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REMAINING USEFUL LIFE PREDICTION MODEL OF THE SPACE STATION

MODEL PREDYKCJI POZOSTAŁEGO CZASU PRACY STACJI KOSMICZNEJ

Space station is a very complex system, and its remaining useful life will be affected by the key equipment, cosmonauts' maintenance activities as well as space environments. It is important for the operation management of a space station to predict its remaining useful life (RUL). A valid RUL prediction model is the key foundation for this issue, which motivates the research presented in this paper. Firstly, different types of space station life are defined. Secondly, the function and performance requirements as well as the operation mission program of the space station are analysed, which are further used to confirm the model development precondition. A life prediction model is then proposed by synthetically taking account of the safety, reliability and maintainability restrictions. Finally, the data requirement for supporting the RUL prediction is determined. Based on this work, a comprehensive procedure for RUL prediction model development is constructed for the operation management engineers of the space station. If the data of the development and operation is adequate, RUL prediction of the space station can be well implemented, and can be further leveraged to support the space station operation management.

***Keywords**: Space station, remaining useful life prediction, key equipment, key activity, Monte Carlo simulation.*

Stacja kosmiczna stanowi wysoce złożony system, którego pozostały czas pracy (ang. remaining useful time, RUL) zależy od kluczowego sprzętu, czynności konserwacyjnych przeprowadzanych przez kosmonautów, a także warunków panujących w kosmosie. Zarządzanie operacyjne stacją kosmiczną wymaga przewidywania RUL. Podstawą tego zagadnienia jest stworzenie prawidłowego modelu predykcji RUL, co jest przedmiotem niniejszej pracy. W artykule, w pierwszej kolejności, zdefiniowano różne kategorie czasu pracy stacji kosmicznej na orbicie. Następnie, przeanalizowano wymagania dotyczące funkcji i eksploatacji stacji a także program jej misji operacyjnych. Wyniki tych analiz wykorzystano do weryfikacji wstępnych warunków koniecznych do budowy modelu. W dalszej kolejności, zaproponowano model predykcji czasu pracy stacji, który w sposób syntetyczny uwzględnia ograniczenia dotyczące bezpieczeństwa, niezawodności i możliwości konserwacji. Na koniec określono rodzaje danych wspierających predykcję RUL. Na podstawie opisanych etapów prac skonstruowano kompleksową procedurę opracowywania modeli predykcji RUL dla inżynierów zarządzania operacyjnego pracujących na stacjach kosmicznych. Jeśli dane dotyczące rozwoju i operacji są prawidłowe, zaprojektowany algorytm predykcji pozostałego czasu pracy stacji kosmicznej można z powodzeniem zaimplementować, a także rozszerzyć tworząc skuteczne narzędzie wsparcia personelu zarządzającego pracą stacji kosmicznej.

***Słowa kluczowe**: Stacja kosmiczna, przewidywanie pozostałego czasu pracy, kluczowy sprzęt, kluczowe działania, symulacja Monte Carlo.*

Acronyms and Abbreviations

RUL	Remaining useful life.
ANNs	Artificial neural networks.
HSMM	Hidden semi-Markov model.
POF	Physics-of-failure.
KF	Kalman filter.
PF	Particle filter.
SPM	Stochastic process model.
DRAMA	Debris risk assessment and mitigation analysis.
MOL	Mission orbital life.
SPL	System platform life.
SML	Specific mission life.
SMSs	Structure and mechanism subsystem.
POSs	Propulsion subsystem.
GNCSs	Guidance navigation and control subsystem.
MCSs	Measurement and communication subsystem.
TCSs	Thermal control subsystem.
POSs	Power subsystem.
ECLSSs	Environment control and life support subsystem.
DTMSs	Docking and transposition mechanism subsystem.
TPSs	Thermal protection subsystem.
ORU	Orbital replacement unit.
FMEA	Failure mode and effect analysis.
JSA	Job safety analysis.
CALCE	Center for Advanced Life Cycle Engineering.
PCoE	Prognostics Center of Excellence.
ISS	International Space Station.
MCS	Monte Carlo Simulation.

Notations

T_P	Propellant service time.
M_0	Amount of propellant in service.
M_c	Deorbit recapture propellant consumption.
M_1	Unusable residue.
M'	Calculation error.
$\overline{M_y}$	Average annual consumption of propellant.

