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The Optimization of Civil Aircraft Product Option Selection Considering the Economy Response with an Improved Non-Dominated Sorting Genetic Algorithm

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Abstract: To serve customized option selection for civil aircraft, a mathematical product option selection optimization model combined with an Improved Non-dominated Sorting Genetic Algorithm for decreasing aircraft fleet maintenance cost was investigated. For airlines, considering the economy and reliability in customized option selection is the most intuitive way to improve aircraft performance to generate the optimal formation configuration. Product option selection usually takes certain indicators as constraints (reliability and economy) to meet and maximize performance through equipment selection (the selected parameters include mean time between failures, price, etc.). To describe the customization needs of airlines by a mathematical model and find the optimal decision through an algorithm, a multi-objective, mathematical product option selection optimization model response with reliability parameters as a decision variable, maintainability as a link, and aircraft fleet maintenance and availability as an objective function is established to serve aircraft option selection in this paper. Next, the multi-objective genetic algorithm is used to solve the model, and the convergence, distribution and fitting accuracy of the objective functions are analyzed. Eventually, the landing gear system is used to verify the effectiveness of the model and method. After optimization, the aircraft fleet maintenance cost is reduced by 20.71%, and the availability is increased by 2.576%. Through the mathematical optimization model, the product configuration is provided for the development of the customization option selection project.

Keywords: reliability; product option selection; aircraft fleet maintenance cost; NSGA-II

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1. Introduction

The option selection of aircraft includes the introduction of models (aerodynamic shape, fuel consumption, weight, etc.) and the selection of airborne products. Product option selection usually takes certain indicators as constraints (reliability and economy) to meet and maximize performance through equipment selection (the selected parameters include mean time between failures, price, etc.) [1,2]. The output of the option selection item is a list containing aircraft configuration information. After option selection, the expected performance of an aircraft is basically determined. The option configuration of products or parts in a typical system of a civil aircraft will directly affect the maintenance cost and the performance of a civil aircraft. These two factors are exactly the key to determining whether the aircraft can occupy the market share. The market share of an aircraft configuration should be judged from the design phase and be changed according to the environment of operation. This is the key way to build a bridge between the initial and continuous airworthiness stages and realize the feedback of customized design needs through data and models. Therefore, it is of certain engineering significance to establish a mathematical product option selection optimization model, which would serve for customer option selection based on a reliability-centered approach, aiming at optimizing the cost and aircraft performance in the light of historical data and customer needs.

There are many ways to improve the reliability levels of products. From the perspective of research and manufacturers, they are more willing to focus on the process of improving. For example, an innovative hybrid decision algorithm solved by the combination of finite element simulation and Tabu search [3], sequential quadratic programming [4], evolutionary algorithm [5], genetic algorithm [6] or exact Markov [7] solves a reliability optimization problem under cost and configuration constraints. Part of the research focuses on building an accurate and dynamic reliability analysis model; paper [8] improves the support vector machine with nonlinear conjugate mapping, and paper [9] improves the line-sampling-method-based slime mold algorithm for simulating the performance response and improving the accuracy and computational efficiency of complex structure reliability modeling. The relationship between uncertain parameters and structural stress is established through the polynomial response surface, the degradation is characterized by gamma stochastic process, and the time-varying reliability of mechanical components is calculated in paper [10]. In paper [11], the reliability analysis is performed by the using of enhanced Form/Sorm and Monte Carlo simulation methods and is used in an application case for managing irregular areas in pipeline lifetimes. Paper [12] introduces the references and progress in multi-objective, multi-disciplinary, high-dimensional and time-varying complex reliability systems and focuses on the advantages of proxy models in analyzing efficiency and accuracy. Another means is to provide good comprehensive support and perfect air material configuration capability for equipment or accessories through the operator's analysis of maintenance engineering during airworthiness. The paper constructs a joint optimization model for LORA and civil aircraft inventory system, introducing the system design [13], cost [14], maintenance strategy [15], support hierarchy [16] or repair level [17,18] into the multi-echelon inventory allocation model and putting forward a method of multistage inventory allocation for civil aircraft spare parts considering the model optimization and configuration. However, for airlines, they pay more attention to the results brought by the level of product reliability. The most direct way is to achieve customized configuration through option selection. Option selection is used to define the functional requirements of a confirmed and deliverable aircraft or the services that customers can choose. If the product option selection can be described by a mathematical model, and the expected cost and performance of the configuration under the existing maintenance capacity can be evaluated so that the performance degradation and cost can always be kept within a controllable range, the selection can be truly carried out under the guidance of customized demand. Based on this, a mathematical product option selection optimization model is proposed to provide support for customization option selection, and there is some research on that. Using different multi-objective approaches to optimize the configuration scheme is very common in other areas, such as building envelope retrofitting considering economic and energy sustainability [19], combined with NSGAII [20] or an audited ε-constraint approach [21] on parallel machine scheduling problems and spillway structure design combining the whale optimization algorithm and an artificial neural network [22]. In aviation, multi-objective particle swarm optimization is used to establish an optimal design model of an electrostatic actuator with multiple objectives, stiffness, weight and power consumption [23]. The NSGA-III algorithm proposed in this paper [24] introduces arithmetic crossover and an adaptive mutation operator to change the crossover and mutation operators, which improves the optimization performance of the algorithm. The hybrid conjugate mean value (HCMV) method is proposed using sufficient conditions for the enhancement of the efficiency and robustness of RBDO in paper [25]. Moreover, paper [12] carried out framed structures optimization in the two life cycles of production and construction under the boundary conditions of material, transportation and installation. For an aircraft aero engine health parameter estimation problem, the papers [26,27] optimized sensor selection to improve the controllability and observability of the dynamic system. Some research has taken aircraft range as a fitness function, with a genetic algorithm or multidisciplinary criteria being used to optimize the aircraft wing, tail and fuselage geometry, thrust requirements, and operation parameters so as to realize aircraft type selection design [28–30]. The multistage reliability-based design optimization approach accounts for such follow-on corrective decisions based on the partial realizations of random parameters at selected stages along the engineering design process, thereby further enhancing the practicality of reliability-based design optimization [31]. The results show that the integrated design process can achieve a more comprehensive performance than can sequential design. However, there are still some shortcomings in these mathematical models. No model can completely describe the customized selection needs, and most of the parameters of the model describe some structural parameters. In a real operation environment, the replacement of the product is key to maintaining a task. In addition, the impact of economic cost is rarely considered in the model, but economic cost is the most concerning factor for airlines. Finally, most of the models focus on some structures or products and do not solve the model for the whole system, so it is impossible to improve the overall situation.

