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Research paper

Development and application of maintenance decision-making support system for aircraft fleet

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ABSTRACT

With the arrival of on-board monitoring systems for aircraft structures, maintainers have access to a near real-time assessment of component health. Due to the traditional reliability assessment methods for aircraft structures lack of the ability to make full use of real-time status information collected by the monitoring systems, a new reliability evaluation method based on the real-time load information is proposed for aircraft structural reliability. Condition-based-maintenance is a maintenance scheme which recommends maintenance decisions according to equipment status collected by monitoring systems over a period of time. As most researches on condition-based maintenance for aircraft focused on solely minimizing maintenance cost or maximizing the availability of single aircraft, a multi-objective decision-making model based on condition-based-maintenance concentrated on both minimizing the maintenance cost and maximizing the availability of a fleet (total number of available aircraft in fleet) is established for an aircraft fleet. Finally, a maintenance decision-making support system (MDMSS) is developed based on the proposed model. The system integrates the process of data acquisition (real-time status information of aircraft), data processing (reliability assessment of aircraft structures) as well as maintenance decision-making. Therefore, it simplifies the complex process of equipment management and takes a step further in engineering application.

1. Introduction

Structure fatigue is a critical problem for aircraft arising from their nature as multiple-component structures, subjected to random dynamic loads during flight [1–4]. The structure is replaced or repaired when the reliability of structure reaches the threshold value given by designer. The reliability analysis methods of aircraft structure are known as stress-life, damage-tolerance, etc. [5]. Currently, the stress-life method is used by the U.S. Navy to account the fatigue damage in aircraft [1], which directly relates service loads to a safe operating life according to the linear cumulative damage [2,3]. The time of structural failure is determined from full-scale fatigue tests, in which the expected service loads are simulated and applied to a specimen in a laboratory environment. To ensure that the structure do not exceed the fatigue life limits during their service, based on the laboratory defined S-N curve and loading cycles in the service spectrum, the fatigue cumulative damage (FCD) is calculated and linearly summed to determine when the structure fails. When FCD reaches 1, either the structure is replaced, or its life is extended by repair. Stress-life method is widely used to determine aircraft and other mechanical structure fatigue life because of its simplicity and practicality [6–8]. However, the exact reliability value of the structure and its components cannot be determined by stress-life method [6,9]. To overcome this weakness, as well as considering that the factors which affect the structure fatigue life exhibit considerable scatter [10–14], the probability-damage-tolerance (PDT) methods are widely studied in recent years, due to its capability in both of handling high reliability problems and taking the stochastic factors into full consideration. Despite their advantages over deterministic analysis methods (e.g., stress-life method), design organizations have been reluctant to adopt even the standard PDT methods or to include them as part of their risk analysis capability. Reason cited include: the complexity of failure modes; lack of available damage data; and safety issues [15].

Lots of studies relating to aircraft reliability have been discussed, the importance of structural and non-structural reliability of aircraft has been extensively studied as well [16–20]. It is difficult to establish a comprehensive reliability model which can take the whole aircraft reliability into consideration, since aircraft is a

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complex system involving mechanical, electrical and hydraulic sub-systems. A practical way is to establish different reliability models for different sub-systems. Each of these sub-systems contains components of the same type (e.g., structural components and non-structural components). Due to the research concerning maintenance of aircraft structure subjected to fatigue loads is insufficient. In addition, more and more advanced fatigue monitoring sensors are applied to collect the loading information of the key structures and the collected information are further used to determine the failure times of structures. Thus, this work discussed the reliability of structures subjected to fatigue loads. With improvement to technology and the increase of the Army's information infrastructure, many aircraft have been outfitted with Health and Usage Monitoring Systems (HUMS). Fatigue monitoring of airframes has developed over decades to the stage where it is now incumbent for aircraft to be fitted with an airborne fatigue monitoring systems [21–23]. With the arrival of these on-board monitoring systems, maintainers have access to a near real-time assessment of component health [24–28]. Gao et al. [29] proposed a new deep quantum inspired neural network to fault diagnosis for aircraft fuel system, which aimed not only to improve flight security, but also to reduce the huge cost due to regular maintenance. Medina-Oliva et al. [30] presented a knowledge structuring scheme of fleets in the marine domain based on ontologies for diagnostic purposes. Al-Dahidi et al. [31] proposed a remaining useful life estimation method based on condition monitoring data for large fleets of similar equipment. Xia et al. [32] proposed a condition-based maintenance policy for intelligent monitored multi-unit series systems with independent machine failure modes. Li et al. [33] used a general expression of stochastic process models depending on both the system age and the system state to describe the degradation processes of systems. In this work, we discussed a way to establish a new reliability evaluation method, in which the linear cumulative damage of stress-life method and crack propagation life model of PDT method are combined to make full use of the real-time load information collected by HUMS.

HUMS utilizes condition-based maintenance (CBM) concepts to minimize unscheduled failures and maintenance costs. CBM is a maintenance scheme that recommends maintenance decisions based on the information collected by condition monitors [34]. It mainly includes three steps: data acquisition, data processing and maintenance decision-making [35–37]. CBM attempts to avoid unnecessary maintenance tasks by taking maintenance actions only when there is evidence of abnormal behaviors of a physical asset or a system (e.g., structures) reaches its failure threshold level. A CBM program, if properly established and effectively implemented, can significantly reduce maintenance cost by reducing the number of unnecessary scheduled preventive maintenance operations or making full use of the system's design life (i.e., maintenance operations are applied only when the system reaches its failure threshold level) [38]. In a CBM framework, maintenance policies will be optimized to minimize the operational costs or maximize the availability of systems. As most existing researches on CBM for aircraft solely focused on reducing maintenance cost or maximizing the availability of single aircraft [39–42], and there are few researches aimed both to minimize cost and to maximize the availability from the perspective of a fleet [43–45]. Feng et al. [46] developed a two-stage dynamic decision-making model aimed to minimize the maintenance cost for an aircraft fleet. Wijk [47] established a cost-effective optimization model for a phase-out scenario of an aircraft fleet. Al-Thani et al. [48] proposed an exact mixed integer programming model focused on maximizing availability for a specific homogeneous fleet type. In this work, a multi-objective decision-making model based on CBM (MODM-CBM) which concentrates on both reducing the maintenance cost and maximizing the availability of a fleet is established for an aircraft fleet. Sun et al. [49] proposed a ordering decision-making methods on spare parts for a new aircraft fleet based on a two-sample prediction.

The engineering application of maintenance decision for aircraft is being widely researched. The United States has the world's most advanced Integrated Maintenance Information System (IMIS) which mainly includes three parts: a Portable Maintenance Aids (PMA), a base-level Maintenance Information Workstations (MIWs) and a theater-level Maintenance Information Processing Center (MIPC) [50]. The employment of IMIS helps both to ensure the reliability of an aircraft fleet and to reduce the maintenance costs. In the US Air Force, a Core Automation Maintenance System (CAMS) [51] and a Reliability and Maintainability Information System (REMIS) [52] are developed to improve the efficiency of aviation equipment management, moreover, the two systems can help collect and analyze the information obtained during the maintenance process of aviation equipment. Additionally, the Pakistan Air Force developed a Logistics Management Information System (LMIS) to manage the real-time information of aviation equipment, LMIS can track the status of each aircraft in fleet and enhance the ability of maintenance support.

In light of the above studies and software development experience obtained from existing researches [53–55], this work developed a maintenance decision-making support system (MDMSS) for an aircraft fleet. MDMSS integrates the process of data acquisition (real-time status information of aircraft), data processing (reliability assessment of aircraft structures) and maintenance decision-making, moreover, it simplifies the complex process of equipment management.

The innovation points and improvements of this paper are listed as follows:

- A new reliability evaluation method based on the real-time load information is proposed for aircraft structural reliability, to make full use of real-time status information collected by the monitoring systems, as well as to handling the high reliability problems of aircraft structures. The new reliability evaluation method not only combines the practicality of the stress-life methods and the ability of handling high reliability problems of PDT methods, but also avoids the disadvantages of traditional stress-life methods and PDT methods (the real-time status information cannot be applied to help determine the reliability of aircraft structures).
- A multi-objective decision-making model based on CBM (MODM-CBM) is established for an aircraft fleet. MODM-CBM concentrates on both reducing the maintenance cost and maximizing the availability of a fleet. Thus, it overcomes the shortcomings of the traditional CBM research which focuses on single aircraft state prognostic and maintenance time.
- A maintenance decision-making support system (MDMSS) is developed. MDMSS integrates the process of data acquisition (real-time status information of aircraft), data processing (reliability assessment of aircraft structures) and maintenance decision-making, moreover, it simplifies the complex process of equipment management as well as takes a step further in engineering application.

The remainder of this paper is organized as follows. Section 2 presents the real-time status information processing. Section 3 introduces the proposed reliability evaluation method based on the real-time load information. Section 4 introduces the proposed multi-objective decision-making model based on CBM. Section 5 illustrates the development of maintenance decision-making support system, MDMSS. Section 6 introduces the system application of MDMSS. Section 7 concludes this paper.

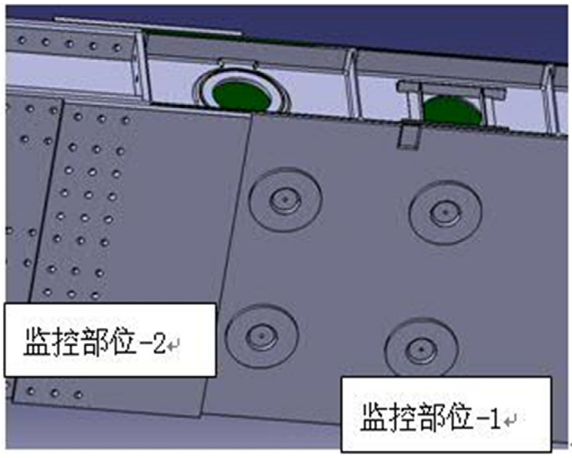

Fig. 1. Monitoring sections of the wing box of aircraft.