T_B	Cycle life.
U_0	Discharge initial output voltage.
U_t	Discharge termination voltage at specified threshold.
d	Linear degradation rate.
T_L	Lower life limit.
T_U	Upper life limit.
T	Total test time.
r	Failure times.
á	Confidence level.
θ	Average life.
ç	Scale parameter the two-parameter Weibull distribution.
m	Shape parameter of two-parameter Weibull distribution.
T_{AMR}	Total time for the specific addition, maintenance and replacement activity.
t_i	i th activity operation time.
m_{AMR}	Total number of specific addition, maintenance and replacement activities.
RUL_S	Space station RUL.
RUL_{Ei}	RUL of the corresponding key equipment.
T_{AMRi}	Key addition, maintenance or replacement activity's time.

1. Introduction

The space station is the most complex spacecraft in the space, and it normally operates with long-life requests due to the high operation cost. The accuracy of remaining useful life (RUL) prediction is of great importance for the life assurance and extension of the space station. The operation decisions are deeply based on the RUL prediction.

The space station consists of thousands of key components, which constitute the main structure and functions of the space station. The space station's life mainly depends on these key components. On the other hand, the cosmonauts' maintenance activity will affect the RUL of the space station under different maintenance quality. In addition, the space environment's influence will be reflected by the key equipment operation state and the cosmonauts' maintenance activity.

After decades of research and application, the approaches of RUL prediction can be divided into two categories, including data-driven approaches and model-based approaches [29]. The classical data-driven approaches, including Bayesian inference [20], machine learning [27], artificial neural networks (ANNs) [36], and hidden semi-Markov model (HSMM) [15], are adopted to the electromechanical rotating equipment's RUL prediction. For the model-based approaches, such as physics-of-failure (POF) [11] [28], Kalman filter (KF) [4], particle filter (PF) [14], and stochastic process model (SPM) [9] are widely used for life prediction of electrical products. In the aerospace field, for the small satellite, the orbit lifetime analysis is examined using AGI's STK [1] and ESA's debris risk assessment and mitigation analysis (DRAMA) [5] lifetime simulation tool during the pre-launch phase [21]. By the certain relation via neural network and the learned network, which can be partly perceived as degradation pattern, the aircraft engine's RUL is predicted [37]. In other fields, the approaches, in the literature about RUL estimation for decision-making in the offshore oil and gas industry, are classified either as physics-based, data-driven based, or fusion-based which is a hybrid of the physics and data driven based methods [31], and the experiment-based approach is also added as the fourth classification [2]. However, most of these methods and their applications mainly focus on the equipment and product RUL prediction. Although Hamed [7] and Zhang [38] paid special attentions to the issue of system-level RUL prediction, this issue still faces many challenges. The space station RUL prediction is much more complex than the other system, because it is a synthesis problem related to the equipment operation, cosmonaut's maintenance activities and conformational changes [23] [24]. It is difficult to use these methods to predict the space station RUL before the prediction rules and preconditions are clear.

This paper aims at developing a model for RUL prediction of a space station by taking account of key equipment states and the cosmonaut orbital maintenance activities. A model building framework is shown in Fig. 1.