The purpose of this paper was to establish a mathematical optimization model based on availability and fleet maintenance cost as the objective function and reliability index as the constraint condition to serve the option selection of aircraft products. For operators, it is the fastest way to improve the overall quality of aircraft. Combined with the operation data and maintenance records of civil aircraft, on the one hand, it is used to establish the objective function related to cost; on the other hand, it is used as a basis to compare whether mathematical optimization can reduce cost and improve performance. Combined with maintenance strategy and operation data, the establishment of a mathematical system option selection optimization model considering economy is an important way to continuously improve aircraft performance by running feedback design requirements and enriches the construction of the aeronautical application problem model. Taking the landing gear system as an application case, the validity of the model and method is verified. By finding the balance between the inherent reliability and operational reliability of the product itself, the system can improve the availability of the system and the maintenance cost of the fleet.

The remaining of this paper is organized as below. Section 2 introduces the construction process of the mathematical product option selection optimization model with aircraft fleet maintenance cost and availability as the objective functions, as well as the basic idea of solving the model combined with the Improved Non-dominated Sorting Genetic Algorithm. In Section 3, the effectiveness of the model is illustrated by decreasing the aircraft fleet maintenance cost and increasing the availability. The convergence rule and fitting accuracy of the objective function are also analyzed. The double-objective model with the best convergence law is selected to carry out the option selection and configuration of the whole landing gear system in Section 4, and some main conclusions are summarized in Section 5.

2. Basic Theory

2.1. Aircraft Fleet Maintenance Cost Analysis Related to Product Option Selection

The economy of civil aircraft occupies a decisive role to measure whether aviation corporations or manufacturers have market competitiveness. Only when a model of aircraft masters the ability of continuing airworthiness and, meanwhile, economic benefits can it take the market share sustainably, especially in the field of civil aviation. The cost of a civil aircraft to perform a flight task generally includes fuel, staff salaries, ownership cost, government taxes and fees, maintenance costs and so on. The economy considered in this article mainly refers to the cost related to the performance of products or aircraft, that is, aircraft fleet maintenance cost (AFMC). It is related to the performance of the product itself, unlike taxes and wages, which have nothing to do with selection optimization. The AFMC should be considered during the conceptual design phase by optimizing and evaluating related parameters. The option selection of aircraft is oriented at the parts or product level, which can be replaceable or maintainable on the line, such as electronic equipment, fitting, and substructure component. This class is generally called Line Replaceable Unit (LRU) and Line Maintainable Part (LMP). They are the smallest units to perform a maintenance task. Historical operation data, demand analysis and framework design provide a base for it; this, in turn will allow for a decomposing reliability index as the constraints and select vital design parameters, mean time between failures (MTBF), during the conceptual design phase. Large complex systems, containing thousands of products (whether installed or backed up) experiencing phases of design, manufacturing, sales, using, maintenance, and scrapping, face great challenges in operated strategy and cost. A certain civil aircraft recommended spare parts list (RSPL) disposes up to 757 kinds of Line Replaceable Units and 789 types of Line Maintainable Parts.

While the outputs of option selection can assess products' reliability levels, they will also directly change the maintainability. The AFMC is directly related to the performance of products, and it can be considered an objective function of optimization. In this paper, matching the fault causes with different maintenance tasks corresponding to different maintenance costs thus establishes the equations relating reliability for a particular system and aircraft fleet maintenance cost by maintainability as a link. Generally speaking, maintenance tasks are mainly divided into five categories: lubrication/service, operation/visual inspection, inspection/function check, and recovery and scrapping. The first four categories can be collectively called 'repair'. This kind of repair task does not require a material cost, but only needs the labor cost. The total cost of carrying out these five maintenance tasks is the AFMC. These can also distinguish between being planned and unplanned by the frequency of occurrence besides categories. The type and frequency of tasks is particularly true for AFMC. Easily speaking, the more reliable the product is, the more complex its manufacturing process is and the more manpower is needed to maintain it; planned maintenance tasks based on product failure characteristics will also increase, resulting in an increase in planned maintenance costs (PMC). However, if we choose products that are relatively unreliable, it may cause sudden or even frequent failures. The resulting costs are unplanned maintenance cost (UPMC). The PMC is directly proportional to the MTBF, and the UPMC is inversely proportional to the MTBF. The mathematical model uses the ratio of the MTBF before and after optimization to quantify the impact on the AFMC in this paper. Then the formula of the AFMC can be described as:

$$\mathrm{AFMC} = \sum_{\mathrm{i}=1}^{\mathrm{n}} \left(\frac{\mathrm{MTBF_i}}{\mathrm{MTBF_i}^*} \times \mathrm{PMC_i} + \frac{\mathrm{MTBF_i}^*}{\mathrm{MTBF_i}} \times \mathrm{UPMC_i} \right) \tag{1}$$

Here, the MTBF with '*' indicated represents the stage before optimization, and the other is the one after optimization.

