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Research on Multi-Objective Optimization Method of eVTOL Connection Structure Based on Convolutional Neural Network and Dwarf Mongoose Optimization Algorithm

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Abstract. This paper studied the fallable structure of the seat and floor connection of the 500kg multi-rotor manned electric vertical take-off and landing (eVTOL) aircraft. In view of the lack of research on fallable structures, especially for seat connection structures, this paper proposes a multi-objective optimization method based on neural network and pygmy mongoose algorithm. By constructing the finite element model and conducting simulation analysis, combined with the CNN surrogate model and DMOA, the optimization of the crashworthiness of the structure was realized. The results show that the proposed optimization method can improve the crashworthiness while ensuring the lightweight of the structure, and provides a new solution for the design of eVTOL seat connection structure.

Keywords: multi-objective optimization method; eVTOL; CNN; DMOA.

1. Introduction

With technological innovation, policy optimization, and the rapid development of low-altitude economy, electric vertical take-off and landing aircraft (eVTOL) have become a research hotspot in aviation due to their advantages in urban commuting, emergency rescue, logistics and tourism. At present, eVTOL aircraft are in the early stage of development, and most of the research focuses on flight performance, power systems and control systems. Zong et al. proposed a hybrid all-electric propulsion system design method to improve energy efficiency [1]. Advances in battery and motor technology and distributed electric propulsion systems have driven the development of eVTOL aircraft. Li et al. compared the path planning algorithms for eVTOL aircraft in urban air mobility [2]. Deng et al. summarized the advantages and disadvantages of different eVTOL aircraft configurations, and compared them with traditional fuel aircraft in terms of performance and economy [3]. However, there is less research on the crash performance of aircraft. At present, the research on the crash performance of eVTOL aircraft has gradually attracted attention. Wang et al. analyzed the application limitations and effects of eVTOL aircraft-level safety mitigation measures (crash resistance and aircraft parachute) [4]. Ding et al. optimized the fall adaptability design of the skid landing gear and energy-absorbing elements, and applied machine learning techniques to predict the stress of the skid landing gear and the energy-absorbing efficiency of the energy-absorbing elements [5].

The current research on fallable structures at the seat-floor junction is limited. This paper focuses on the fall-fitting structure connecting the eVTOL seat and floor. Traditional energy-absorbing designs rely heavily on empirical formulas and experimental verification, which are time-consuming and labor-intensive. These methods also struggle to accurately predict energy absorption under complex dynamic loads. Additionally, the geometric parameters, material properties, and manufacturing processes of the connection structure interact in complex ways, making optimization difficult. Therefore, a new optimization method is needed to balance energy absorption and lightweight design. This paper proposes a multi-objective optimization method for the eVTOL connection structure based on neural networks and the pygmy mongoose algorithm.

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2. Research Object and Parameter Range

This study focuses on the fallable structure connecting the seat and floor in a 500kg multi-rotor manned eVTOL aircraft. Key parameters include material properties, cross-sectional shape, mass (M), cell number (N), wall thickness (T), cell outer length (L), and height (H). The mass constraint model is:

$$M = N \cdot \left\{L^2 - 2 \cdot \left[1 - \left(2 + \sqrt{2}\right) \cdot T\right]^2\right\}^{1.5} \cdot \rho \tag{1}$$

The constraints are: $M \in [10,13]kg$ and $L > (2 + \sqrt{2}\ \ )T$.

879 valid samples were generated for optimization.

2.1 Material Properties

In aviation, despite the growing use of composite materials, they still have significant drawbacks. Maintenance of composites is complex, requiring strict environmental control and lengthy processes, leading to high costs. Additionally, recycling composites is challenging due to complex separation and high catalyst costs, despite good recovery rates[6]. Therefore, aluminum alloys remain popular for fallable structures due to their strength, low density, and corrosion resistance.