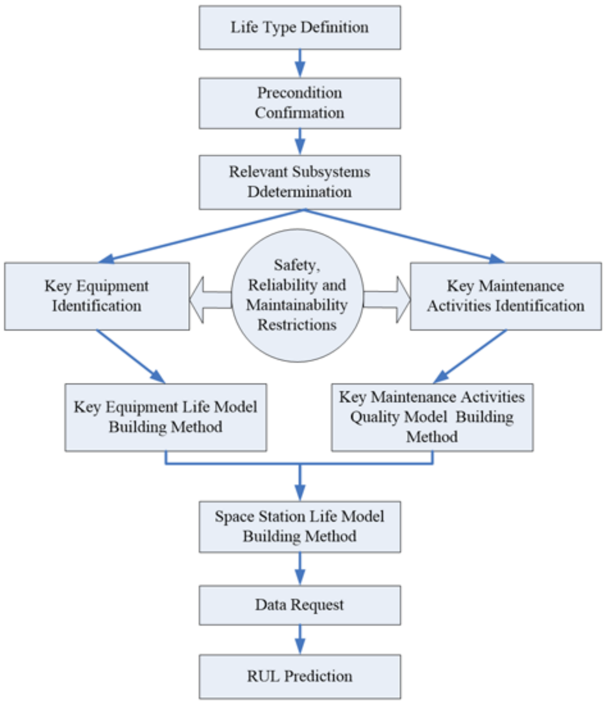

Fig. 1. Model building framework of space station RUL prediction

Firstly, different types of space station life will be studied. This aspect is mainly out of the consideration that different types of life definition will affect the research scope of this paper, and the precondition will be confirmed according to the life type, including the function and performance requirements and composition of the space station. When the factors that affecting different types of space station life have been analyzed, the relevant subsystems can be listed out for further model development. Through the safety, reliability and maintainability restriction and further adopting practical analysis methods, the key equipment and the key maintenance activities will be identified. After the feature analysis, the life prediction model will be developed based on the equipment types and maintenance time [18] [19]. After defining the RUL function and giving the calculation method, the RUL prediction model of space station will be constructed. Based on the relevant data, the space station RUL can be predicted.

The rest of the paper is organized as follows. First, the types of the space station life will be studied according to the engineering practice. Then, the main functions of the space station will be decomposed in accordance with relevant space station subsystems. According to the safety, reliability and maintainability restrictions, the key equipment and maintenance activities will be identified, and their RUL prediction model building methods will be given. After that, the space station RUL model can be built, and the data request will be presented., Then, the case study is given to validate the model. Finally, the work conclusion and the future work will be addressed.

2. Types of space station life definition

For the space station, there are three types of orbital lives, including the mission orbital life (MOL), the system platform life (SPL) and the specific mission life (SML) [10]. MOL means the lifetime spent on maintaining the mission orbit, which depends on the propellant and resource consumption, and it generally refers to the time interval between orbit to deorbit. SPL represents the lifetime when the space station has the ability of autonomous flight in mission orbit. SML indicates the lifetime when the space station can perform specific missions of the mission plan. SML is the time which is spent on a specific mission, for example, orbit adjustment or rendezvous and docking, by the space station.

Normally, MOL and SML mainly depend on the propellant residue, and are unrelated to the cosmonauts' maintenance activities and the key equipment operation states. Thus, the RUL prediction of the space station is primarily for SPL.

3. Model Building Precondition

The function and performance requirements are the criteria for space station RUL prediction. The operation mission program is one of the influence factors of the space station RUL prediction. Through the aforementioned analysis, the precondition of the life prediction model can be confirmed.

3.1. Function and Performance Requirements

The space station provides living and work environment for the cosmonauts and ensures the planned test in the orbit can be carried out. The space station must satisfy some functions and performances requirements, such as the structural bearing function, gas seal function, and orbit adjustment function etc. The main functions of the space station are shown in Fig. 2. The losses of the above-mentioned functions will cause serious safety consequences and lead to the end of the space station life.

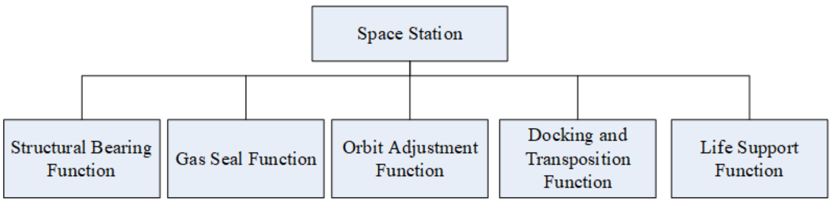

Fig. 2. Main Functions of Space Station.

3.2. Composition

The space station includes structure and mechanism subsystem (SMSs), propulsion subsystem (PRSs), guidance navigation and control subsystem (GNCSs), measurement and communication subsystem (MCSs), thermal control subsystem (TCSs), power subsystem (POSs), environment control and life support subsystem (ECLSSs), docking and transposition mechanism subsystem (DTMSs), and thermal protection subsystem (TPSs). Some of the above-mentioned subsystem are relevant to a specific function, and the relationship is described as shown in Fig. 3.

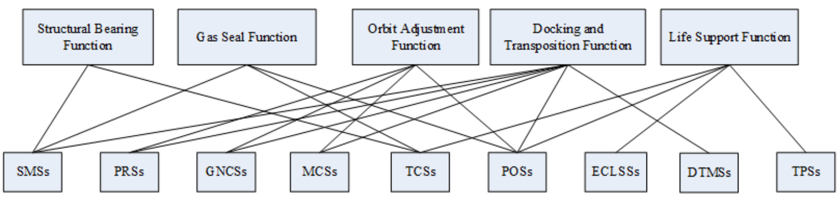

Fig. 3. Relationship Between Main Functions and Relevant Subsystems

3.3. Operation Mission Program

Generally speaking, the operation mission program will be confirmed before the flight mission, which includes the orbital replacement unit (ORU) transport plan, the propellant filling plan, and the crew plan. All these plans will affect the orbital life of the space station. The emergency flight missions are not included in the scope of this paper.