The labor cost is necessarily paid during maintenance. Beyond that, the removal tasks also need to pay for additional material fees for updating the new product. Specially, the planned removal tasks can be a routine work based on the initial configuration of the aircraft by default, and the labor cost is unrequired. The unit of cost is unified as per flight hour. So, PMC and UPMC are each divided into two categories: planned repair cost ($\mathrm{PC_{rep}}$), planned removal cost ($\mathrm{PC_{rem}}$), unplanned repair cost ($\mathrm{UPC_{rep}}$) and unplanned removal cost ($\mathrm{UPC_{rem}}$).

$$\begin{gathered} \mathrm{PC_{rep}} = \tfrac{\mathrm{h} \times \mathrm{R_{ate}}}{\mathrm{MTBM}}(\mathrm{FH}) \qquad \mathrm{PC_{rem}} = \tfrac{\mathrm{P_{rice}} \times \mathrm{QPA}}{\mathrm{MTBF^*}}(\mathrm{FH}) \\ \mathrm{UPC_{rep}} = \mathrm{NUM} \times \mathrm{h} \times \mathrm{R_{ate}}(\mathrm{FH}) \qquad \mathrm{UPC_{rem}} = \mathrm{NUM} \times (\mathrm{P_{rice}} + \mathrm{h} \times \mathrm{R_{ate}})(\mathrm{FH}) \end{gathered} \tag{2}$$

Here, MTBM—Mean Time between Maintenance for planned maintenance, h—mean working hour for maintenance, $\mathrm{P_{rice}}$—unit price of products, NUM—unit frequency of planned or unplanned maintenance, $\mathrm{R_{ate}}$—labor rate, and QPA—product quantity per aircraft.

2.2. Product Availability Analysis of Civil Aircraft

Reliability, maintainability, economy and availability are the four common qualities of civil aircraft. The AFMC, when the formula connects reliability, maintainability and economy, is established in Section 2.1 and has become the one objectives of optimization.

Furthermore, it is often necessary to set up multiple objectives with interactions for optimizing. The most ideal state for a civil aircraft is to use as little maintenance cost as possible to obtain the best product performance. The paper takes availability into account, connected with reliability and maintainability, which is necessary in order to identify the performance or characterization of products.

Product availability refers to the probability that the product can work normally at any time when performing the task. According to its physical meaning, if a period of MTBF is taken as a cycle, the availability can be characterized as the ratio of normal working time to MTBF in this cycle. In practical terms, when a product fails, a certain maintenance task will be implemented to restore it to the original. The period of time is mean time to repair (MTTR) or mean shop processing time (MSPT). It should be noted that MSPT usually takes calendar day as a unit, which can be converted into flight hours (FH), consistent with MTBF. Moreover, the planned maintenance tasks, intervals and working hours will be delivered along with the design phase to ensure the operation safety of the aircraft, to ensure that the performance of the products is within a controllable range. Therefore, a certain proportion of time is used to perform the planned maintenance tasks in a cycle. Remove these parts, and the rest is the normal working time of the product in a cycle. The relationship between MTBF, MTTR or MSPT and planned maintenance time is shown in Figure 1.

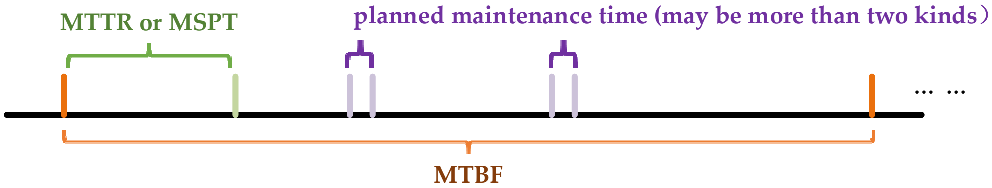


Figure 1. Physical meaning diagram of availability. MTIR—mean time to repair, MSPT—mean shop processing time, MTBF—mean time between failures.

Therefore, the formula of product availability is:

$$A = \frac{\mathrm{MTBF} - \mathrm{MTTR} - \sum \frac{\mathrm{MTBF}}{\mathrm{MTBM}} \times h}{\mathrm{MTBF}} \text{ or } A = \frac{\mathrm{MTBF} - \mathrm{MSPT} \times h_p - \sum \frac{\mathrm{MTBF}}{\mathrm{MTBM}} \times h}{\mathrm{MTBF}} \quad (3)$$

Here, h_p—the average daily service time of the product to facilitate the conversion of units.

2.3. A Mathematical Product Option Selection Optimization Model for Civil Aircraft

The model formulation comprehensively takes reliability, maintainability, availability, economy and other operational constraints into consideration, making the optimized option selection decision-making scheme under the multi-objective cycle iteration more in line with the economic needs of operators. Taking reliability parameters as input variables and maintainability as a link, the relationship connected with the AFMC or availability is established. The general form of an option selection mathematical model for multi-objective optimization is:

$$\begin{array}{ll} \min & f_i\ (x_1, x_2, x_3, \ldots x_n) \\ \text{s.t.} & x_n \geq x_n{}'(i = 1, 2, \ldots n) \end{array} \quad (4)$$