Alcoa 7075-T6 was chosen for this structure due to its high specific strength, toughness, and excellent processing and welding properties, making it ideal for critical components[7]. Below is a comparison of key aerospace aluminum alloys:

Table 1. A comparison of the performance and application of several specific aluminum alloys

Types of aluminum alloys	density（g/cm³）	Tensile strength（MPa）	Yield strength（MPa）	Key features	apply
2024	2.78	470-480	325-345	High strength and fatigue resistance	Wing and fuselage structure
6061	2.70	240-310	145-275	Versatility, corrosion resistance, machinability	Structural parts, aircraft accessories
7075	2.81	540-590	470-505	Excellent strength-to-weight ratio	Critical structural components
7050	2.83	460-520	370-460	Excellent toughness, stress corrosion crack resistance	Aircraft wing spars, bulkheads

2.2 Parameter Settings

The structure is a multi-cell design with a square cross-section to evenly distribute loads and reduce deflection. The central area has a smaller triangular shape to enhance energy absorption.

The mass range is 10-13 kg to balance energy absorption and structural integrity without excessive weight. The cell number ranges from 1 to 30, balancing energy absorption and manufacturing complexity. Wall Thickness ranges from 1 to 5 mm in 0.1 mm increments, avoiding thin-walled instability. Ranges from 1 to 58 mm in 0.5 mm increments, constrained by mass and structural requirements.The height can be obtained according to Equation (1).

3. Establishment, Verification and Simulation of Finite Element Model

In the simulation process, in order to quickly screen out representative samples from a large number of samples, random traversal sampling (SUS) is usually used, the algorithm calculates the spacing of the pointers P=F/N, randomly generates the starting pointer position Start, calculates the position Pointers of each pointer, and selects N individuals according to the position of each pointer. This method can effectively draw samples from the design space for subsequent explicit dynamics simulation analysis. In this paper, 100 samples are selected by random traversal sampling for subsequent modeling and simulation.

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3.1 Modeling

SolidWorks is a powerful 3D modeling software that is widely used in the field of mechanical design. Take one of the models as an example, the geometric dimensions of the model are N=1, T=4mm, L=17mm, H=16.329322mm. The modeling process is as follows, specify the upward datum, enter the sketch drawing, draw the cross-section, and then perform operations such as extrusion to complete the modeling of the part. The flat plate 1 connected to the member simulates the part connected to the seat, and the side length is $L1 = L + 5mm$The thickness of H1=5mm not only ensures that the entire cross-section of the component is covered, but also avoids the impact of excessive mass on the crushing process of the component. Plate 2 is constructed 10 mm above the plane to provide acceleration impact with side length $L2 = 2L1$ and thickness H2 = 5mm.The resulting model is as follows:

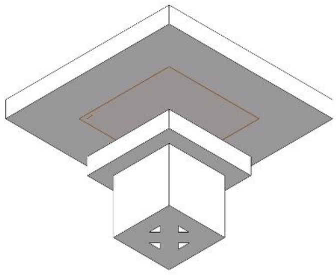

Fig. 1 The resulting model

Similarly, 100 samples were modeled.

3.2 Simulation

LS-DYNA is explicit kinetic analysis software developed by LSTC, based on the finite element method. It simulates dynamic problems like structural dynamics, collisions, explosions, and metal forming using an explicit time integration algorithm suitable for instantaneous events. In the crash process, the fall-fitting structure absorbs the impact kinetic energy through structural deformation and destruction, to achieve the purpose of protecting the safety of the occupants[8].

3.2.1 Basic Principles

Dynamics simulations follow Newton's laws, combining momentum and energy conservation, and use differential equations to describe responses. Finite element analysis discretizes structures, focusing on material models, element types, boundary conditions, and load application. Key numerical techniques include time integration, contact algorithms, and precision control.

3.2.2 Simulation process

The material is Aluminum alloy 7075-T6, and the strain rate effect is ignored in this paper because the strain rate of aluminum alloy is not sensitive[9]. The member and plate 1 are treated as a whole, the stiffness behavior is set to flexible, and the stiffness behavior of plate 2 is set to rigidity.

In order to analyze the influence of mesh size on the simulation results, the mesh size of 0.5mm, 1.0mm, 1.5mm, and 3.0mm was used to mesh the model. The results show that the gap between the simulation results is the smallest when the grid size is 0.5mm and 1.5mm. To improve the computing efficiency, the grid size of the component and plate 1 is 1.5mm. To avoid penetration, the number of grids of plate 2 is 1.