This paper defines the orbital life of the space station and analyzes the preconditions as following:

(1) One of the loss of the main functions indicates the end of the space station life;
(2) ORU, propellant, and the astronauts' maintenance abilities in the orbit are adequate;
(3) The life of the space station mainly depends on the cosmonauts' maintenance activities and the key equipment operation states;
(4) The influence of space environment on the life of space station is reflected by the astronauts and equipment health states.

4. Model Building Methods

4.1. Relationships Between Main Functions and Relevant Subsystems

In Fig. 3 major functions are related to the SMSs, TCSs, and POSs subsystem. Accordingly, these three subsystems are the key subsystems. But for the space station, providing the proper living and work environment is the foundation of its application, the ECLSSs is also the key subsystem of the space station. Through the determination of the key subsystems, the key equipment and the key maintenance activities should be identified according to the safety, reliability and maintainability restrictions, and provide the model objectives.

4.2. Key Equipment and Key Maintenance Activities Identification based on Safety, Reliability and Maintainability Restrictions

Both the key equipment operation states and the cosmonauts' maintenance activities must first satisfy the safety requirements. For the key equipment, they should be reliable and replaceable. Through the safety, reliability and maintainability restrictions, the key equipment and key maintenance activities can be identified. The identification process is shown in Fig. 4.

Failure Mode and Effect Analysis (FMEA) [25] is an effective method to identify the potential failures and key equipment related to system reliability. In the FMEA, the space station is treated as the initial indenture level. The composing subsystem and equipment are separately treated as the indenture level and the lowest indenture level. By calculating the risk priority number of each equipment, the importance of all the equipment is ordered to identify the key equipment. In total, 203 equipment of 9 subsystems have been analysed, and the 6 most critical equipment has been identified based on their risk priority number 90, 81, 80, 72, 70, and 64, over 60 respectively.

Job Safety Analysis (JSA) [16] [41] is an efficient, proactive measure for safety or risk assessment, which is usually utilized to identify potential hazard factors existing in operation and maintenance process and further to determine risk mitigation measures. We have obtained all the 34 maintenance activities and identified potential hazards of each activity. The risk of each hazard is accessed using the product of consequence severity and occurrence likelihood. Both the severity rates and the likelihood rates range from 1 to 5, and the risk rating of each hazard equals to their product which ranges from 1 to 25. By adding the risk rating of each hazard, the importance of all the maintenance activities is ordered by the sum of the risk rating, and we can identify the 6 most critical maintenance activities based on their sum number 73, 71, 67, 59, 53, 51 and 49, over 45 respectively.

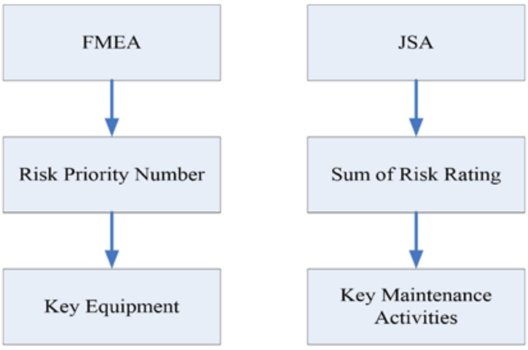

Fig. 4. Identification Process of Key Equipment and Key Maintenance Activities

Through the identification, the 6 most critical equipment and key maintenance activities are shown in Table 1.

Table 1. Key equipment and key activity of space station

NO.	Key Equipment	NO.	Key Activity
1	Main frame structure	1	Leakage Maintenance
2	Propellant	2	Propellant Addition
3	Lithium-ions Battery / Solar Cell Wing	3	Solar Cell Wing/Power Supply Replacement
4	Drive Mechanism/ Docking Mechanism	4	Drive Mechanism/ Docking Mechanism Replacement
5	Environmental Control and life support Equipment	5	Environmental control and life support Equipment Replacement
6	Sensors	6	Sensors Replacement

Through the identifications, the key equipment and key activities can be classified and used to build the model for the RUL prediction.

4.3. Life model building methods for key equipment

considering the life characteristics, the key equipment of the space station can be classified into four types, including the resource consuming, the performance degradation, the random fault and others. Each type has its life characteristic parameters, and the life model building methods are dependent on these parameters.