When operated in daily life, the maintenance staff or airlines use the typical systems decided by ATA in the Reliability Monthly Report, unless a certain product breaks down frequently and will be tracked for a period with special attention. This classification is followed in the thesis to maximize the overall availability and minimize the related AFMC on the whole system level. The objective functions are expressed as the form of summing the objective function of a single product. In addition, it is also necessary to uniformly minimize the model, which takes the availability function reciprocally. Finally, a mathematical optimization model for products option selection can be expressed as:

$$\begin{aligned} \min \quad & f_1\ (x_1, x_2, x_3, \ldots, x_n) = 1/(\sum_{i=1}^{n} \frac{x_i - MSPT \times h_p - \sum \frac{x_i}{MTBM} \times h}{x_i}) \\ \min \quad & f_2\ (x_1, x_2, x_3, \ldots, x_n) = \sum_{i=1}^{n} (\frac{x_i}{x_i{}^*} \times PMC_i + \frac{x_i{}^*}{x_i} \times UPMC_i) \\ \text{s.t.} \quad & x_i \geq x_i{}' \quad (i = 1, 2, 3, \ldots, n) \end{aligned} \tag{5}$$

The above model uses a unified AFMC calculation without paying attention to the nature of planned and unplanned costs. The PMC is directly proportional to MTBF, and the UPMC is inversely proportional to MTBF. The astringency for objective functions is not consistent with the PMC or UPMC. In order to quantify the impact or make decisions for different costs, AFMC can also be divided into two objective functions.

$$\begin{aligned} \min \quad & f_1\ (x_1, x_2, x_3, \ldots, x_n) = 1/(\sum_{i=1}^{n} \frac{x_i - MSPT \times h_p - \sum \frac{x_i}{MTBM} \times h}{x_i}) \\ \min \quad & f_2\ (x_1, x_2, x_3, \ldots, x_n) = \sum_{i=1}^{n} (\frac{x_i}{x_i{}^*} \times PMC_i) \\ \min \quad & f_3\ (x_1, x_2, x_3, \ldots, x_n) = \sum_{i=1}^{n} (\frac{x_i{}^*}{x_i} \times UPMC_i) \\ \text{s.t.} \quad & x_i \geq x_i{}' \quad (i = 1, 2, 3, \ldots, n) \end{aligned} \tag{6}$$

The performance of the two models is compared by solving them, respectively. Thus, we can analyze whether the algorithm can maintain uniform convergence for different linear relationships. External maintenance can also ensure product performance, such as the increase or decrease in maintenance tasks and MTBM. However, they do not directly improve the performance of the product directly through the selection and optimization. By directly optimizing the product itself in the design or operation stage, we can find a balance between planned and unplanned costs, so that cost control can be controlled within a controllable range. This is the focus of this study and the hypothesis of building the model. The existing planned maintenance task (which also represents the existing maintenance capability) is used as a known input to build the model. For example, when establishing the objective function of availability, the MTBM of planned maintenance task is used. When establishing the AFMC objective function, the MTBM and 'h' of the planned maintenance task are used.

2.4. Multi Objective Decision Making on Product Option Selection Based on NSGA-II

Different kinds of decision-making requirements are needed to meet in multi-objective optimization problems, and the objective functions converging in different directions should be balanced through the selection mechanism of an optimization scheme. Parts of multi-objective optimization algorithms use weight indexes to decompose the losses of each objective function, and its operation speed and convergence accuracy are limited [32–34]. In fact, its essence is still a single objective optimization problem. If the dimension of the two objective functions cannot be unified, one scheme will even swallow up another one; however, the Improved Non-dominated Sorting Genetic Algorithm attaches importance to the convergence of each objective function. It can search the optimal scheme globally through the basic operation of the genetic algorithm and the advantages of biological evolution law, with a strong optimization ability and high operation accuracy. The convergence of the objective function is expressed in multi-dimensions, and the elite individuals are searched in the global space. At the same time, the introduction of an elite retention mechanism can also speed up the convergence speed.

The method provides an objective means of assessing the product option selection for aircraft systems in the stages of aircraft design or in motion, leading to the minimization of subsequent maintenance actions and thus reducing the operating cost. The steps of multi-objective cyclic optimization (Figure 2) based on the algorithm to generate a decision are as follows:

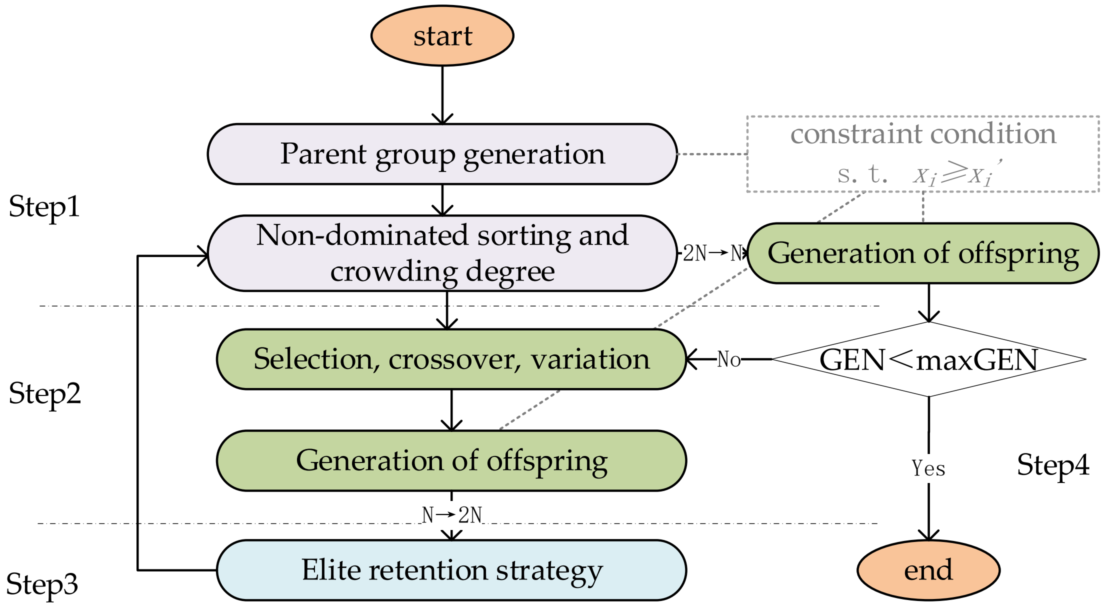


Figure 2. Framework of NSGAII. (NSGAII: non-dominated sorted genetic algorithm-II, GEN: genetic.)