At the bottom end of the member, it is a fixed support, which simulates the connection with the body. Statistics show that the vertical velocity of civil aircraft structure crash test is usually in the range of 6.1~9.14 m/s[10]. Therefore, the impact velocity of plate 2 v=9.0 m/s is set, and all translational degrees of freedom except the vertical direction are constrained.

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The end condition is that the component is fully compressed, and the final deformation of the component is shown in the figure.

Similarly, 100 randomly selected samples were simulated.

4. Multi-Objective Optimization of Structure

By combining the prediction ability of the neural network and the search ability of the optimization algorithm, the system can optimize the crashworthiness of the structure under the premise of satisfying the mass constraints, and achieve a balance between lightweight and high crashworthiness.

4.1 Fallability Evaluation Index

Three indexes—Specific Energy Absorption (SEA), Initial Peak Crush Force (IPCF), and Mean Crush Force (MCF)—were used to evaluate the fallability of structures. SEA, which measures energy absorption per unit mass, is given higher weight due to its crucial role in reducing transmitted forces and enhancing safety during impacts. IPCF indicates the initial peak load during collision, with lower values reducing injury risk. MCF reflects the average crush load in the stable crushing stage, with higher values showing consistent energy absorption. The expressions for SEA and MCF are as follows:

$$\begin{cases} EA = \int_0^d F(x)\,dx \\ SEA = \frac{EA}{M} \\ MCF = \frac{EA}{d} \end{cases} \tag{2}$$

where EA is the total energy absorption, F(x) is the instantaneous impact force during the collision, d is the effective compressive displacement, and m is the total mass of the component.

To achieve additivity, the three indicators were normalized and named normalized_SEA 、 normalized_IPCF and normalized_MCF, and then calculate the total evaluation score according to the importance proportion of the distribution, and the total evaluation system is expressed as follows:

$$Score = normalized\_SEA - 0.5 * normalized\_IPCF + 0.5 * normalized\_MCF \tag{3}$$

4.2 Neural Network Training

The following diagram illustrates the streamlined process from data processing to model training and evaluation using a CNN architecture, highlighting key steps for efficient simulation and optimization.

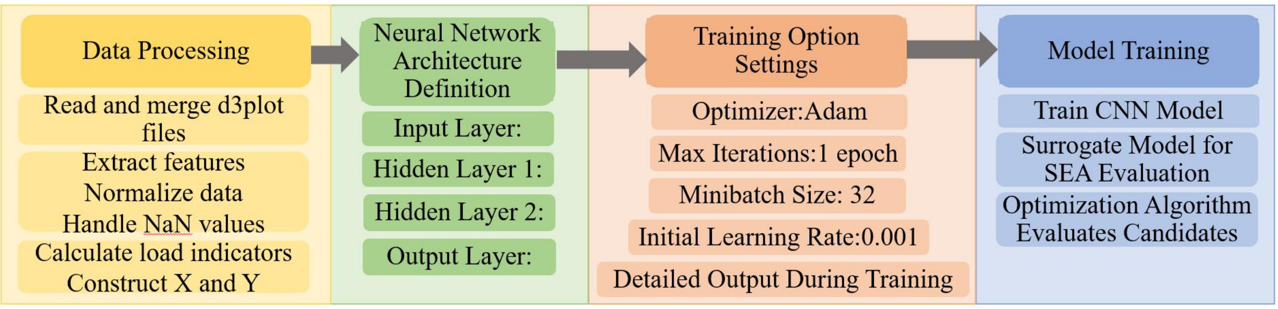

Fig. 2 Efficient CNN-based simulation and optimization flowchart

4.3 DMOA Optimization Algorithm

The DMOA algorithm leverages the SEA predictions from the neural network to evaluate parameter combinations and guide the search for the optimal solution.

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4.3.1 Define the Optimization Problem

The goal is to find optimal parameters (number of cells, wall thickness, edge length) that maximize structural crashworthiness metrics (SEA, initial peak load, average crush load) predicted by the CNN model. Parameter bounds are set as LB = [1, 1, 1] and UB = [30, 5, 58].

4.3.2 Optimization Process

The population, consisting of 20 individuals with randomly generated parameter values within the bounds, is initialized.