For the resource consuming equipment, the life characteristic parameters are variables that characterizes the residual quantity of the equipment. The life model is built based on the result of life characteristic parameters analysis and the equipment's own life characteristic. Take the propellant as an example, the life characteristic parameters can be the propellant service time, and the life model is described as [12]:

$$T_P = \frac{M_0 - (M_c + M_1 + M')}{\overline{M_y}} \tag{1}$$

where T_P is the propellant service time, M_0、M_c、M_1、M' represents the amount of propellant in service, deorbit recapture propellant consumption, unusable residue, and calculation error respectively, and $\overline{M_y}$ is average annual consumption of propellant.

For the performance degradation type equipment, the life characteristic parameters are the state variables which show the work performance of the equipment. The life model is built on the changing trends of life characteristic parameters and the equipment's own life characteristic. Recent studies of the battery RUL prediction are focus on the model-based methods [26] [8] [33] [39]. Take the lithium-ions battery as an example, Yu et al. [35] proposed a method for making early predictions of remaining discharge time considering information by decomposing the discharge model into three stages according to the changes of output voltage. This method is consistent with engineering practice. Like the above method, the lithium-ions battery life characteristic parameter can be the output voltage and output current, and the life model is shown as:

$$T_B = \frac{U_0 - U_t}{d} \tag{2}$$

where T_B is the cycle life, U_0 is the discharge initial output voltage, U_t is the discharge termination voltage at specified threshold, and d is the linear degradation rate. In fact, d is not linear. But in engineering, in the absence of enough test sample support, the application of the above equation has a certain practical feasibility. Center for Advanced Life Cycle Engineering (CALCE) of University of Maryland and Prognostics Center of Excellence (PCoE) of NASA's degradation law study results for lithium-ions battery is shown in Table 2.

Through Table 2, we can find that there are three stage degradation rates for the lithium-ions battery, which include early degradation rate, intermediate degradation rate and terminal degradation rate. Accordingly, we can approximately assume that the intermediate average degradation rate is 4 times of the early average degradation rate, and the terminal average degradation rate is 2-3 times of the early average degradation rate.

For the random fault type equipment, the life characteristic parameters change trends are not obvious, or have the short duration, which should be identified earlier and paid enough attentions. The random fault type equipment lives mostly obey the exponential distribution. Take the star sensor as an example, the life characteristic is the number of failure times, and the life model is shown as the equation (3) [13]:

Table 2. Lithium-ions battery degradation law study results

Sampleing Period	Average Degradation Rate in Different Charge-discharge Cycle				
	Early	Intermediate			Terminal
	1-30	31-60	61-90	91-120	121-150
1000-1500s	0.000067	0.00043	0.0003	0.00017	0.0001
1500-2000s	0.0002	-0.0001	0.00017	0.0003	0.00087

$$(T_L, T_U) = \left(\frac{2T}{\chi^2_{\alpha/2}(2r)}, \frac{2T}{\chi^2_{1-\alpha/2}(2r)} \right) \tag{3}$$

where T_L is the lower life limit, T_U is the upper life limit, T is total test time, r is the failures, and α is the confidence level.

Table 3. Propellant tank test data on the ground

Blowdown Life			Temperature Alternation Life		
NO.	Blowdown Times	Result	NO.	Alternation Times	Result
1	6	Success	1	12000	Success
2	5	Success	2	13000	Success
3	5	Success	3	10000	Success
4	3	Success	4	12340	Success
5	4	Success	5	14300	Success
6	4	Success	6	13200	Success
7	5	Success	7	12000	Success
8	7	Success	8	11000	Success
9	4	Success	9	13000	Success
10	4	Success	10	10000	Success
11	4	Success	11	10000	Success
12	6	Success	12	15200	Success
13	5	Success	13	12780	Success
14	4	Success	14	14200	Success
15	4	Success	15	13000	Success
16	6	Success	16	12450	Success
17	4	Success	17	12000	Success
18	5	Success	18	13500	Success
19	5	Success	19	12000	Success
20	8	Success	20	10000	Success
21	5	Success	21	10000	Success
22	5	Success	22	12000	Success
23	4	Success	23	10000	Success

For the last type equipment, for example of the propellant tank and membrane in the creep pump, the life characteristic parameters are the number of actions, and it cannot be accurately predicted in space and is generally tested on the ground. Table 3 shows the propellant tank test data from ground tests. Zieja et al. [42] provided a probabilistic method for evaluating the durability of components and device assemblies which operate under the impact of destructive processes. For the propellant tank and membrane in the creep pump, they work under the impact of destructive processes, and the presented two methods for determining the durability can be used for the ground test.