STEP 1: The initial population with a scale of 'n' is generated randomly, and the population is classified by non-dominated sorting. The non-dominated meaning is that any decision variable X_a corresponding to the objective $f_i(x)$ in the population satisfies Equation (7), and the decision variable is called a non-dominated solution. This step finds all non-dominated solution sets f_i from the solution set f and marks the non-dominated sorting in number one. Then, it finds all non-dominated solutions in f-f_i, and its non-dominated sorting number is two. This repeats until f-F_I is an empty set, and the non-dominated sorting is completed.

$$\begin{aligned} &\forall i = 1, 2, \ldots n \quad f_i\ (X_a) \leq f_i(X_b) \\ &\exists i = 1, 2, \ldots n \quad f_i\ (X_a) < f_i(X_b) \end{aligned} \tag{7}$$

STEP 2: The basic operations, such as selection, crossover and mutation, are used to generate a new population. The purpose of selection is to select crossover individuals. The choice is based on the crowding degree. The calculation of the crowding degree is expressed in Equation (8). The higher the crowding degree, the higher the density in the space around the point, the more obvious is the advantage. Cross operations simulate binary crossover, crossover points are randomly selected from two parents, and the offspring are gradually convergent with evolution. The offspring produced after crossing enter variation, and the offspring produced by the mutation are compared with the individuals with higher crowding degrees, preferentially entering the new population.

$$n_d = n_d + (f_m(i+1) - f_m(i-1)) / \left(f_m^{max} - f_m^{min}\right) \tag{8}$$

STEP 3: In order to keep the excellent individuals in the cycle or iteration as much as possible, the algorithm adopts the elite retention strategy to expand the population size for basic operations to '2N'. Through the non-dominated sorting and crowding degree of individuals, the individual's number of 'N' are selected to enter the sub-population. This can reduce the amount of calculation and accelerate the convergence speed of the algorithm.

STEP 4: Repeat steps two and three until the end condition of the algorithm is met, that is, the number of iterations exceeds the initial setting. The best population and the last generation are output.

3. Case Study

3.1. Necessity and Data Preparation for Optimization

The landing gear can realize the take-off and landing function of aircraft. It is a typical system to ensure the flight safety of aircraft. The landing gear system of a civil aircraft contains 61 kinds of functional products that are confirmed by option selection. According to statistics, the proportion of unplanned events in the landing gear system is the largest since a civil aircraft has been in operation for 5 years, accounting for 17%, as shown in Figure 3.

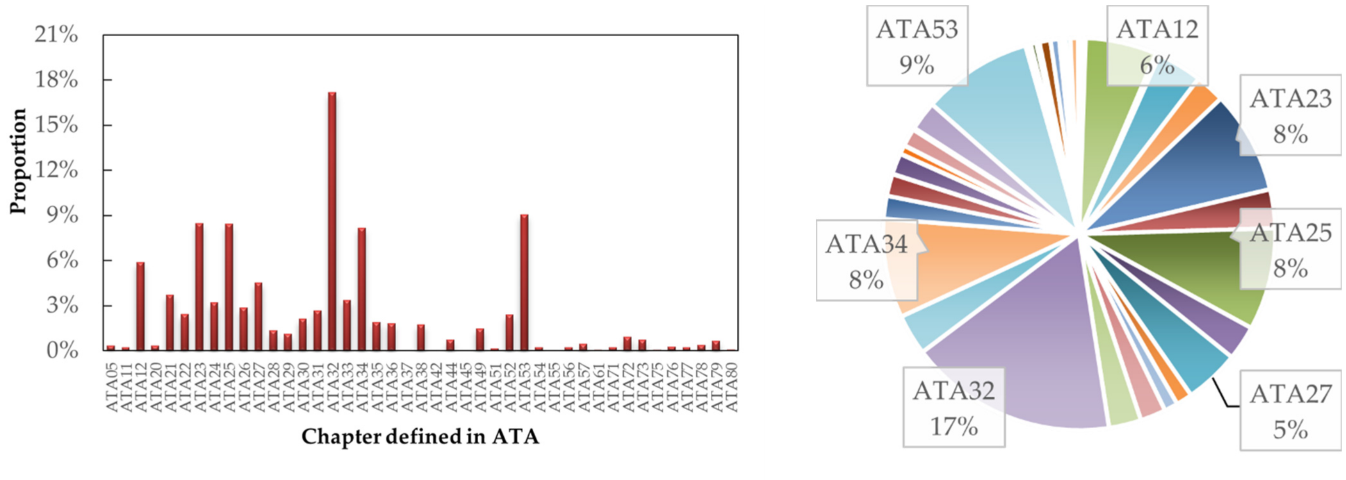


Figure 3. Proportion of fault maintenance records in typical systems. (ATA: Air transport association). (**a**) Histogram of percentages; (**b**) Pie chart of percentages.

The landing gear product option selection configuration (the MTBF of the 61 products) determined by reliability constraints before optimization is shown in Figure 4. As shown on the right, 28% of the products are inconsistent with the design stage in actual operation, due to the use of environmental and maintenance methods. In such a state of operation, the AFMC of landing gear system has reached 510.5 USD/FH. Unplanned maintenance events have so far been inevitable, so a certain optimization model is reasonably constructed to make the policy on product option selection achieve the purpose of minimizing maintenance measures and reducing the AFMC.