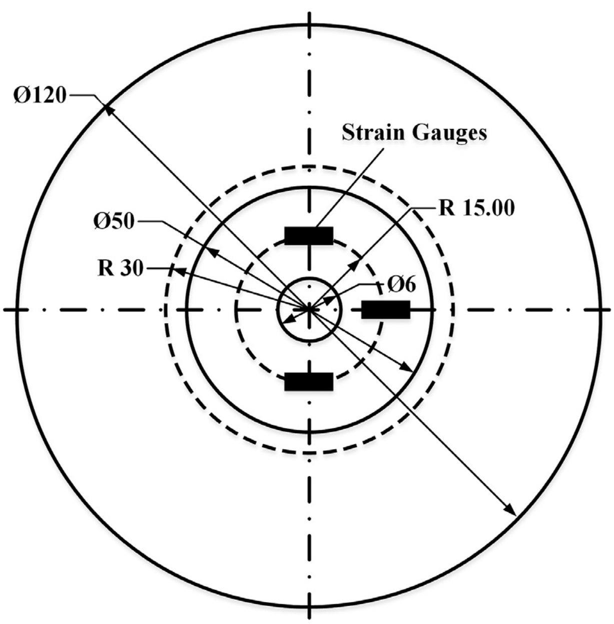

Fig. 2. The locations of strain gauges.

2. Real-time status information processing

2.1. Problem statement

Fig. 1 shows that two sections of the wing box which is a typical structure of aircraft are fitted with fatigue monitoring systems, as subjected to the random dynamic loads during flight. The specific locations of strain gauges (sensors) for the two sections are shown in Fig. 2.

As the real-time information collected by these strain gauges are micro strain data, a conversion process is required to convert the micro strain data into load information. It will cause calculation error when using the classical mechanics to complete the signal conversion (micro strain data→stresses), due to there is depression around the center hole of wing box, as well as the difficulty in establish a precise mechanical model. Consequently, the back-propagation artificial neural network (BP-ANN) is applied to complete the signal conversion process since there is no need for BP-ANN to establish a precise model [56–58].

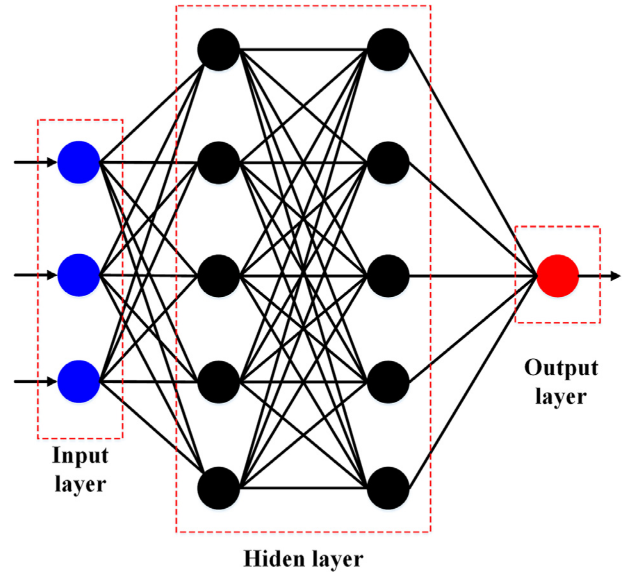

Fig. 3. Structure of BP-ANN with two hidden layers.

2.2. Theory of BPANN

2.2.1. Structure of BP-ANN

The BP-ANN is the most widely used ANN type. It includes input layer, hidden layers and output layer. A BP-ANN with two hidden layers is shown in Fig. 3.

Each cell of the network is a neuron. For input layers, the input of a neuron is its output. For hidden layer and output layer, the total input of the jth neuron is

$$s_j = \sum_{i=1}^{n} w_{ji} y_i - \theta_j \tag{1}$$

where i refers to the neuron of the previous layer connecting with the jth neuron; θ_j is the threshold of the jth neuron, and $w_{ij}$is the weight connecting the ith neuron and the jth neuron. Using sigmoid function as the activation function of the network, the total output of the jth neuron is

$$y_j = f(s_j) = \frac{1}{1 + e^{-s_j}} \tag{2}$$

2.2.2. BP learning algorithm

BP-ANN is a typical kind of feed-foreword network, of which the learning process can be divided into two phases, the forward phase and the backward phase. The basic theory of the BP-ANN is to adjust the weights and thresholds for minimizing the prediction error parameter as follows:

$$E = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \tag{3}$$

where n is the number of neurons in the output layer; x and y are respectively the actual output value and expectation value of the output layer; E is the prediction error. The learning process terminates when E is less than a predefined value ε.

The basic updating rules of the weights and thresholds from output layer to a hidden layer are

$$w_{jk}(t+1) = w_{jk}(t) + \eta E_k o_j \tag{4}$$

$$\theta_{jk}(t+1) = \theta_{jk}(t) + \eta E_k o_j \tag{5}$$

where t refers to the tth iteration; w_{jk} is the weight value of jth neuron in the hidden layer to kth neuron in the output layer; E_k is

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Table 1
25 micro strain data.

No.	Strain gauge 1/$\mu\varepsilon$	Strain gauge 2/$\mu\varepsilon$	Strain gauge 3/$\mu\varepsilon$	Stress/GPa
1	2.84	2.53	−44.1	198
2	5.5	4.91	−85.4	384
3	**8.26**	**7.36**	**−128**	**577**
4	11.0	9.81	−171	769
5	13.8	12.3	−213	961
6	**16.5**	**14.7**	**−256**	**1150**
7	19.3	17.2	−299	1350
8	25.2	21.3	−341	1540
9	2.75	2.45	−42.7	192
10	5.36	4.59	−76.9	369
11	8.11	7.04	−120	561
12	**10.9**	**9.49**	**−162**	**754**
13	13.6	11.9	−205	946
14	16.4	14.4	−248	1140
15	18.8	16.2	−290	1330
16	24.1	20.9	−333	1520
17	2.46	2.22	−25.7	162
18	**5.43**	**4.75**	**−81.1**	**377**
19	7.97	6.27	−111	546
20	10.7	9.17	−154	739
21	13.5	11.6	−196	931
22	16.2	14.1	−239	1120
23	19	16.5	−282	1320
24	23.4	19	−325	1510
25	4.27	5.21	−68.4	354

Table 2
The predict result by BP-ANN.

No.	Observed value/GPa	BP-ANN/GPa	Prediction error
3	577	575.2	0.31%
6	1150	1145.5	0.39%
12	754	755.8	0.23%
18	377	376.3	0.18%

the error of kth neuron in the output layer; o_j is the output value of jth neuron in the hidden layer; η is the learning rate.

The above updating rules can be extended to the weights and thresholds from input layer to hidden layer. The process of BP-ANN is as follows:

a) Initialize the neural network.
b) Each fabric pattern is implemented as follows:
   1) Calculate the prediction errors of output and hidden layers.
   2) Adjust the weights and thresholds of output and hidden layers.
c) If stopping criteria is satisfied, then stop and output EP. Otherwise, go to b).

2.3. Case study

In this work, a BP-ANN is established to complete the signal conversion process. The activation functions of the hidden layers and output layer are respectively Logsig functions and Purelin functions, and the structure of the BP-ANN is shown in Fig. 3. Table 1 shows 25 micro strain data and its corresponding stress data obtained by finite element method. Four micro strain data (3, 6 12 and 18) are selected as the test data and the rest of 25 data are the train data.

The predict result by the BP-ANN is shown in Table 2.

The predict result demonstrates the effectiveness and feasibility of the BP-ANN established in this work. Based on BP-ANN, the micro strain data are converted into load information.

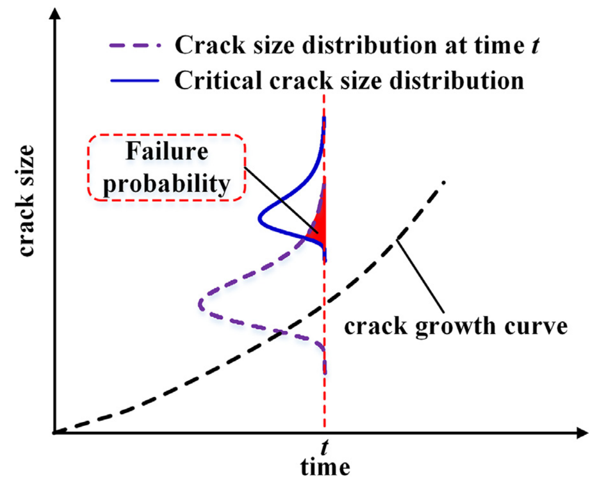

Fig. 4. Schematic representation of crack propagation life model.

3. Reliability evaluation method based on the real-time load information

With the development of technology, aircrafts are fitted with an airborne fatigue monitoring systems. These systems typically collect fatigue data is simply used for the calculation of the stress-life method or the inspection interval of the airframe, nevertheless, the exact reliability value of the airframe cannot be determined according to the collected information. The PDT methods cannot make full use of the collected real-time load information for reliability assessment, in spite of its ability to handle high reliability problem. Thus, we need to build a connection between stress-life method and PDT method, and in this connection the ability to use collected load information of stress-life method and the ability to calculate reliability of PDT method are combined.

3.1. Stress-life method

Stress-life method directly relates service loads to a safe operating life based on linear FCD [2,3]. According to linear FCD, each loading cycle is presumed to cause a specific amount of damage which can be linearly summed and structure fails when the FCD reaches 1. The linear FCD can be stated as follows:

$$D = \sum_i dam_i \tag{6}$$

$$dam_i = n_i/N_i \tag{7}$$

where $n_i (i=1,\ 2,\ldots,\ k)$ is the number of stress cycles applied at stress S_i. N_i is the number of loading cycles to failure at stress S_i. dam_i is the FCD value caused by n_i stress cycles. Failure occurs when $D \geq 1$.

3.2. Probability damage tolerance method

The failure probability calculation model based on crack propagation life model of PDT is illustrated by Fig. 4 and defined in Eq. (8).

$$PoF(t) = \iint f_a(a|t) f_{a_c}(a_c)\, da\, da_c \tag{8}$$

where $f_{a_c}(a_c)$ is the distribution of the critical crack size, a_c. $f_a(a|t)$ is the distribution of crack size, a, at t. The independent variable t can be regarded as either stress cycles, or flight hours.