Because of the larger design margin, the propellant tank and membrane rarely fail in the ground tests, their RUL can be predicted by the equation (4) [17]

$$\theta = \eta\Gamma\left(1+\frac{1}{m}\right) \tag{4}$$

where θ is the average life, η and m are the scale parameter and the shape parameter of two-parameter Wei-bull distribution.

4.4. Quality Model Building Method for Key Maintenance Activities

The masses of up-link supplies, which are expected to be shipped to the International Space Station (ISS) between assembly period (2006-2010) and after the assembly (2011-2015), are illustrated in Fig. 5. According to this, the maintenance supplies account for about 1/4 of up-link supplies.

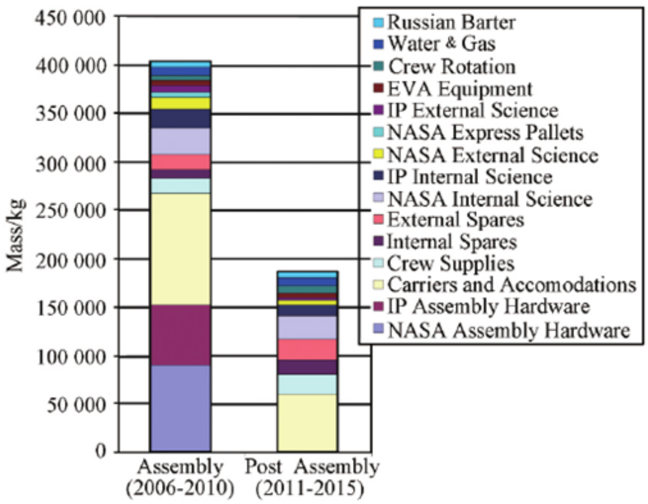

Fig. 5. Spare Parts of ISS

The maintenance activities quality will affect the maintenance supplies as well as the replacements of failed equipment. The perfect maintenance will extend the RUL by replacing the failed equipment with a new one. However, disturbed by human factors, the maintenance activities sometimes fail to accomplish the replacement tasks at a given time, and this issue has already become another important influence factor, which limits the space station life as well as the equipment operation states. Thus, the quality of the maintenance activities is as same important as the equipment life.

At present, most maintenance criteria focus on maintenance level and maintenance strategy [32]. For the space station, the maintenance time is the most important aspect. Most maintenance activity failures are caused by the lack of maintenance time in emergency situations. As a result, the maintenance time is a synthetic parameter, which can represent the cosmonauts' maintenance skill and capacity. On the other hand, maintenance time information can be easily collected both on the ground and on the orbit. Table 4 shows the orbital maintenance time spent on the ISS [30]. In Table 4, ACPM represents the America cabin preventive maintenance time, ACCM represents the America cabin correctional maintenance time, RCPM represents the Russian cabin preventive maintenance time, and PCCM represents the Russian cabin correctional maintenance time, respectively. Through Table 4, we can figure out that the maintenance capacity is limited compared with the ISS life request. Through Fig. 5 and Table 4, we can find that the orbital maintenance time is important to the ISS operation because of many masses maintenance supplies. Thus, the quality model of maintenance activities can be developed based on the maintenance time. Recently, the maintenance time studies are focusing on the maintenance time modeling and estimation [22] [40] [34].

Babishin et al. [3] proposed a complex optimization method for the non-periodic inspection and maintenance of the multicomponent system, such as the space station, and gave the maintenance decision determined methods for the k-out-of-n, hard-type and soft-type components. Because of the restrict of the safety request, the maintenance activity safety is a factor that must be considered. Gill [6] presented an original method of optimization of the technical object maintenance system taking account of risk analysis results. Based on the original form, the original risk valuation pattern, and four-stage calculation algorithm, the proper maintenance-related decisions will be made. But for the space station, most maintenance activities are the serial operation modes because of the equipment's high-level reliability, so the quality model of each maintenance activity can be shown as the equation (5):

$$T = t_1 + t_2 + \cdots + t_m = \sum_{i=1}^{m} t_i \tag{5}$$

where T is the total time for the specific addition, maintenance and replacement activity, t_i is the i^{th} activity operation time, and m is the total number of specific additions, maintenance and replacement activities.