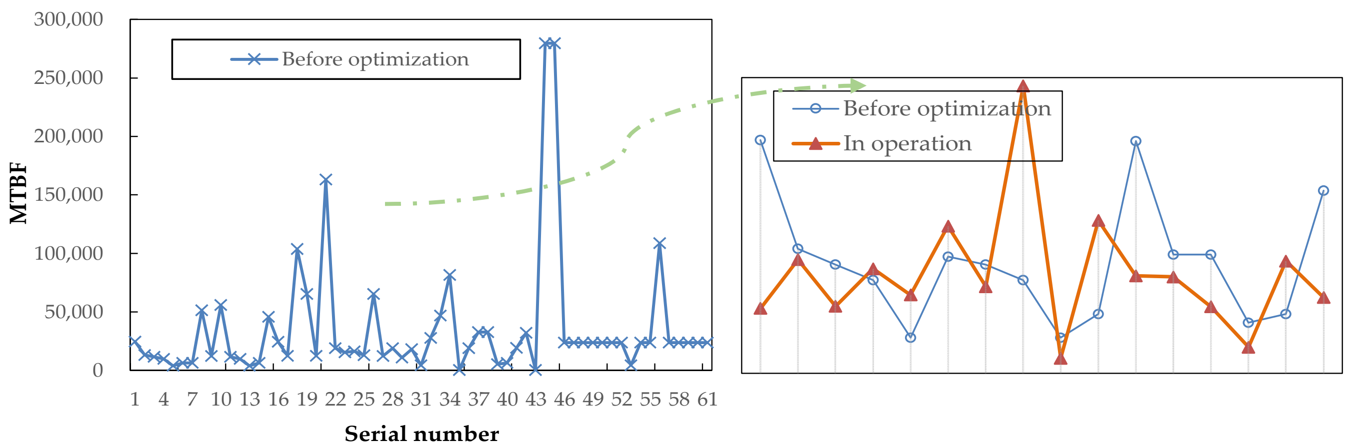


Figure 4. Product life information before optimization. (**a**) Product life; (**b**) Comparison of design and operating life.

The different maintenance costs of the landing gear system are further shown in Figure 5. The comparison results clearly show that in the maintenance cost of aircraft fleet, the maintenance tasks of unplanned classes tend to be much higher than planned costs. So, the model also focuses on finding a balance between planned and unplanned costs, serving the AFMC in annual flight hours.

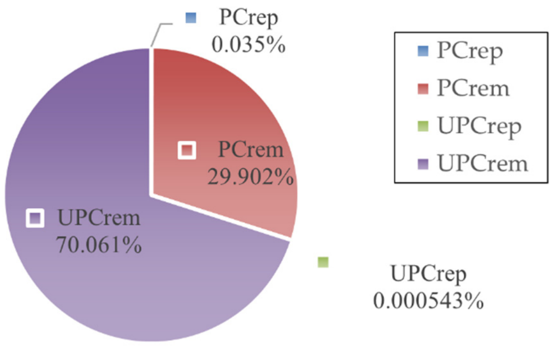


Figure 5. Different maintenance costs of the landing gear system.

All the parameters needed to build the model are shown in Table 1. Each product should be analyzed through customer demand, market demand and historical operation data to obtain the reliability index as the constraint condition, which is also the constraint condition of the model selection. In addition, it is necessary to introduce the QPA, work hours, rates, price, MTBF before optimization, MSPT of product and the unit frequency of unplanned repair or maintenance. Because of the limitation of space, this article only shows some data.

Table 1. Data preparation for optimization.

Part Name	QPA	Price	Rate	MTBM/FH	h(PC_{rep})
Temperature sensor	4	60,610	40	/	/
Brake assembly	4	562,700	40	48	0.2
Check valve	6	6620	40	12,000	0.2
Wheel, MLG	4	205,500	40	48	0.2
Steering control valve	1	475,600	40	/	/
…	…	…	…	…	…
Part Name	**h(UPC_{rep})**	**h(UPC_{rem})**	**NUM(UPC_{rep}) /FH^{-1}**	**NUM(UPC_{rem}) /FH^{-1}**	**MSPT /DAY^{-1}**
Temperature sensor	0.5	0.5	9.61261×10^{-5}	9.61261×10^{-5}	30
Brake assembly	0.5	0.5	0.000192252	9.61261×10^{-5}	30
Check valve	/	/	/	/	30
Wheel, MLG	/	0.5	/	0.006856996	30
Steering control valve	0.5	/	0.000352462	/	30
…	…	…	…	…	…

3.2. Convergence of Objective Function

The option selection of the whole system is more suitable for the improvement of aircraft types or the development of new models. However, if the contradiction of is more prominent in the process of the operation on a product, the model can also be optimized according to the characteristics of one. This section takes brake assembly as an example to optimize through mathematical models. More importantly, the convergence of the objective functions is illustrated through this typical example. The relationship between the objective function and the option selection decision is shown in Figure 6. On the left, the dual-objective mathematical optimization model is displayed, and the three-object mathematical optimization model is displayed on the right. The optimal option selection of the brake assembly is MTBF = 9472FH, and 9782FH before optimization.