$f_a(a|t)$ is calculated by considering the initial effective flaws, a_0, at time zero and evolving it based on a stochastic fatigue crack growth model. Many probabilistic or stochastic models have been proposed in the present studies [59–61]. Among them, Yang and Manning have suggested the following stochastic modeling of fatigue crack growth after investigations of crack propagation in fastener holes of aircrafts under spectrum loading:

$$\frac{da(t)}{dt} = X(t)Q[a(t)]^b \tag{9}$$

Where $X(t)$ is a stationary lognormal random process having a unit mean-value, Q and b are constants to be evaluated from the crack growth observation. According to Yang and Manning, the probability structure of the stochastic fatigue crack growth process can be obtained analytically. $f_a(a|t)$ can be obtained by integrating Eq. (9) and is described as follows:

$$f_a(a|t) = [(1-b)XQt + a_0{}^{-b+1}]^{b-1} \tag{10}$$

3.3. Reliability evaluation method based on the real-time load information

The number of stress cycles n_{ij} applied at stress S_{ij} during the ith flight can be obtained by the fatigue monitoring systems, where j is the number of different stresses during the ith flight and t_i is the flight time of ith flight. Then the total flight time is $t = \sum_t t_t$ and total number of stress cycles is $n = \sum_t \sum_j n_{ij}$. Clearly, there exists a corresponding relation between t and n. $f_a(a\backslash t)$ is further transformed into $f_a(a\backslash n)$. According to the Stress-life method, the following equation is acquired:

$$dam = \sum_i \sum_j n_{ij}/N_{ij} \tag{11}$$

where N_{ij} is the number of loading cycles to failure at stress S_{ij}. It is obvious that there exists a corresponding relation between *dam* and n, in other words, each total flight time t corresponds to a total number of stress cycles n and each n corresponds to a CFD *dam*. Correspondingly, Eq. (12) can be obtained. Finally, by inputting Eq. (12) into Eq. (8), the Eq. (13) is derived.

$$f_a(a|dam) \cong f_a(a|t) \tag{12}$$

$$PoF(dam) = \iint f_a(a|dam) f_{a_c}(a_c) da da_c \tag{13}$$

From Eq. (13), if the crack size distribution as a function of FCD *dam* (Eq. (4)) can be obtained, a new reliability evaluation method based on the real-time load information can be established. From the existing researches [62,63], it is obtained that the crack size distribution at specific loading cycles is mostly likely followed log-normal probability distribution as follows:

$$f_a(a|n) = \frac{1}{\sqrt{2\pi} a\sigma(n)} \exp\left(\left(\frac{\ln a - u(n)}{\sigma(n)}\right)^2\right) \tag{14}$$

According to Eq. (12), it is obvious that the crack size distribution at FCD *dam* can be stated as follows:

$$f_a(a|dam) = \frac{1}{\sqrt{2\pi} a\sigma(dam)} \exp\left(\left(\frac{\ln a - u(dam)}{\sigma(dam)}\right)^2\right) \tag{15}$$

If $u(dam)$ and $\sigma(dam)$ can be determined, then the failure probability of structure at *dam* is obtained. To build the two models: $u(dam)$ and $\sigma(dam)$, we need to analyze the fatigue crack growth data from a statistical viewpoint.

3.3.1. Crack growth data

Two crack growth data of constant-amplitude loading used in this paper come from Wu [62]. The data are the results of a prophase research of aircraft structural reliability. The experiment material is 2024-T351 aluminum alloy which is widely used in aircraft manufacturing. The first set, named CA1 (constant-amplitude loading set 1) hereafter for simplicity, consists of 30 specimens. They were tested under a sinusoidal load of $p_{peak} = 4.5$ kN and $p_{trough} = 0.9$ kN, or in terms of stress ratio, $R = p_{trough}/p_{peak} = 0.2$, which results in stresses oscillating between 14.08 MPa and 70.41 MPa. The second set consists of 10 specimens and is named CA2; CA2 under $p_{peak} = 6.118$ and $p_{trough} = 3.882$ kN, or $R = 0.63$. The experimental fatigue crack growth curves of CA1 and CA2 are shown in Fig. 5.

Table 3
The u at different *dam*.

dam	0.1840	0.2760	0.3679	0.4599	0.5519	0.6439	0.7359
μ	2.9424	2.9718	3.0055	3.0373	3.0753	3.1253	3.1831
dam	0.1084	0.2168	0.3252	0.4336	0.5420	0.6504	0.8671
μ	2.9224	2.9630	3.0006	3.0413	3.0858	3.1409	3.2859

3.3.2. Modeling of u(dam) *and* σ(dam)

a) Modeling of $u(dam)$

The mean loading cycles at fracture is calculated as the average number of loading cycles to failure of all specimens, and the results are $N_{CA1} = 54{,}356$ and $N_{CA2} = 230{,}645$. The statistical results of mean (u) of crack size log-normal probability distribution at different *dam*, for CA1 and CA2 are shown in Table 3.

Based on analyzing the data shown in Table 3, the trend of u as a function of *dam* is fitted by the exponential model. The regression results for CA1 and CA2 are shown in Fig. 6a and b, respectively.

From Fig. 6, it is clearly that the exponential model is a good fit to $u(dam)$.

b) Modeling of $\sigma(dam)$

The statistical deviation (σ) of crack size log-normal probability distribution at different *dam* for CA1 and CA2 are shown in Table 4.

The trend of σ as a function of *dam* is fitted by the exponential regression model according to the data shown in Table 4. The regression results are shown in Fig. 7.

From Fig. 7, it is clearly that the exponential model is a good fit to $\sigma(dam)$.

According to the above two models: $u(dam)$ and $\sigma(dam)$, a new reliability evaluation method based on the real-time load information is established in Eq. (16) and detailed illustrated in Fig. 8.

$$PoF(dam_1) = \int_{a_c}\int_a \frac{1}{\sqrt{2\pi}\sigma(dam_1)} \exp\left(-\left(\frac{\ln a - \mu(dam_1)}{\sigma(dam_1)}\right)^2\right) \times f_{a_c}(a_c) da da_c \tag{16}$$

where dam_1 is calculated and linearly summed by stress-life method according to the real-time load information obtained during the flight; $f_{a_c}(a_c)$ is the distribution of the critical crack size a_c and it is determined by fatigue tests.

4. Multi-objective decision-making model based on CBM

More and more advanced fatigue monitoring sensors are applied to collect the loading information of the key structures and the collected information are used to determine the failure times of structures. Additionally, aircraft maintenance program develops from tradition corrective maintenance and preventive maintenance to CBM. Thus, a multi-objective decision-making model based on CBM for an aircraft fleet is established.

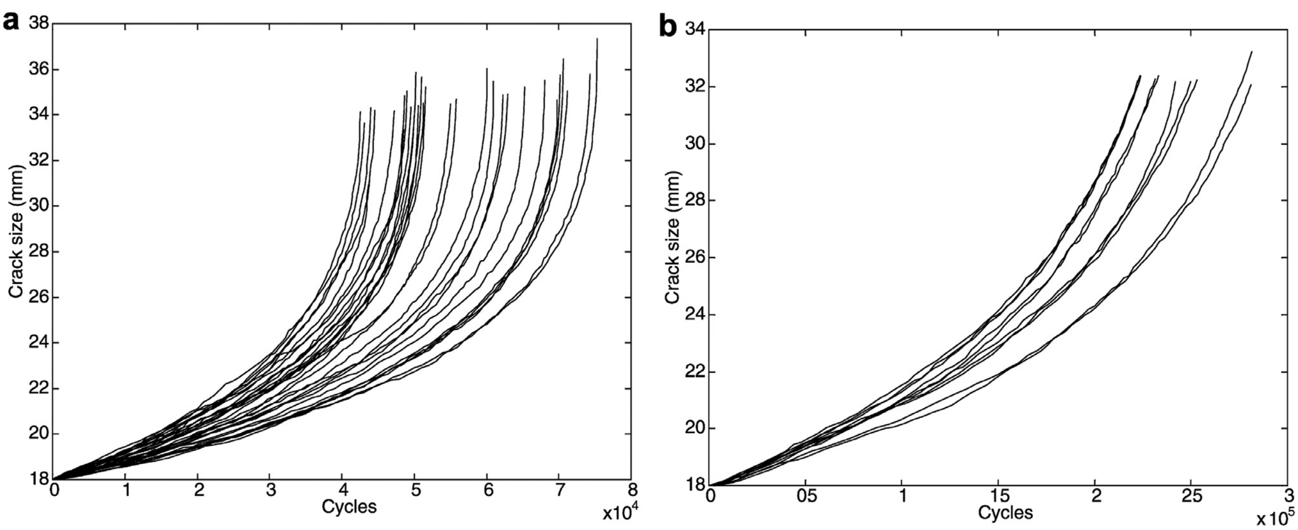

Fig. 5. Experimental crack growth curves of data set; a) CA1 and b) CA2 [62].

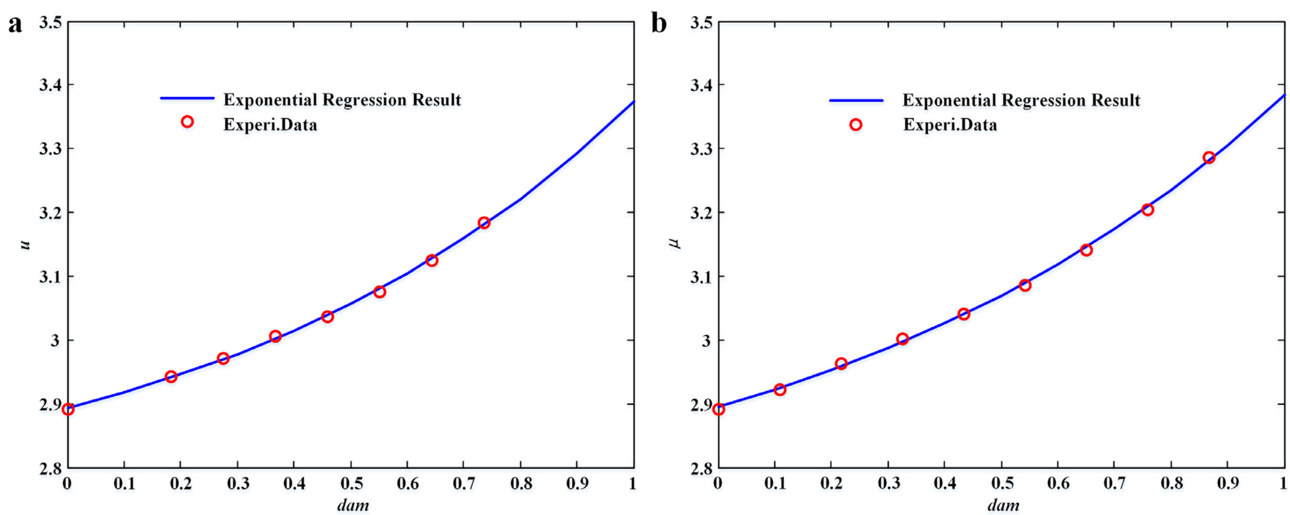

Fig. 6. Regression results of u; a) CA1 and b) CA2.