4.5. Life Model Building Method for Space Station

After proposing the life model of the key equipment and the key maintenance activities, the space station life model is shown in Fig. 6. Because of the complexity, RUL prediction for the space station cannot be implemented through an analytic method, and the Monte Carlo Simulation (MCS) is a useful method for the space station RUL prediction. First, the initial parameters, i.e., the simulation time M, should be set. Then, the key equipment and key maintenance activities' parameters should be identified. After that, through MCS the simulation results of key equipment life and the key maintenance activities time can be obtained. After defining the space station RUL and checking the simulation times, the space station RUL can be simulated.

In Table 1, the key equipment and key maintenance activities are established, and the space station RUL is determined by them. Through the analysis of the space station function and mission pro-

Table 4. Orbital maintenance time spent on International Space Station

Maintenance Order	Crew Member	ACPM/h	ACCM/h	RCPM/h	RCCM/h	Total/h
1	0	2	8	1	40	51
2	3	8	3	19	14	44
3	3	24	148	138	81	391
4	3	39	19	130	13	201
5	3	63	46	206	123	438
6	3	60	102	196	45	403
7	3	55	103	211	93	462
8	2	80	28	244	53	405
9	2	64	104	184	97	449
10	2	147	101	186	58	492
11	2	73	96	186	97	452
12	2	42	46	117	70	275
Total	28	657	804	1818	784	4063

Table 5. Data request of space station RUL prediction

Type of Equipment or Activity	Life Characteristic Parameters	Orbital Observation Parameters	Ground Test Parameters
Main frame structure	Fatigue Strength	Crack Growth Rate	Vibration Parameters
Propellant	Residual quantity	Residual quantity	Residual quantity
Lithium-ions Battery/Solar Cell Wing	Output Voltage, Output Current	Output Voltage, Output Current	Output Voltage, Output Current
Propellant Tanks	Number of Actions	Orbital Pressure Differences	Successful Actions Times
Drive Mechanism/Docking Mechanism	Output Voltage, Output Current Journal Temperature	Output Voltage, Output Current	Journal Temperature
Environmental Control and life support Equipment	Work Time	Normal Output Time	Normal Output Time
Sensors	Normal Output Time	Output Voltage, Output Current	Output Voltage, Output Current
Addition Activity	Addition Time	Addition Time	Addition Time
Replacement Activity	Replacement Time	Replacement Time	Reparation Time and Replacement Time
Maintenance Activity	Maintenance Time	Maintenance Time	Check Time and Maintenance Time

Table 6. Key equipment RUL prediction parameters and key activity time

Key Equipment	Prediction Parameters	Key Activity	Activity Time/h
Main frame structure	Fatigue Strength	Leakage Maintenance	2.38
Propellant	Residual quantity	Propellant Addition	4.87
Lithium-ions Battery/Solar Cell Wing	Output Voltage, Output Current	Solar Cell Wing/Power Supply Replacement	4.98
Drive Mechanism/Docking Mechanism	Output Voltage, Output Current Journal Temperature	Drive Mechanism/Docking Mechanism Replacement	3.23
Environmental Control and life support Equipment	Work Time	Environmental Control and life support Equipment Replacement	2.14
Sensors	Normal Output Time	Sensors Replacement	0.54

Table 7. Space station RUL simulation results

Simulation Times	Failed Key Equipment	RUL Mean Value/a
100	Propellant	9.67
200	Main frame structure	8.34
300	Solar Cell Wing	9.65
400	Solar Cell Wing	10.12
500	Sensors	11.43
600	Main frame structure	8.93
700	Docking Mechanism	11.54
800	Propellant	10.16
900	Sensors	11.23
1000	Environmental Control and life support Equipment	10.29
Total RUL Mean Value		10.136

gram, failure of any key equipment will lead to the end of the life of the space station, and maintenance and replacement activities are the only way to prolong the life of key equipment. So, the space station's RUL depends on each key equipment and its maintenance or replacement activity. If the maintenance or replacement time is shorter than its key equipment's RUL, the space station main function can be brought into full play. Otherwise, the space station will face the risk of loss main function, which means the end of the space station life. So, the space station's RUL prediction can be divided into two steps. The first step is to judge whether the maintenance or replacement time is shorter than the key equipment's RUL or not, and the second step is to confirm the shortest RUL of the key equipment. Based on the above analysis, the space station's RUL can be described by the equation (6):

$$RUL_S = \begin{cases} \min\{RUL_{Ei}\} & RUL_{Ei} \geq T_{AMRi} \\ RUL_{Ei} & RUL_{Ei} < T_{AMRi} \end{cases} \tag{6}$$

