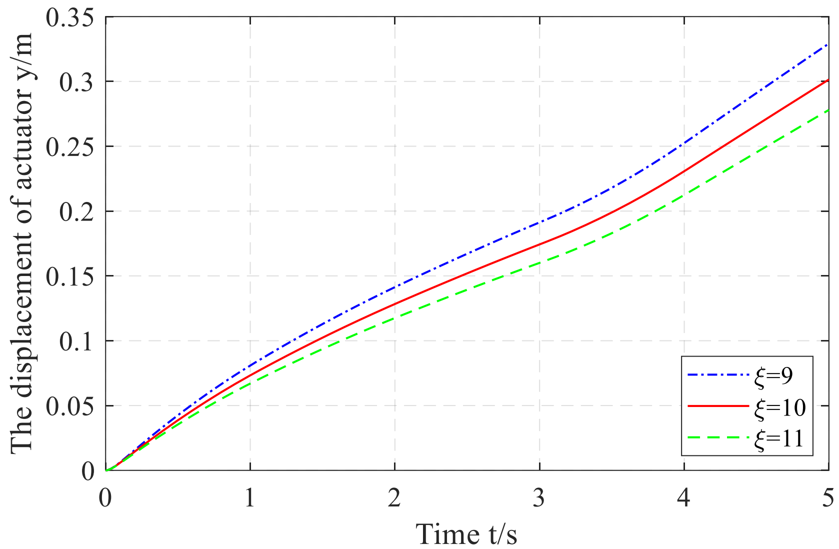

Figure 7 –The variation of retracting time response of LG with the over-damped ratio.

4.3 Flight data verification

Statistical process control （SPC）is a method of quality control that employs statistical methods to monitor and control a process. One of the key tools used in SPC is control charts. The control chart is an effective method to judge and predict whether the quality of the production process has abnormal fluctuations. The control lines of the control chart are determined using the 3σ.

There are three common sets of rules for detecting signals: 1）The Western Electric rules；2）The Wheeler rules；3）The Nelson rules. The most important principle for choosing a set of rules is that making a choice before the data is inspected. The Nelson rules are adopted as the method to determine whether some measured variables are out of control (unpredictable versus consistent).

The LG R/E time data sets are collected, which are obtained from 123 continuous flight sorties, containing the retraction time of the nose, left, and right LG. The health monitoring of aircraft LG is carried out in Minitab by applying the Nelson discrimination criterion of SPC.

The Shewhart charts of the aircraft's LG retraction time are drawn. The Nelson rules are applied for health status monitoring. Figure 8~10 shows control charts about the retraction time of the nose, left, and right LG, respectively. The Nelson rules detect abnormal sorties, which are marked red. These red dots indicate that the LG retraction time is abnormal. The abnormal reason is the main hydraulic pressure abnormal or the LG failure. However, the three LG systems all give an alarm. The only cause is the main hydraulic system abnormal. Thus, the LG R/E time as a health state feature parameter is verified.

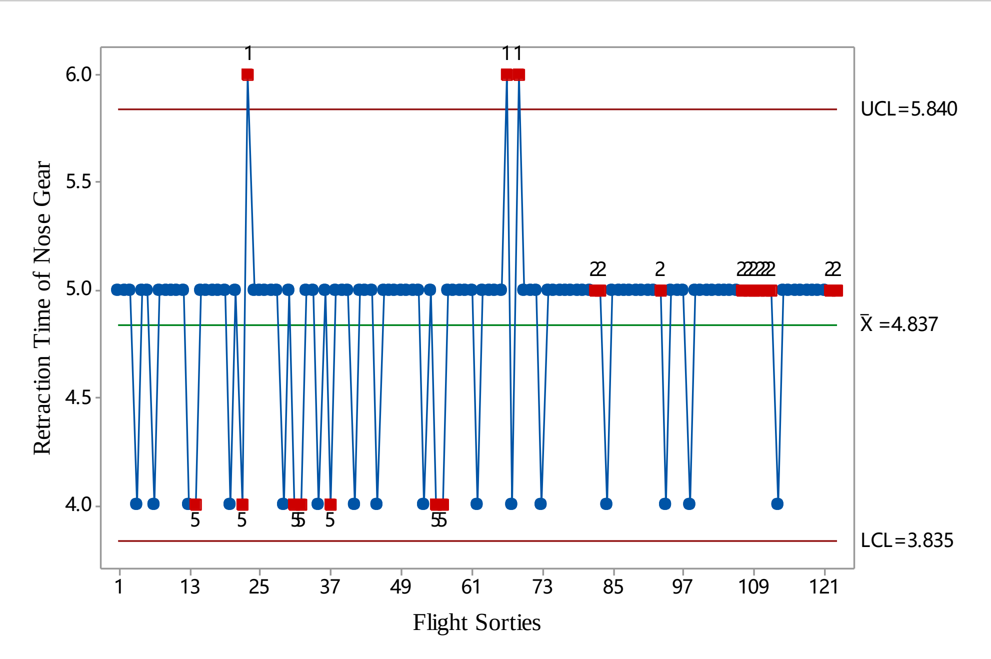

Figure 8 –Control chart test results of the nose LG retraction time.