Table 4
The σ at different *dam*.

CA1	*dam*	0.1840	0.2760	0.3679	0.4599	0.5519	0.6439	0.7359
	σ	0.0122	0.0187	0.0261	0.0346	0.0434	0.0592	0.0836
CA2	*dam*	0.1084	0.2168	0.3252	0.4336	0.5420	0.6504	0.8671
	σ	0.0055	0.0093	0.0129	0.0196	0.0270	0.0339	0.0437

4.1. Maintenance cost optimization model

A maintenance cost optimization model consisting of two sub-models: 1) useful remaining life wasting model and 2) crack repair cost model, is established.

1) Useful remaining life wasting model $f(dam|t_{repair})$

It will cause useful remaining life wasting, if the unrepairable key structure is replaced for safety when small fatigue cracks appear, due to the failure time cannot be accurately determined. In addition, the repairable structure which is repaired when small fatigue cracks appear will cause useful remaining life wasting as the repair of structure may change the stress distribution and accelerate wear. Therefore, replacing or repairing the structure when it close to failure can reduce the waste of useful remaining life. Fig. 9a shows the structure damage as a function of flight hour.

In Fig. 9a, *dam* is the structure damage at time to repair the structure (t_{repair}). The dotted red curve represents the waste of useful remaining life. According to the above analyses, a useful remaining life wasting model is established in Eq. (17).

$$f(dam|t_{repair}) = C_{structure} \times (1 - dam(t_{repair})) \tag{17}$$

where $C_{structure}$ is a factor representing the cost caused by wasting of useful remaining life per damage. t_{repair} is the time to repair the structure.

2) Crack repair cost model $\varphi(a)$

Different components, different structures, and different crack sizes demand different repair means. Primary airframe structures are often designed to be repairable [59]. Fig. 9b presents an example of the repair means of structure at different damage degrees.

In Fig. 9b, t_{design} is the design life of aircraft. Different damages correspond to different repair means and different repair means

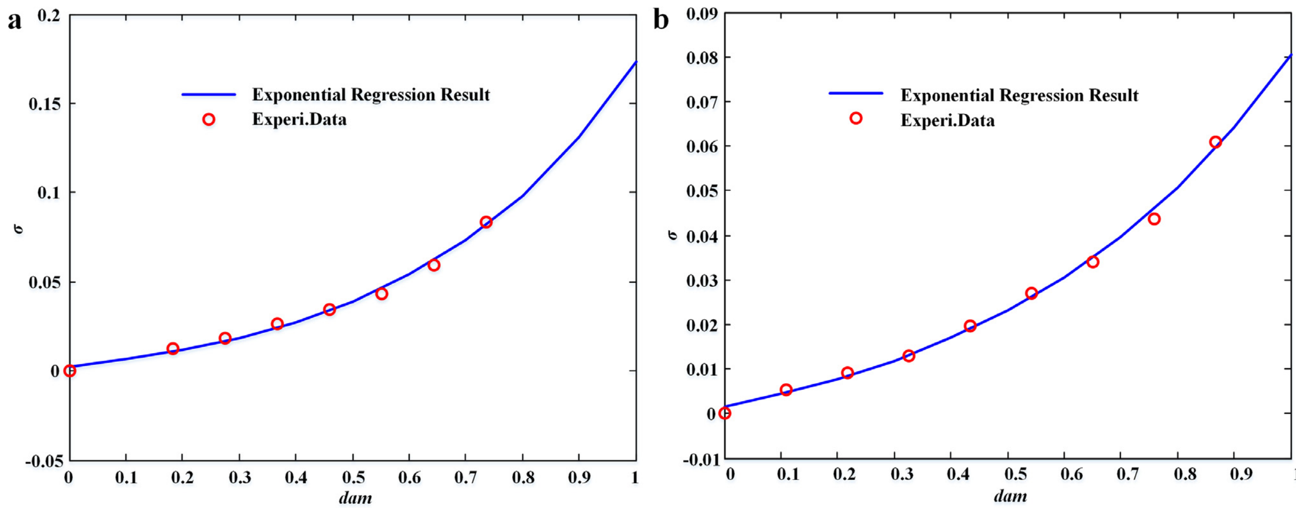

Fig. 7. Regression results of σ; a) CA1 and b) CA2.

correspond to different repair costs. As shown in Fig. 9b, there is no need to repair the structure when the damage is between 0 and dam_1; a stop drill alone method [64–66] or patching technology [67–69] is applied when the damage degree is between dam_1 and dam_2, and the repair cost is c_1; an overhaul is required when the damage degree grows to (dam_2, dam_3], and the repair cost is c_2; the structure needs to be replaced when the damage degree grows to (dam_3, 1], and the cost is c_3. According to the above analyses, a crack repair cost model is established in Eq. (18).

$$\varphi(dam) = \begin{cases} 0(0 \le dam < dam_1) \\ c_1(dam_1 \le dam < dam_2) \\ c_2(dam_2 \le dam < dam_3) \\ c_3(dam_3 \le dam \le 1) \end{cases} \tag{18}$$

where dam is the structure damage. c_1, c_2 and c_3 are the repair costs.

A maintenance cost optimization model for the structures of an aircraft is established in Eq. (19) according to the above two sub-models.

$$\text{minimize } \mathrm{Mc}(t) = \sum_{i=1}^{ns} \left(f(dam_i(t)) + \varphi(dam_i(t))\right)$$
$$subject \text{ to } PoF_i(dam_i(t)) \le 10^{-7} \; for \; i = 1, \ldots, ns \tag{19}$$

where ns is the number of structures that are fitted with monitoring systems; t is the time to repair the ns structures (i.e., the structures will be repaired at one downtime); $dam_i(t)$ is the FCD of ith structure at t; $PoF_i(dam_i(t))$ is the failure probability of ith structure at t.

4.2. Availability optimization model for an aircraft fleet

An availability optimization model for an aircraft fleet, which aims to minimize the sum of overlapping lengths of any two aircrafts' repair times in fleet (i.e., to maximize the availability), is established in Eq. (20).

$$\min \; \mathrm{Ol}(t_1, t_2, \ldots, t_l) = \sum_{i=1}^{l} \sum_{j=1}^{d_i} \sum_{k=1, k\neq i}^{l} \delta(t_i + j, t_k)$$
$$\text{subject to } \delta(t_i + j, t_k) = \begin{cases} 1, 0 \le (t_i + j) - t_k \le d_k \\ 0, (t_i+j)-t_k < 0 \text{ or } (t_i+j)-t_k > d_k \end{cases} \; for \; i, k = 1, \ldots, l, k \ne i$$
$$PoF_i(dam_i(t_i)) \le 10^{-7} \; for \; i = 1, \ldots, l$$
$$R\_S = \{t_1, t_2, \ldots, t_l\}$$
$$R\_D = \{d_1, d_2, \ldots, d_l\} \tag{20}$$

where l is the number of aircrafts in fleet. t_i (i = 1, …, l) is the time to repair the ith aircraft; R_S is a set of t_i. d_i (i = 1, …, l) is the repair time needed by the ith aircraft (i.e., the repair time is determined by the structural damage degree, structural complexity, maintenance manuals and maintenance experience); R_D is a set of d_i. $PoF_i(dam_i(t_i))$ is the failure probability of the ith aircraft at ti and it determines by the structure which has the biggest failure probability.

4.3. MODM-CBM

The objective of MODM-CBM is to schedule an appropriate maintenance plan for minimizing maintenance costs and maintaining a high level of readiness by taking full advantage of the status information of structures. Fig. 10 shows the process of maintenance decision-making for an aircraft fleet, and every aircraft has several key structures that are fitted with monitoring systems.

As shown in Fig. 10, the structure damage is estimate through processing the load data obtained by monitoring system. The trend of structure damage (dam) is predicted according to the flight plans and history damage data, and the $PoF_i(dam_i(t))$ in Eq. (11) and $PoF_i(dam_i(t_i))$ in Eq. (12) are determined. From the above analyses, a MODM-CBM for a fleet is established through combining the above maintenance cost optimization model and availability optimization model. The combination process is shown in Fig. 11.

MODM-CBM is described as follows:

$$\min \; F(t_1, t_2, \ldots, t_l) = \left(\sum_{i=1}^{l} \mathrm{Mc}_i(t_i), Ol(t_1, t_2, \ldots, t_l)\right)$$
$$\text{subject to } PoF_i(dam_i(t_i)) \le 10^{-7} \; for \; i = 1, \ldots, l \tag{21}$$

where $\mathrm{Mc}_i(t_i)$ is the maintenance cost optimization model of the ith aircraft; $Ol(t_1, t_2, \ldots, t_l)$ is the availability optimization model of the fleet; $PoF_i(dam_i(t_i))$ is the same as above.

4.4. Case study

4.4.1. Assumptions and data

A fleet of 10 aircrafts is considered to develop and validate the proposed model. Each aircraft consists of 3 repairable structures (A, B and C) with predictable residual useful life (RULs) obtained