The fitness of each individual is evaluated using a function that considers SEA, initial peak load, average crush load, and mass constraints.

In each iteration:

Select Leader: Identify the individual with the best fitness.

Spawn New Individuals: Generate new individuals by adjusting parameters based on the leader.

Apply Boundaries and Step Control: Ensure new parameters are within bounds and meet design requirements.

Assess New Individuals: Calculate their fitness.

Update Population: Replace individuals with better-performing new ones.

The process repeats for 50 iterations, updating the best solutions. The algorithm returns the optimal parameter combination and corresponding fitness value.

The optimization results are as follows:

Table 2 Optimal variable values

variable	Optimal variable values
Number of multiple cells	21
Thin-walled thickness	1.4149 mm
Side length	57.1525 mm

5. Analysis of the Optimized Results

The CNN and DMOA algorithm optimization process used in this study successfully improved the crash resistance of the eVTOL seat-floor connection structure, and ensured the lightweight of the structure. The deformation and stress changes of the optimized structure during the impact process are shown in Fig. 3. As can be observed from the graph, the structure exhibits significant deformation peaks at about 100 ms and 400 ms, which correspond to the moment when the structure is subjected to the maximum impact force. The stress values (red dotted line) also increase significantly at these times, indicating that the structure is under a high load during these times. The optimized structure can absorb these impact forces effectively without excessive permanent deformation, which is essential for the safety of passengers. Fig. 4 shows the change in the Specific Energy Absorption (SEA)value of the optimized structure throughout the simulation, which remains close to zero throughout the process, indicating that the structure can absorb energy efficiently without transferring excessive impact force to passengers. This energy absorption capacity is an important indicator for evaluating the crashworthiness of the structure, and the optimized structure performs well in this indicator.

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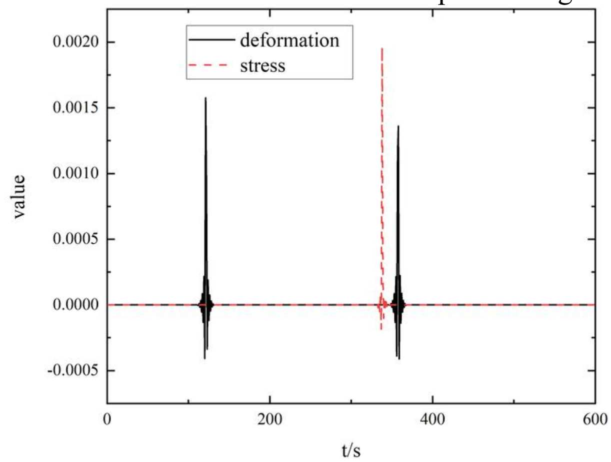

Fig. 3 Deformation and Stress Variation of the Optimized Structure

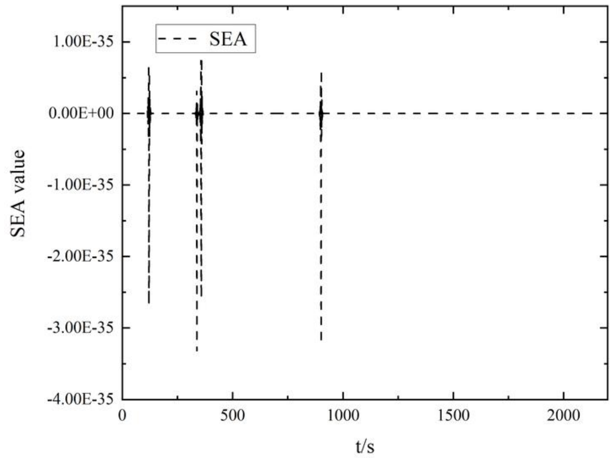

Fig. 4 SEA Variation of the Optimized Structure

6. Summary

This study conducted a multi-objective optimization on the seat-floor junction structure of a 500kg eVTOL using CNN and DMOA. It balanced SEA, IPCF, and MCF to achieve lightweight and high crashworthiness. The method improved optimization efficiency and robustness, showing significant advantages over traditional approaches. It has important engineering value and potential for future applications.

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