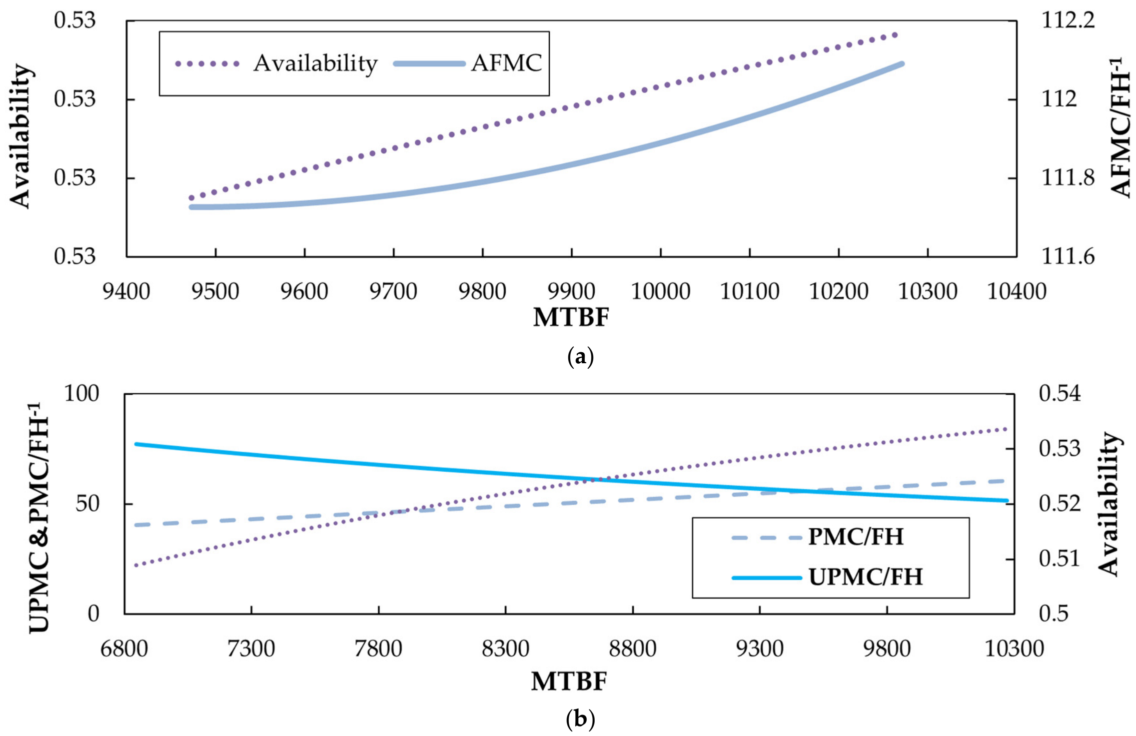


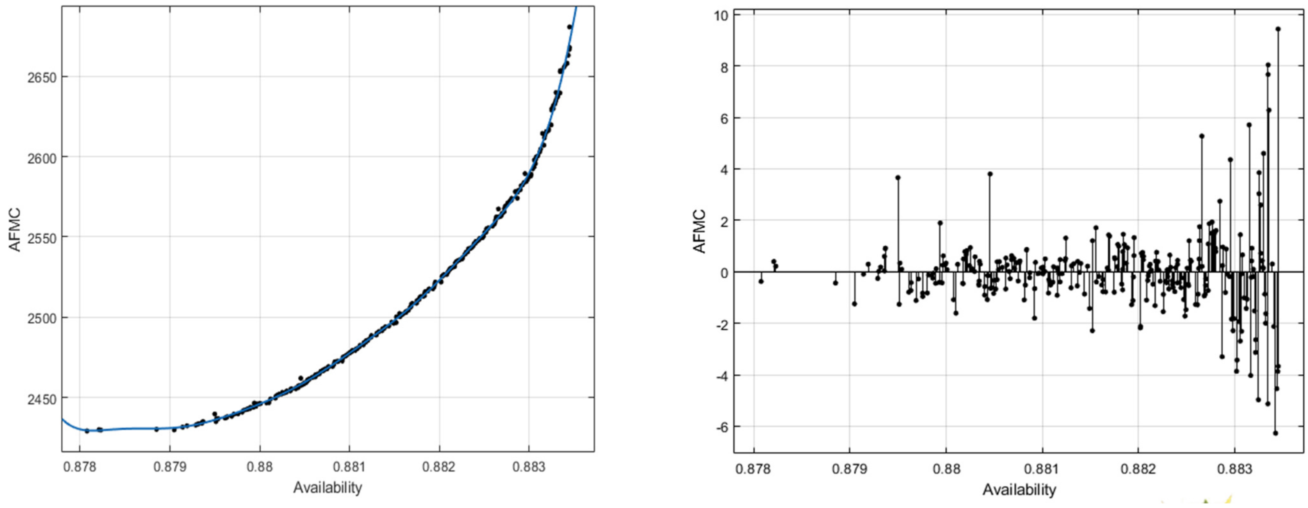
Figure 6. Convergence of objective function. (**a**) Dual-objective model iteration results; (**b**) Three-objective model iteration results.

The brake assembly is already a product with frequent planned maintenance tasks in the system; the change of availability is still not obvious under the option selection decision. The target results of the final scheme have few differences between the two models. The model considering the dual-objective model locates the optimal solution area faster and searches for more elite individuals of the neighborhood in the subsequent iteration process, all of which is to increase efficiency and global search ability. For the case itself, the cost optimization needs not require too high of an accuracy, but this is the inherent merit of the model itself, and it can also reduce the number of iterations through this feature, thus resulting in less time to solve the model. This analysis provides a model comparison for the subsequent option selection of the whole system, so the dual-objective mathematical optimization model is used to solve the problem later.