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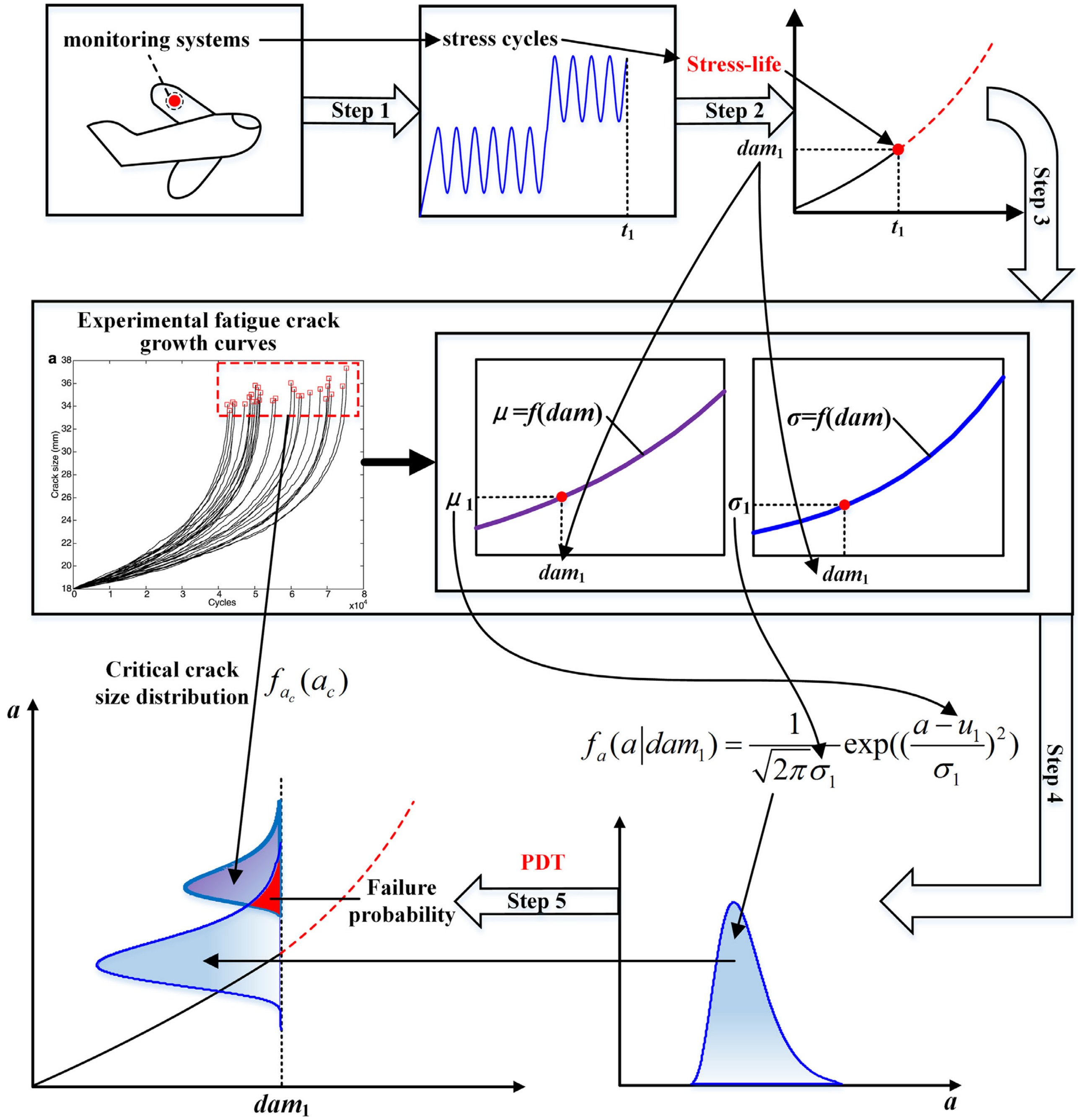

Fig. 8. The reliability evaluation method based on the real-time load information.

by the proposed reliability model. The RULs and current damage values of the 10 aircrafts are presented in Table 5. The repair methods, time, and cost of structures with different damage are given in Table 6. The threshold of structure failure probability *PoF* is 10^{-7}. The $C_{structure}$ in Eq. (12) for structures A, B and C are respectively 2700, 4100 and 2800.

4.4.2. Results and analysis

Various methods, such as branch-and-bound search, integer programming, dynamic programming, as well as heuristic techniques, have been investigated for multi-objective maintenance decision-making problem. However, these techniques require specific domain knowledge of the problem, and the computational time increases dramatically with the problem size. In addition, some solutions generated could even be trapped in local optima. Multi-objective evolutionary algorithms were reported to overcome shortcomings of traditional methods. Among them, elitist non-dominated sorting genetic algorithm (NSGA-II) have received great attentions and have been proven to perform well on lots of real-world problems [70,71]. Thus, in this work, NSGA-II is selected to solve the proposed model.

The optimization result of the proposed model obtained by NSGA-II is shown in Fig. 12a. Three of the non-dominated solutions are illustrated by Gantt charts presented in Fig. 12b, c and d, respectively. Fig. 12b shows the fleet maintenance information when the maintenance cost is minimized and availability of fleet is minimized (the objective of the proposed model is both to minimize the maintenance cost and to maximize the availability of fleet).

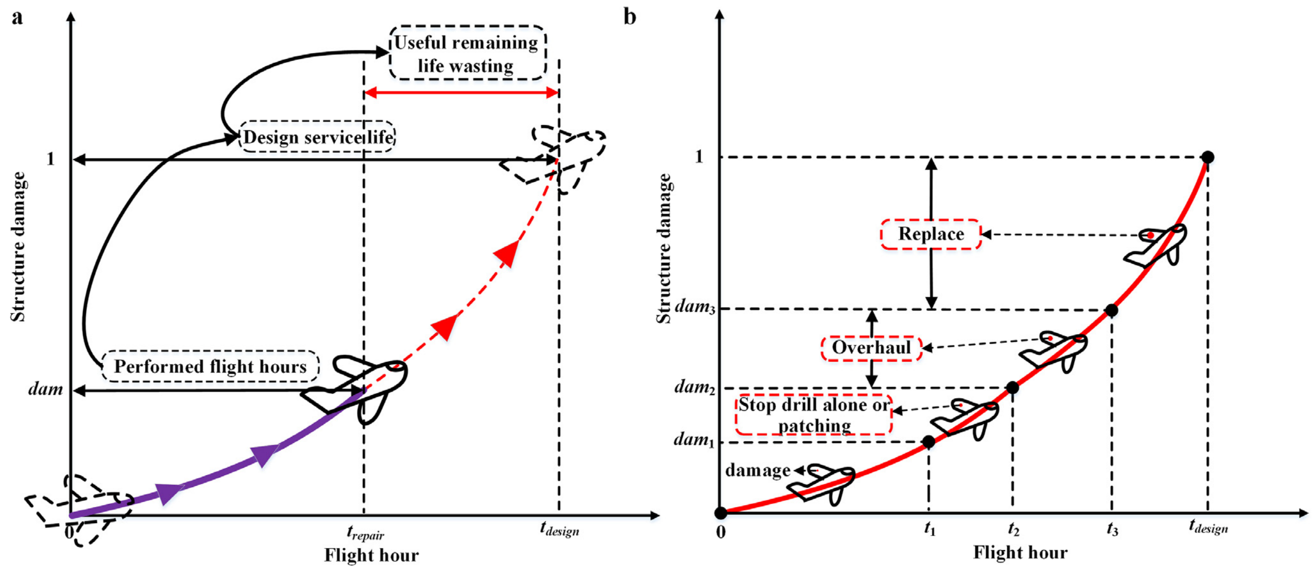

Fig. 9. a) The structure damage as a function of flight hour; b) Repair methods of structure at different damage degrees.

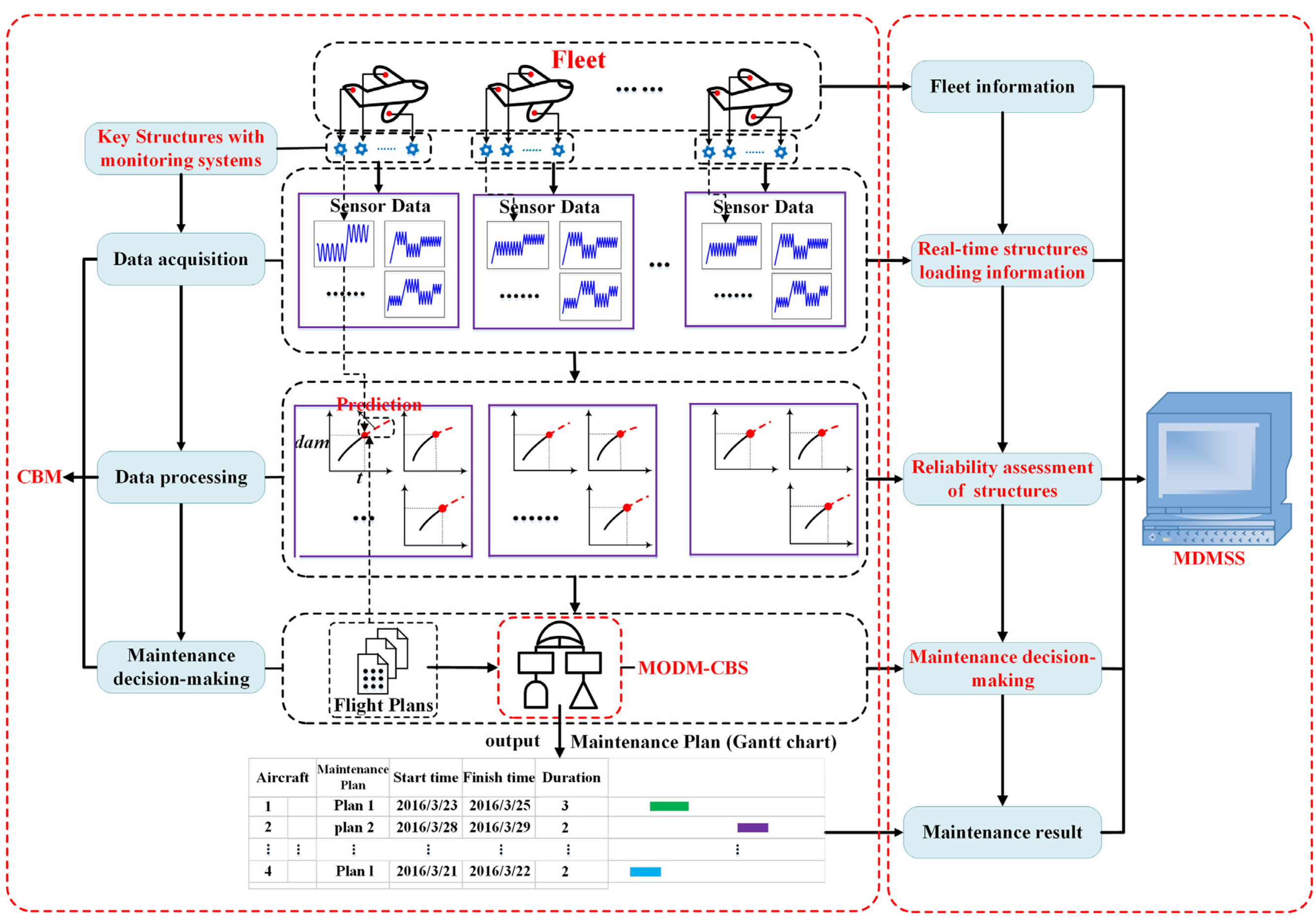

Fig. 10. The process of maintenance decision-making for an aircraft fleet.

Fig. 12d shows the fleet maintenance information when the maintenance cost is maximized and availability of fleet is maximized. A trade-off solution is illustrated in Fig. 12c. Decision maker can select an appropriate solution according to the maintenance resource of equipment safeguard and task requirement.