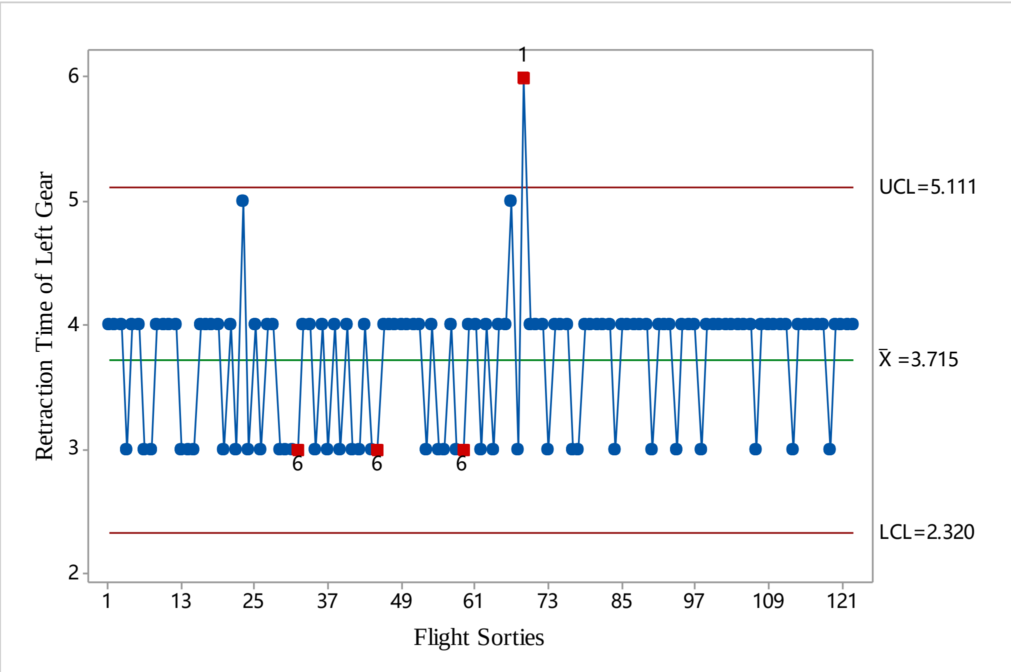

Figure 9 – Control chart test results of the left LG stowed time.

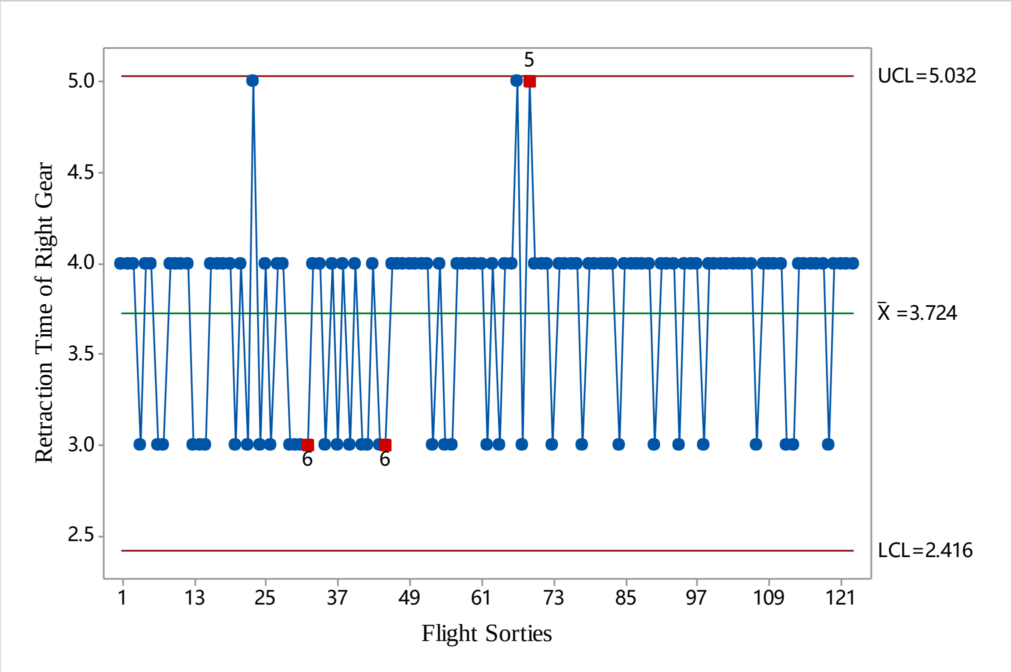

Figure 10 – Control chart test results of the right LG stowed time.

5. Conclusion

This paper proposes a model-based health feature parameters selection approach. It takes a typical civil aircraft LG retracting system as the research object. The mathematical model between the main hydraulic pressure and the actuator displacement of the LG is established by combining with theoretical knowledge of control systems. The model simulation results verify the validity of the LG R/E time as the LG health feature parameters. Moreover, the factual LG R/E time from flight data is used to monitor the LG health state by Nelson rules of SPC. The advantage of this health monitoring approach is that the monitoring parameters focus on flight recorder data. The additional sensors are not needed. And this monitoring approach is simple and effective.

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7. Copyright Statement

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