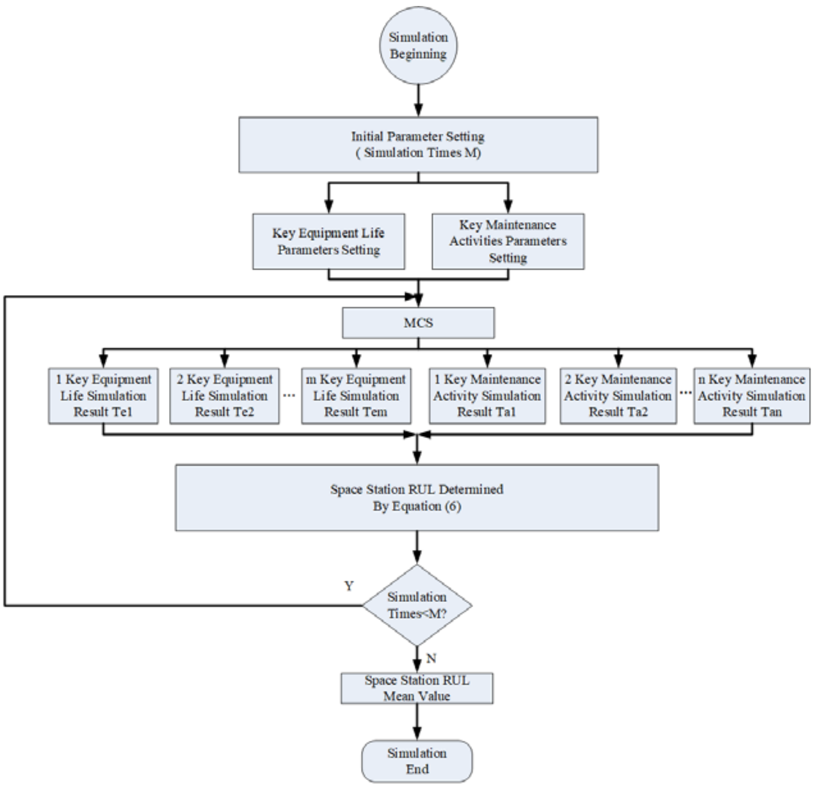

Fig. 6. RUL Prediction Model of Space Station

where RUL_S is the space station RUL, RUL_{Ei} (i from 1 to 6) is the RUL of the corresponding key equipment, and T_{AMRi} (i from 1 to 6) is the key addition, maintenance or replacement activity's time.

At this point, the prediction model of the space station RUL is built, and its application and rationality will be demonstrated through the subsequent case study.

5. Case study

For the key equipment, the orbital observation data and ground test data mostly have the same types. For the key addition, maintenance and replacement activities, each breakdown of the activity time needs to be counted, and they should be verified by ground tests or virtual maintenance when orbital data collected is difficult. Table 5 shows the key equipment and key addition, maintenance and replacement activities data request of the space station RUL prediction.

In this paper, according to the engineering practice, the key equipment RUL prediction parameters, and the key addition, maintenance and replacement time obtained by the ground or virtual test are shown in Table 6. By setting the simulation time as M=1000 and implementing the simulation, the space station RUL results are obtained and shown in Table 7.

According to the Table 6, the space station RUL simulation results are shown in Table 7. Through the Table 7, the space station RUL can be predicted at 10.136 years at average.

6. Conclusion

This paper defines different types of lifetime for the space station, and further establishes a relationship between the main functions, the key equipment as well as the addition, maintenance and replacement activities. Through the identification of the model building methods for the key equipment and for the addition, maintenance and replacement activities, a RUL prediction model is proposed for the space station. Finally, the data request for implementing the RUL prediction is determined.

For the key equipment, this paper gives their prediction methods. For the key addition, maintenance and replacement activities, this paper introduces the activity time calculation methods. For the space station in the system level, this paper determines the RUL prediction algorithm based on the relationship between the RUL of key equipment as well as the addition, maintenance and replacement activity times. According to engineering practice data, this paper adopts the MCS method and predicts the space station RUL as 10.136 years at average.

In the future, the relationship between the space station RUL and the key functions, the key equipment and the key activities will be further quantified. In addition, the key equipment RUL and the key activities time prediction algorithms and their corresponding models will be further determined according to the ground test data or the orbital operation data.

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