Multi-objective Optimization Design of Wing Structure with the Model Management Framework

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Abstract: Evolutionary algorithm is time-consuming because of the large number of evolutions and much times of finite element analysis, when it is used to optimize the wing structure of a certain high altitude long endurance unmanned aviation vehicle(UAV). In order to improve efficiency it is proposed to construct a model management framework to perform the multi-objective optimization design of wing structure. The sufficient accurate approximation models of objective and constraint functions in the wing structure optimization model are built when using the model management framework, therefore in the evolutionary algorithm a number of finite element analyses can be avoided and the satisfactory multi-objective optimization results of the wing structure of the high altitude long endurance UAV are obtained.

Key words: wing structure; UAV; multi-objective optimization; model management framework; SM-MOPSO

基于模型管理框架的机翼结构多目标优化设计. 安伟刚, 李为吉, 苟仲秋. 中国航空学报(英文版), 2006, 19(1): 31-35.

摘 要: 采用演化算法对某高空长航时无人机机翼结构进行多目标优化设计时, 由于需要大量的演化迭代和很多次的有限元分析计算, 使演化算法相当耗时。为了提高效率, 采用模型管理框架对该机翼结构进行多目标优化设计。采用模型管理框架可以建立满足精度要求的目标及约束的近似模型, 使演化算法不仅避免了大量的有限元分析计算, 而且获得了满意的该高空长航时无人机机翼结构的多目标优化设计结果。

关键词: 机翼结构; 无人机; 多目标优化; 模型管理框架; 单纯形法-多目标粒子群优化算法
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After the geometry parameters of a certain high altitude long endurance UAV are determined, it is necessary to perform the multi-objective optimization design of the UAV's wing structure in order to reduce the mass of wing structure and prolong the UAV's endurance. However, it is very time-consuming to optimize the wing structure by using the evolutionary algorithm because of the large number of evolutions and much times of finite element analysis. In order to improve the efficiency, the model management frame-work is used to build sufficient accurate approxima-tion models of objective and constraint functions in the wing structure optimization model. By using these accurate approximation models, evolutionary algorithm can avoid a number of finite element analyses and obtain a good Pareto set quickly. It is a successful attempt to use models management framework in engineering optimization design.

1 Multi-objective Optimization Model of the Wing Structure

Fig. 1 shows the wing structure of a certain high altitude long endurance UAV. Table1 shows the geometry parameters of the wing structure.

The configuration of the wing structure is dual beams that are designed in 34% and 67% of the wing root chord. There are 28 ribs and the space between every two neighboring ribs is 700 mm. The skin adopts carbon fiber (epoxy resin) composite material. The fibers of composite material are oriented at 0°, −45°, +45° and 90°. The material

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of beam is 30CrMnSiA, and the material of ribs and stringers is LY12.

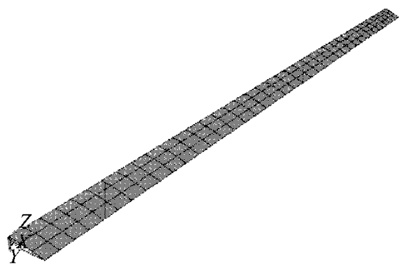

Fig. 1 The wing structure of a certain high altitude long endurance UAV

Table 1 The geometry parameters of the wing

Geometry parameters	Value
Span	23.330 m
Root chord	1.372 m
Tip chord	0.494 m
Wing area	21.767 m^2
Taper ratio	2.78
Mean aerodynamic chord	1.001 m
Quarter chord line sweep angle	5.9°
Airfoil thickness ratio(root)	18%
Airfoil thickness ratio(tip)	14%
Dihedral angle	0°
Incidence angle	0°

Design vector is(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9), in which x_1, x_2, x_3, x_4, x_5 and x_6 are the thicknesses of wing skin from root chord to tip chord and x_7, x_8 and x_9 are the thicknesses of beam web from root chord to tip chord. The unit of design variables is millimeter. The objectives of optimization design are to minimize the mass and maximum vertical displacement of wing structure under a certain flight condition. The aerodynamic load is obtained by CFD software. The finite element analyses of wing structure are computed by Aeronautic and Astronautics Structure Analysis software. The optimization model is written below:

$$\begin{aligned} &\text{Min} \quad f_1 = W(X) \\ &\text{Min} \quad f_2 = L_{\max} \\ &\text{S.T:} \quad \sigma_i \leqslant [\sigma_i],\ i = 1, 2, 3, 4 \\ &\qquad\quad 0.5 \leqslant x_i \leqslant 12,\ i = 1, \cdots, 9 \end{aligned} \tag{1}$$

where W is the mass of wing structure; $L_{\max}$ is the maximum vertical displacement of wing structure; $[\sigma_i]$ is the allowable stress.

2 Multi-objective Model Management Framework

Because of the lack of sampling data and the large numbers of dimensions for the wing structure optimization in present paper, it is difficulty to build approximation models of the whole searching space with sufficient accuracy. In order to overcome this difficulty the model management framework is adopted to use and manipulate approximation models[1]. Here Ref.[2] is refered and a multi-objective model management framework is proposed. The model management framework used in this paper has three procedures: ①determining the initial sampling points with uniform random number; ②adopting the radial basis function neural network to build approximation models of objective and constraint functions; ③in every n generation, some modifying points are selected by roulette wheel and recomputed by finite element analyses. Then these results are used to update approximation models. The three procedures are described as follows.