5. Development of maintenance decision-making support system, MDMSS

The maintenance decision-making support system, MDMSS, is developed for maintenance decision-making of an aircraft fleet. As shown in Fig. 6, MDMSS covers the process of data acquisition

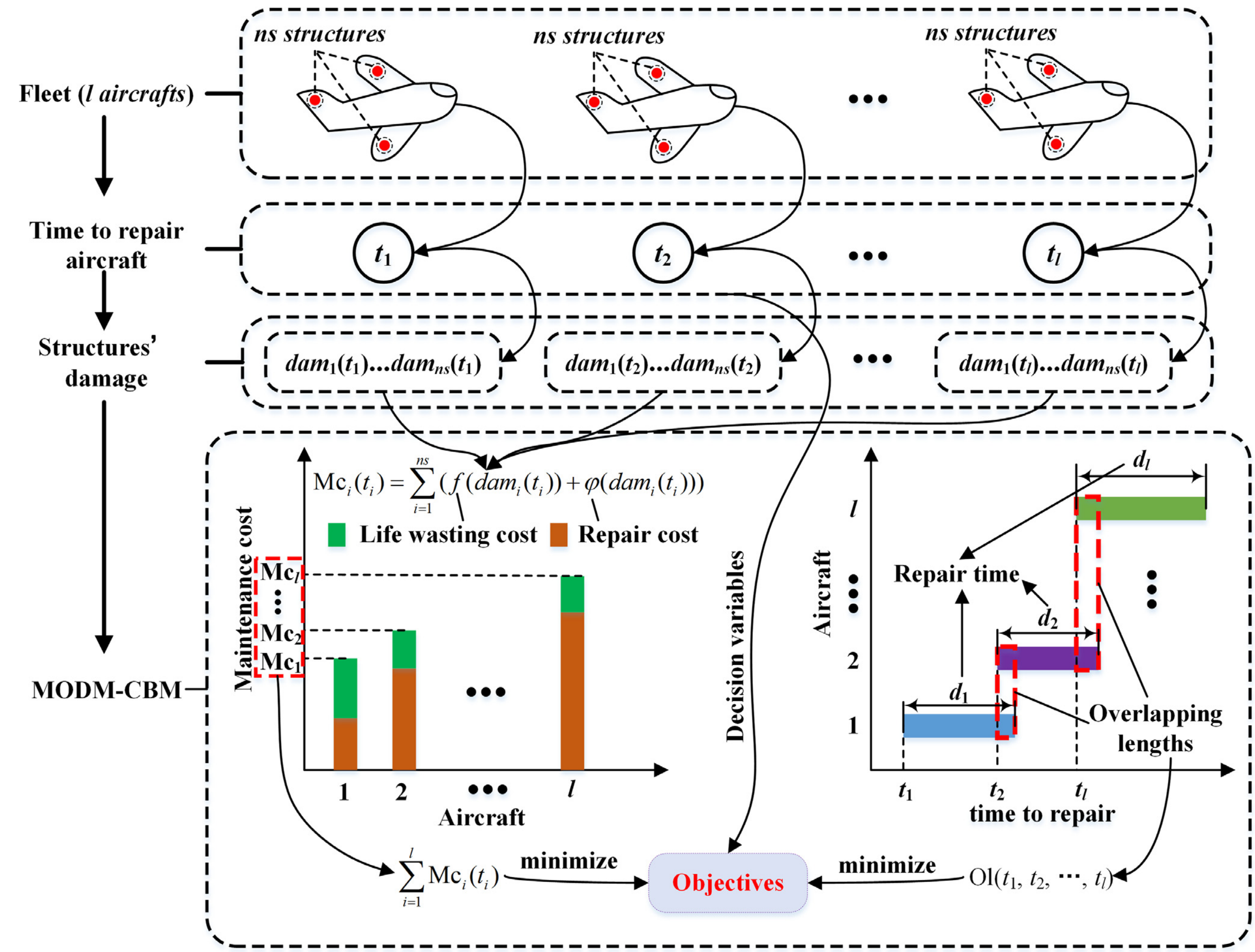

Fig. 11. The combination process of maintenance cost optimization model and availability optimization model.

Table 5
RULs and current damage values of 10 aircrafts.

Aircraft	1	2	3	4	5	6	7	8	9	10	
RULs	A	520.2	421.5	386.4	615.3	482.6	561.3	673.2	496.2	522.3	564.3
	B	574.3	516.4	516.4	651.5	570.5	617.5	697.5	574.9	596.6	622.8
	C	494.9	399.1	364.5	601.7	453.4	550.1	686.0	474.0	514.3	542.0
Damage	A	0.551	0.660	0.695	0.424	0.595	0.499	0.329	0.579	0.549	0.496
	B	0.426	0.512	0.512	0.285	0.432	0.352	0.176	0.425	0.389	0.342
	C	0.621	0.712	0.742	0.501	0.662	0.562	0.384	0.642	0.601	0.571

Table 6
Repair methods, time, and cost of structure with different damage.

Structure	A			B			C		
Damage	0.4–0.6	0.6–0.8	0.8–1	0.4–0.5	0.5–0.7	0.7–1	0.4–0.6	0.6–0.8	0.8–1
Method	1	2	3	1	2	3	1	2	3
Time (day)	7	20	14	7	28	14	7	22	14
Cost (yuan)	2000	4000	5400	2800	6200	8200	2400	4600	5600

(real-time status information of aircraft), data processing (reliability assessment of aircraft structures) and maintenance decision-making, as well as databases. The framework of MDMSS is a typical 3-layer system based on Java Swing, and the general structure is shown in Fig. 13.

MDMSS is developed by integrating MyEclipse 10.0 and SQL Server under windows operation system. The system realizes information management, reliability assessment of structures, and maintenance decision-making, etc. With Win32 API, the UI is released by calling additional programming. The data are stored in the database and operated by SQL coding. The connections between the sub-systems are made on the basis of the basic integrated code of the system.

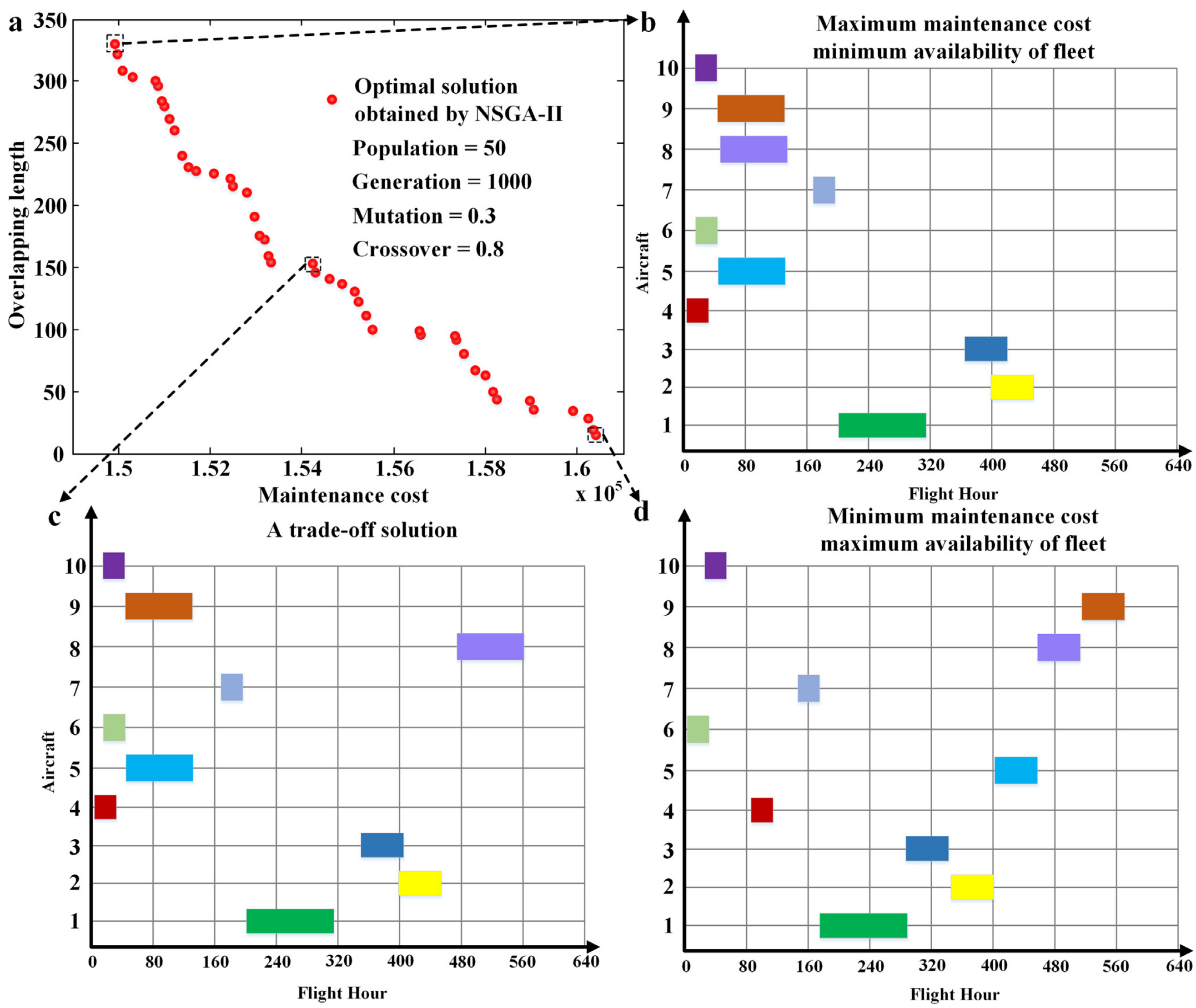

Fig. 12. a) The optimization result of the proposed model obtained by NSGA-II; b) The fleet maintenance information when the maintenance cost is minimized and availability of fleet is minimized; c) A trade-off solution; d) The fleet maintenance information when the maintenance cost is maximized and availability of fleet is maximized.

6. System application

6.1. Outline of MDMSS

The MDMSS covers the whole process from collection of real-time status information to maintenance decision-making of a fleet. As shown in Fig. 14, the main window of *MDMSS* is shown when user login to the system, and on the top of the window, user can choose the system's main categories. The basic information of fleets stored in database are shown as a tree (located at the right side of the window). If user clicks the tree node, then the basic information of the fleet that is represented by the clicked tree node will present.

6.2. Sub-systems of MDMSS

The system includes four main sub-systems: real-time status information processing sub-system, reliability assessment sub-system, maintenance decision-making sub-system, and document management sub-system. The detailed functions of each sub-systems are as follows.