4. Validation and Verification Process

4.1. Product Option Selection Decision Based on the Mathematical Optimization Model

Taking all 61 products of the landing gear system as optimization objects, a mathematical optimization model for product selection was constructed. The distribution relationship and convergence accuracy between availability and the AFMC is shown in Figure 7. For 61 categories of individuals in the decision space optimization, when the number of iterations was 100, the decision space tended to converge and stabilized after the 200th generation. When the number of iterations was 300, the population is the result, and the two objective functions have a certain convergence in the decision space, which is consistent with the condition of the end of iteration. This indicates that there is a certain functional relationship between the maintenance cost and availability of an aircraft fleet. The convergence relationship between the two indicates that the optimal solution found by one algorithm after repeated iterations is subject to the same change rules, and they can converge into a curve. Second, there is a certain nonlinear relationship between cost and performance. Reasonable choice can control the two parties in a certain range. It is reasonable and effective to control and evaluate the performance of an aircraft system through option selection so as to meet the airlines customizing design demand.



(**a**) (**b**)

Figure 7. Distribution and convergence accuracy between availability and AFMC. (AFMC: Aircraft fleet maintenance cost). (**a**) Distribution law; (**b**) Convergence accuracy.

4.2. Impacts on Aircraft Fleet Maintenance Cost and Product Availability

Before and after optimization, the functional relationship between availability and the AFMC presents a good convergence and convergence accuracy and is also within the controllable range. In addition, the most important goal of product selection through a mathematical optimization model was to enhance product availability and reduce maintenance costs. After 300 iterations, according to the non-dominated sorting and crowding degree, the algorithm outputs the optimal decision plan among the 300 population individuals. For 300 kinds of decision-making schemes, the advantages and disadvantages are compared again according to the fitness function; the optimized decision scheme is shown in Figure 8. The results in Table 2 show that the AFMC was reduced by 20.71%, and availability increased by 2.576%. The validity of the model and method has been verified.

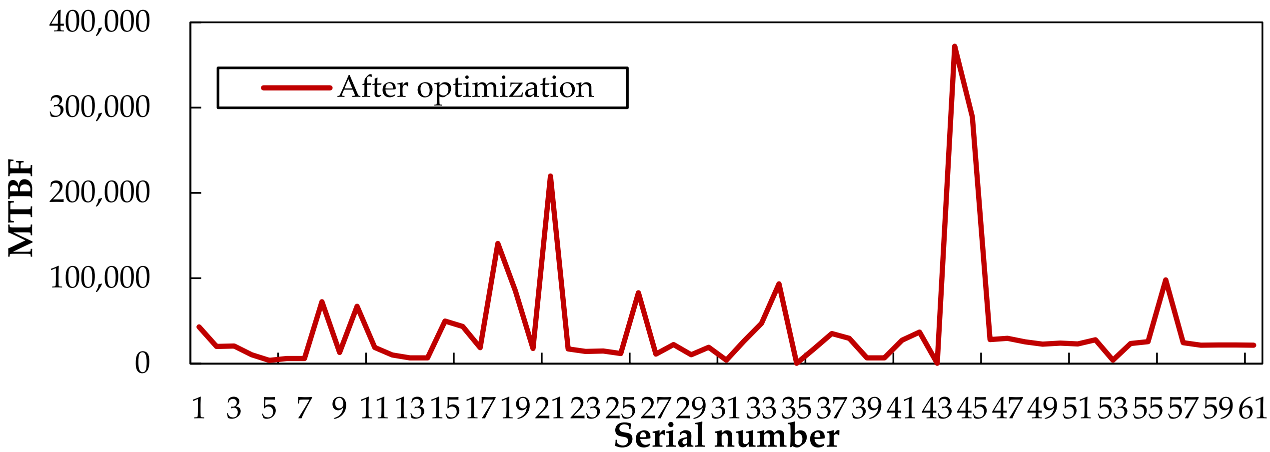


Figure 8. Product life information after optimization. MTBF—mean time between failures.

Table 2. Comparison of optimization objectives.

State	Availability	AFMC/USD
Before optimization	0.856017805	510.5
After optimization	0.878076474	404.85

5. Conclusions

In this paper, a mathematical product option selection optimization model was set up to describe the customizing design demands of civil aircraft in airlines. The model was solved by the Improved Non-dominated Sorting Genetic Algorithm, and the regression functional between economy and availability was fitted by curve fitting so as to output the optimal decision-making configuration under the objective on fleet maintenance cost and availability. Some main conclusions are summarized as below.

(1) The fitness function used in a multi-objective genetic algorithm can well solve the contradiction between different variables and objective functions. Therefore, for the cases to be solved in this paper, the model of the double objective function is better because it can lock and reduce the optimization space faster.

(2) The model combines the actual operation data of civil aircraft, simulating the influence of the operating environment on reliability through data and also designing feedback requirements through data. Taking the landing gear system as an application case, the results show that if the product option selection configurated by mathematics model is used, the availability of the system is increased by 2.57%, and the maintenance cost of the fleet is reduced by 20.71%.

(3) Unplanned maintenance events have so far been inevitable. However, the planned maintenance strategy can reduce unplanned failure. The unplanned frequency of products' programmed planned maintenance tasks is far lower than others. If we further consider the increase or decrease of maintenance tasks and introduce them in some way, we can combine the product itself and comprehensive support to build a model. The calculation of costs will also be more accurate.

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Nomenclature

AFMC	aircraft fleet maintenance cost	RSPL	recommended spare parts list
FH	flight hour	PC_{rem}	planned removal cost
HCMV	hybrid conjugate mean value	PC_{rep}	planned repair cost
LMP	Line Maintainable Part	PMC	planned maintenance costs
LRU	Line Replaceable Unit	UPC_{rem}	unplanned removal cost
MTBF	mean time between failures	UPC_{rep}	unplanned repair cost
MSPT	mean shop processing time	UPMC	unplanned maintenance cost
MTTR	mean time to repair		

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