2.1 Determining initial sampling points

Many papers suggest that the initial sampling points should be determined by experimental design. In methods of experimental design, uniform design is recommended because it can afford better searching space coverage than other experimental design, such as Latin hypercubes, orthogonal arrays[3]. In the multi-objective optimization model of wing structure, the searching space is very large because of the high dimensions and wide range of each variable. Therefore, the number of initial sampling points should be taken large enough. In the present case, it is taken as 400. Because it is unable to find uniform design table of 400 experiments in any existing references, so in the wing structure optimization of the present paper, the initial sampling points are determined by uniform random number instead of uniform design. Uniform random number not only affords uniform initial sampling points but also is easy to be obtained.

2.2 Radial basis function neural network (RBFNN)

Several methods[4] have been developed to construct approximation models, such as response surface, kriging, radial basis function neural network and so on. In this research, the radial basis function neural network is adopted as approximation method for following reasons[5].

(1) Complex engineering systems cannot often be expressed by explicit numerical functions. It is unknown how much error will occur if explicit numerical functions are used to approximate the complex engineering systems. When radial basis function neural network is used to approximate data, it likes a black box. This character is very fit to approximate the complex engineering systems.

(2) Neural network has excellent ability to approximate to functions, which has been proved theoretically.

(3) For large or scarce sample set, radial basis function performs better than response surface and kriging when accuracy and robustness are considered[6]. Radial basis function neural network inherits the superiority of radial basis function because it adopts radial basis function.

Consider an objective or constraint function $f(x)$ to be approximated by a RBFNN. The output of a RBFNN is given by[7]

$$y = \sum_{i=1}^{N} w_i \varphi_i(\boldsymbol{x}) \approx f(\boldsymbol{x}) \tag{2}$$

$\varphi_i(x)$ is the basis function which is assumed to be the Gaussian function:

$$\varphi_i(x) = \exp\left(-\frac{\| \boldsymbol{x} - c_i \|}{\sigma_i^2}\right) \tag{3}$$

where $\boldsymbol{x}$ is the input vector, N indicates the total number of neurons in the network, c_i, σ_i and w_i refer to the center, width and weight of the ith neuron, and $\|\cdot\|$ denotes the Euclidean norm. In the model management framework, by using initial sampling points set that includes design vectors, objective vectors and constraint vectors, k-means clustering is used to determine the c_i, k-nearest neighbor heuristic to determine the σ_i, and the multiple linear regressions to determine the w_i. After these parameters are determined, a RBFNN is constructed. The RBFNN is the approximation model of objective or constraint function, therefore, the objective or constraint can be calculated by RBFNN instead of finite element analysis.

2.3 Selecting modifying points

In the model management framework, m individuals are selected to modify the approximation models every n generation. How to select the points that can efficiently modify the approximation models is the key to building sufficient accurate approximation models. In this research, each of Pareto individuals is assigned fitness using Eq. (4) in design space,

$$f_i = \min\{ \| p_i - s_j \|_2 \}, j = 1, 2, \cdots, n \tag{4}$$

where p_i is the ith Pareto individual, n is the number of sampling points, s_j is the jth sampling points, and f_i is the fitness of p_i.

According to fitness, some modifying points are selected by roulette wheel and recompute these points are recomputed by finite element analyses. Not only every Pareto individual has chance to be selected as modifying points, but also the more isolated the points are the more chances they have. The modifying points recomputed by finite element analyses are added to sampling points set and a new RBFNN is constructed. The new RBFNN will be more accurate than before.

3 Interaction between SM-MOPSO and the Model Management Framework

When objectives and constraints are computed by approximation models, evolutionary algorithm often get a shorter Pareto front that can not include those near the extremum. So in order to extend Pareto curve it is necessary to adopt evolutionary algorithm with strong local searching ability. SM-MOPSO proposed by the present authors in Ref. [8], is a new hybrid algorithm that integrates MOPSO (multiple objective particle swarm optimization) with SM (simple method). SM-MOPSO not only inherits all the merits of MOPSO but also has strong local searching ability. Therefore, in multi-objective optimization design of the wing structure the SM-MOPSO is adopted. The interaction between SM-MOPSO and the model management framework is showed in Fig. 2.