6.2.1. Real-time status information processing sub-system

The real-time status information processing sub-system includes the following main function module: real-time status information import, signal conversion, filtering and rain-flow counting, and FCD calculation.

The detailed function modules of real-time status information processing sub-system are as follows:

- Real-time status information import: the real-time status information of structures are collected by strain sensors mounted on the aircraft, and the collected information (i.e., the information collected by strain sensors is electrical signals) is imported into the database by user in text form.
- Signal conversion: the electrical signals are converted into fatigue loads, and the conversion process is shown in Fig. 15.
- Filtering and rain-flow counting: the fatigue loads are filtered to remove the loads that fail to satisfy the threshold value (given by designer), and then the filtered fatigue loads are calculated by the rain-flow counting method. The whole process is shown in Fig. 16.

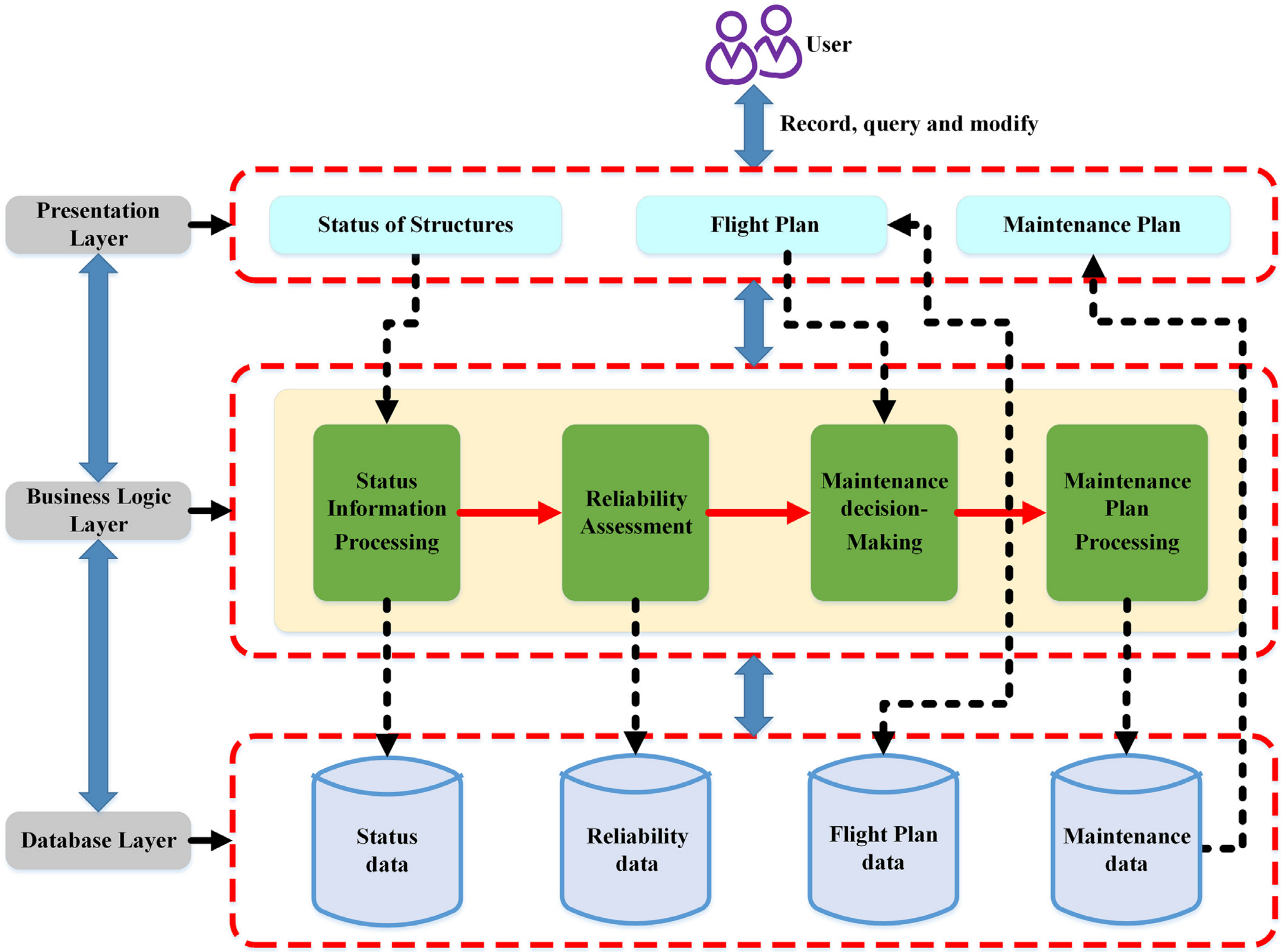

Fig. 13. General structure of MDMSS.

Fig. 14. The main window of MDMSS.

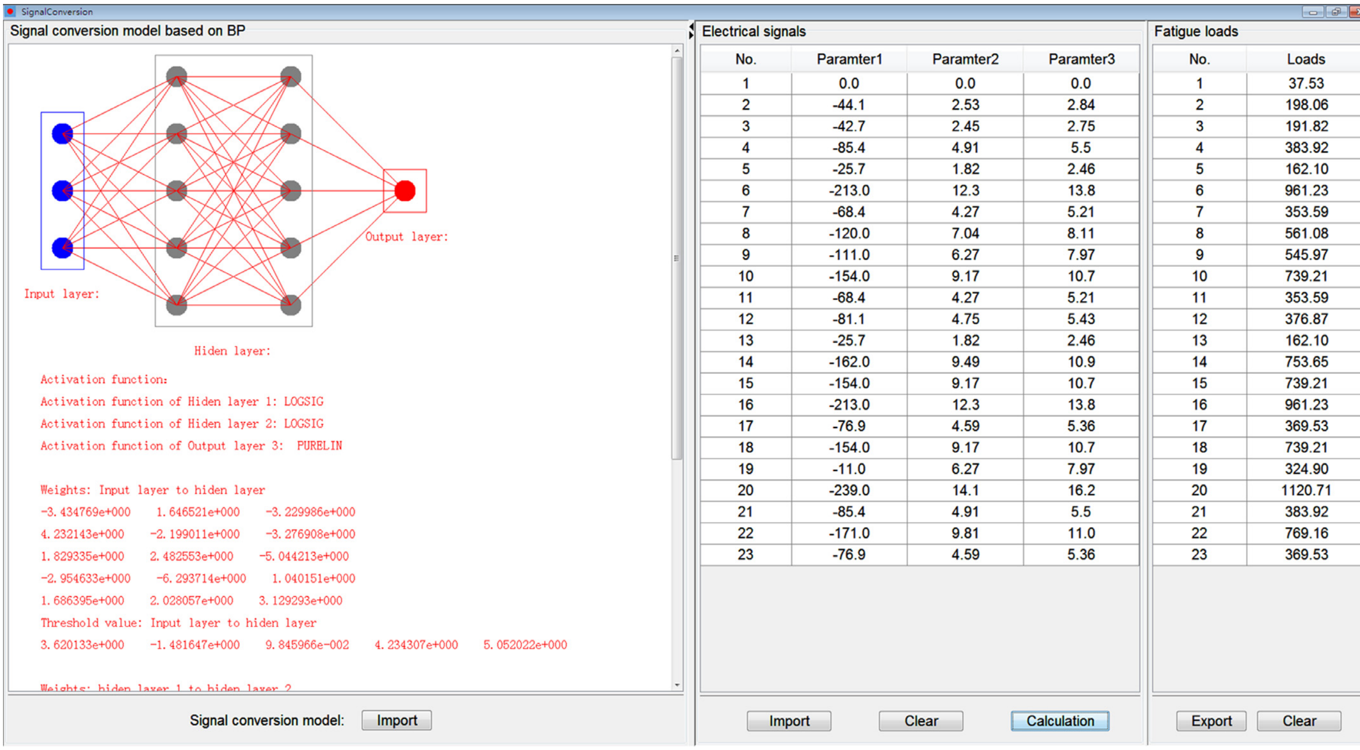

Fig. 15. The interface of signal conversion.

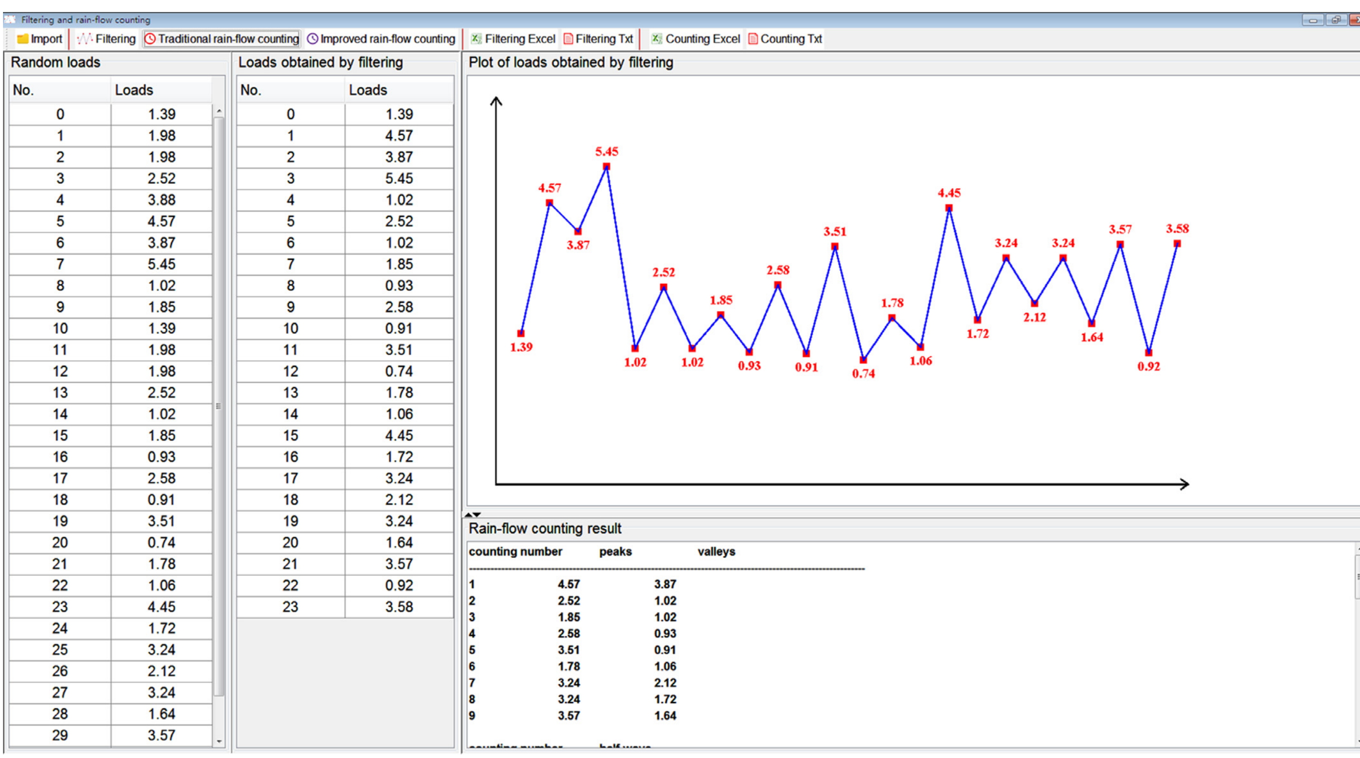

Fig. 16. The interface of filtering and rain-flow counting.

- FCD calculation: the FCD value is calculated according to rain-flow counting result.

6.2.2. Reliability assessment sub-system

The reliability assessment sub-system is developed to obtain the reliability information of structures according to the FCD value and the proposed reliability evaluation method. This sub-system includes the following function modules: parameters input, Monte-Carlo computer simulation, reliability information presentation.

The detailed information of each function module is described as follows:

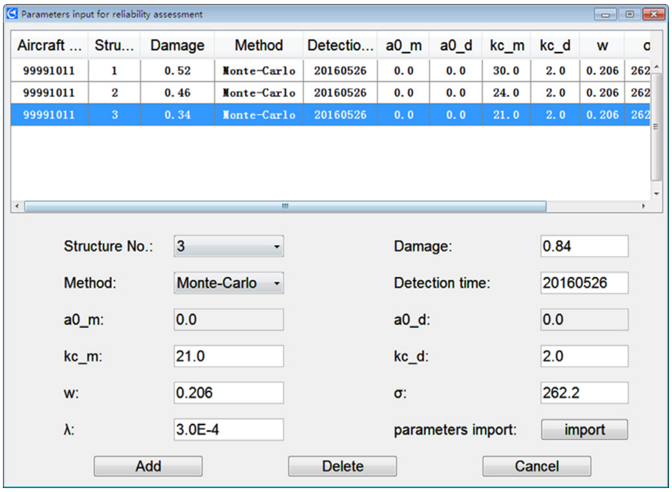

Fig. 17. The interface of parameters input.

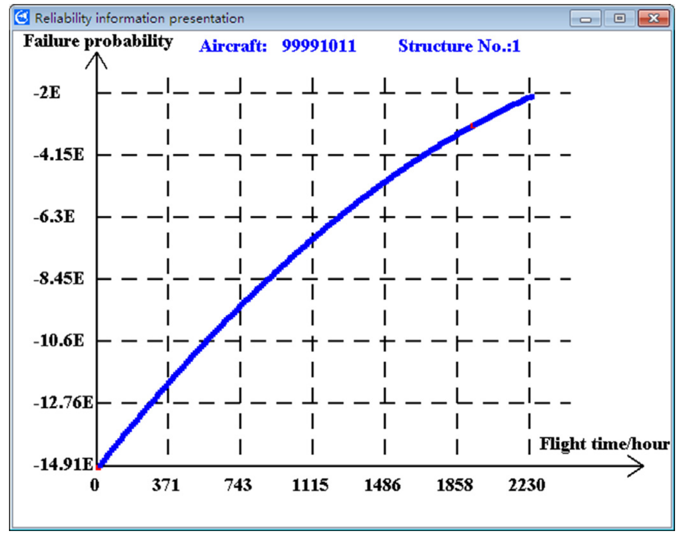

Fig. 18. The interface of reliability information presentation of a structure.

- Parameters input: the parameters that are needed by the reliability assessment model are inputted by user, and the UI is shown in Fig. 17.
- Monte-Carlo computer simulation: the reliability assessment model is solved by Monte-Carlo computer simulation.
- Reliability information presentation: the reliability information of structure obtained by Monte-Carlo computer simulation is presented by a failure probability curve shown in Fig. 18.

6.2.3. Maintenance decision-making sub-system

The maintenance decision-making sub-system is the core of MDMSS, and other sub-systems are auxiliary of it. It is designed to integrate the process of data acquisition (real-time status information of aircraft), data processing (reliability assessment of structures) and maintenance decision-making, moreover, it simplifies the complex process of fleet management. This sub-system has the following function modules: fleet reliability information input, maintenance decision-making modeling and optimization, maintenance plan presentation, and maintenance plan adjustment.

The detailed function modules of maintenance decision-making sub-system are as follows:

- Fleet reliability information input: the structures' reliability information of each aircraft in fleet, which is needed for making maintenance plan, is inputted by user.
- Maintenance decision-making modeling and optimization: A multi-objective maintenance decision-making model is established for the fleet according to the above fleet reliability information, and then it is optimized by the NSGA-II which is coded and embedded into the module.

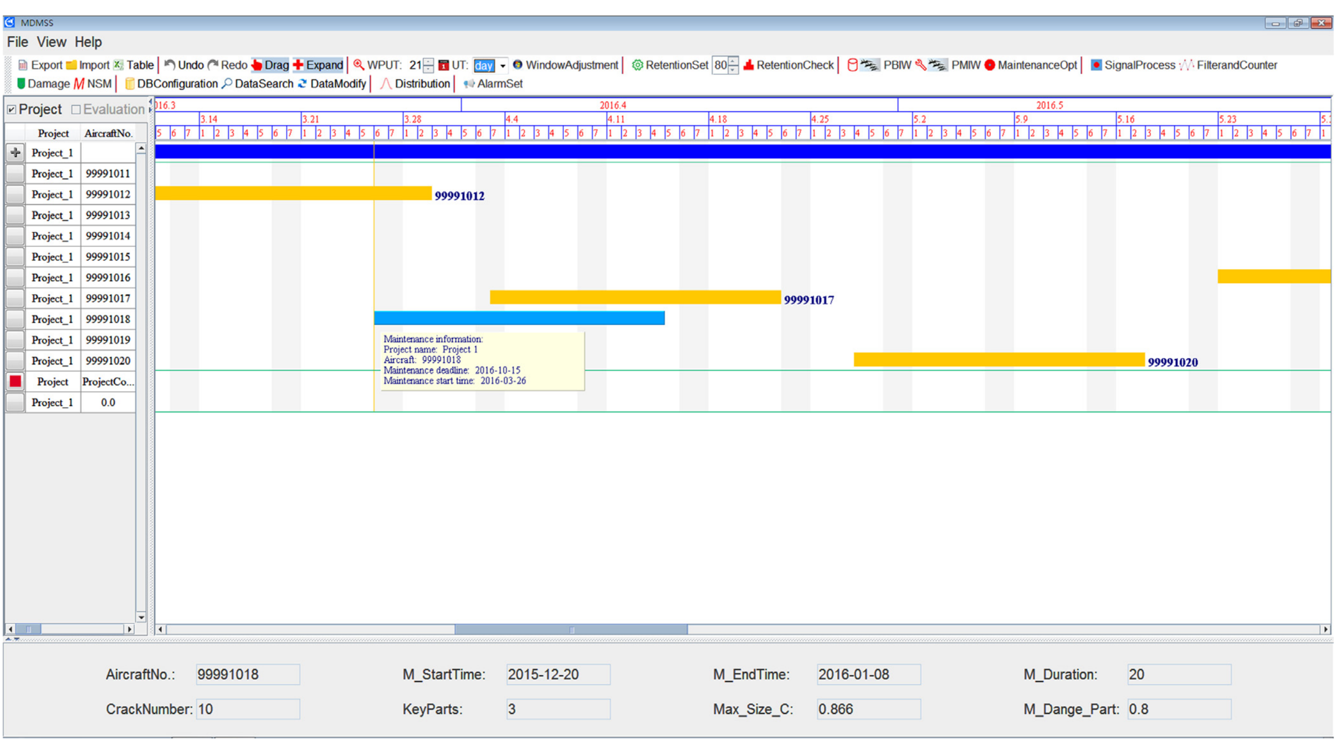

Fig. 19. The interface of maintenance plan presentation.

- Maintenance plan presentation: The optimization results of the above multi-objective maintenance decision-making model is presented by a Gantt chart shown in Fig. 19.
- Maintenance plan adjustment: The decision maker (user) can adjust the maintenance plan of the fleet through dragging the Gantt bar which represents the aircraft to adjust. The decision maker is adjusting one aircraft of the fleet, as shown in Fig. 19.

7. Conclusion

Due to the traditional reliability assessment methods lack the ability to make the full use of real-time status information collected by the monitoring systems, a new reliability evaluation method based on the real-time load information is proposed for aircraft structural reliability. Furthermore, a multi-objective decision-making model based on CBM (MODM-CBM) is established. MODM-CBM aims not only minimizing the maintenance cost, but also maximizing the availability of fleet. Thus, it avoids the disadvantages of traditional CBM which focused on solely minimizing maintenance cost or maximizing the availability of single aircraft. Finally, a maintenance decision-making support system (MDMSS) is developed based on the proposed model for integrating the process of data acquisition (real-time status information of aircraft), data processing (reliability assessment of structures) and maintenance decision-making. In particular, MDMSS simplifies the complex process of equipment management.

The following bullet points summarize the contributions of our work:

- The proposed reliability evaluation method combines the practicality of stress-life method and the ability of handle high reliability problem of PDT method.
- The proposed maintenance decision-making model is established from the perspective of a fleet instead of single aircraft, which accords with engineering practice. Additionally, it makes full use of reliability information of an aircraft fleet to schedule an appropriate maintenance plan for reducing maintenance costs and maintaining a high level of readiness, simultaneously.
- MDMSS satisfies the requirements of engineering practice and takes a step further in practical application.

Although the preliminary test results show that the proposed reliability assessment method, and maintenance decision-making model are potentially useful for solving medium scale problems, more case studies should be conducted, so that the effectiveness of the model and its limitations may be better grasped. In addition, with the arrival of on-board monitoring systems, as well as maintenance decision-making for multi-fleet has attracted more and more attentions, maintenance decision-making based on CBM for multi-fleet could be a direction of future research. What's more, modification and testing of the model could also be directions for future research. Finally, the non-structural reliability of aircraft fleet is very important for the fleet maintenance. A consideration about the non-structural reliability of aircraft should be discussed in the future, in order to improve functional and behavioral reliability of aircraft fleet.

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