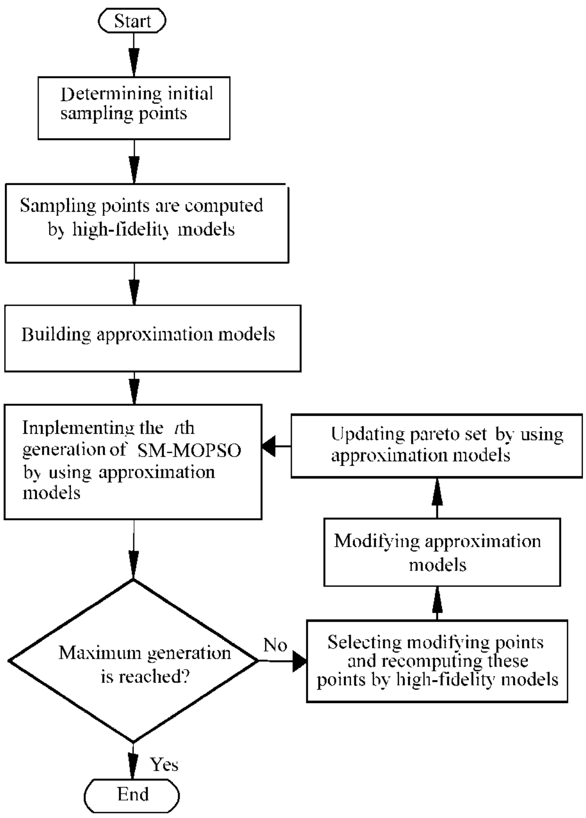

Fig. 2 Interaction between SM-MOPSO and the model management framework

In order to validate the effectiveness of the interaction between SM-MOPSO and the model management framework, a testing function proposed by Deb[9] is used,

$$\text{Min } f_1(x_1, x_2) = x_1$$

$$\text{Min } f_2(x_1, x_2) = (1 + 10x_2)\cdot \left[1 - \left(\frac{x_1}{1+x_2}\right)^{\alpha} - \frac{x_1}{1+x_2}\sin(2\pi q x_1)\right] \quad (5)$$

where $0 \leqslant x_1, x_2 \leqslant 1$, $\alpha = 2$, and $q = 2$. This problem has disconnected Pareto front and consistent with 2 Pareto curves.

In the optimization, the parameters of SM-MOPSO are determined by experience, they are: the number of population 81; maximum generation 50; the number of initial sampling points 81; and the number of modifying points of every generation 10. The optimization of the testing function is continuously calculated for three times. The best result is showed in Fig. 3. In Fig. 3, MMF is the abbreviation for the model management framework. It is obvious that by using the model management framework and SM-MOPSO good optimization results can be obtained.

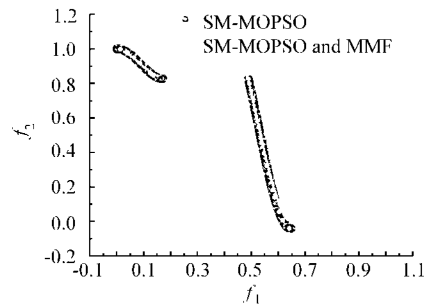

Fig. 3 The Pareto front of the testing function

4 Results of Optimization Design of Wing Structure

The SM-MOPSO and the model management framework are adopted to perform the multi-objective optimization design of the wing structure. The parameters are determined by experience, they are: the number of population 400; the maximum generation 100; the number of initial sampling points 400; and the number of modifying points of every generation 10.

The optimization results are showed in Fig. 4 and Table 2. In Table 2, TP is the abbreviation for testing points. Fig. 4 shows the uniform Pareto front of the wing structure optimization. In order to test the error of the Pareto front, four individuals A, B, C and D showed in Fig. 4, are selected to be recomputed by finite element analysis. Table 2 shows that the error of Pareto individuals is accepted. The maximum relative error of objective functions is only 2.78%. If the approximation models are not adopted, the finite element analyses will run 40 000 times. However, when the approximation models are used, the finite element analyses only run 1 400 times. The CPU time of optimization design is 4296.75 s, which can be accepted by designers.

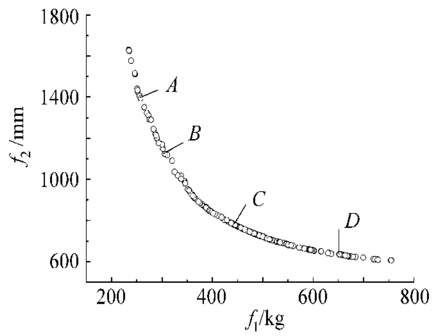

Fig. 4 The Pareto front of the wing structure optimization

Table 2 Error of testing points

TP	Approximation results		Finite element results		Error/%
	f_1/kg	f_2/mm	f_1/kg	f_2/mm	
A	257.8	1394	252.9	1398.1	1.93
B	305.7	1124	297.4	1133.3	2.78
C	439.2	785.8	436.9	785.8	0.52
D	652.1	636.8	648.8	640.3	0.51

5 Conclusion

(1) As seen from Fig. 4, the masses of different designs remarkably differs. So it is very necessary to use optimization design in the field of aeronautics and astronautics.

(2) To multi-objective optimization design of the wing structure in the present paper, it takes little time to obtain good Pareto set by using the model management framework and SM-MOPSO. Pareto front can obviously show the relation between mass objective and displacement objective. In Pareto set, decision-makers can easily select a satisfactory design according to their preference.

(3) The model management framework and SM-MOPSO introduced in the present paper can be used to solve multi-objective engineering problems efficiently. It has good prospect in the airplane design as well as in other complex systems optimization designs.

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Biography:

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