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UAV Wing Design via Efficient Global Optimization

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Abstract— **Effective wing design plays an important role in determining the flight performance of fixed-wing unmanned aerial vehicles (UAVs), which require basic aerodynamic principles. The process of engineering such aircraft is entrenched in navigating intricate computational challenges, especially in the realm of aerodynamics computation, mostly within computation-nal fluid dynamics. This study utilizes of the Efficient Global Optimization (EGO) algorithm as a robust and innovative approach tailored to address the multi-faceted complexities inherent in UAV wing design. This study employs the Efficient Global Optimization (EGO) algorithm to solve the challenges inherent in UAV wing design. Implementing Latin Hypercube Sampling (LHS) strategically for experiment designing and adding sampling points guided by the Expected Improvement (EI) for single-objective optimization, the primary objective is to enhance the lift-to-drag ratio, a crucial metric defining overall operational efficiency. The solution of this method was obtained with aerodynamic evaluation performed through Vortex Lattice simulation in VSPAERO software. These design methodologies for optimizing UAV wing design focus on achieving an efficiency increase of up to 16.56% in the lift-to-drag ratio when compared to the initial rectangular wing configuration. This enhancement represents the efficacy of the proposed approach in enhancing UAV wing designs, contributing to improved flight performance.**

Keywords-Efficient global optimization, UAV Wing design, VSPAERO, Aerodynamics computation

I. Introduction

Efficient Global Optimization (EGO) algorithm represents a breakthrough algorithmic approach that has become pivotal in addressing the computational complexities inherent in various engineering problems, especially within the domain of aircraft design [1-3]. The unique strength of EGO lies in its ability to effectively manage the substantial computational demands associated with optimization tasks. By surrogate models, EGO optimizes the utilization of computational resources, strategically sampling data to enhance model accuracy iteratively. Traditionally centered around the Ordinary Kriging model, initially designed for single-objective optimization, EGO has been the focus of extensive research endeavors aimed at its application across a wide spectrum of engineering challenges [4-6]. This algorithm's adaptability and efficiency have positioned it as a promising solution for diverse optimization needs, driving its exploration and implementation by numerous researchers within the realm of engineering problem-solving.

In this specific study, the application of the EGO method offers a promising approach to address the intricate challenge of unmanned aerial vehicles (UAVs) wing design. This methodology is further complemented by the utilization of the Vortex Lattice Equation integrated into VSPAERO software, providing a comprehensive aerodynamic evaluation of diverse UAV wing configurations to increase efficiency for fixed-wing UAVs, which is shown in Fig. 1.

Fig. 1. Fixed-wing unmanned aerial vehicles (UAVs)

II. Efficient Global optimization

The Efficient Global Optimization (EGO) procedure [7], delineated in Fig. 2, initiates by

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generating samples through the design of experiment technique (DoE) [8]. Within this study, Latin Hypercube Sampling (LHS) [9] has been specifically chosen for this process due to its ability to preserve data diversity and allow for user-defined control over the number of experiments. The subsequent step involves constructing the surrogate model. For single-fidelity optimization, the Kriging method is employed, while for optimization, Once the surrogate model is established, identifying an additional sample point for optimization involves maximizing the Expected Improvement (EI) through genetic algorithms [10]

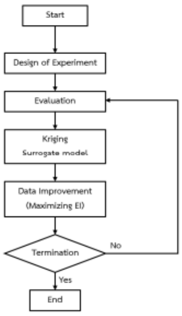


Fig. 2. Flowchart of EGO.

A. *Kriging surrogate model*

The ordinary Kriging model [11] functions to predict the unknown function $\hat{y}(x)$ as

$$\hat{y}(x) = \mu(x) - \varepsilon(x) \tag{1}$$

where $\mu(x)$ and $\varepsilon(x)$ represent the global model and local model, respectively. The global model, denoted as $\mu(x)$, is articulated as

$$\mu(x) = \frac{1^T R^{-1} F}{1^T R^{-1} 1} \tag{2}$$

where the matrix R is the correlations among the sample points, while F represents a vector housing the evaluation values assigned to each sampling point. Within the framework of the Kriging surrogate model, μ signifies the constant global model. The local model, denoted as $\varepsilon(x)$, is articulated as follows

$$\varepsilon(x) = r(x)^{-1} R^{-1}(F - 1\mu) \tag{3}$$

the vector $r(x)$ represents a collection of sampling points in terms of x, with its correlations, particularly between $\varepsilon(x)$ and $\varepsilon(x^i)$, determined by the distance between x and x^i. Within the Kriging surrogate model, the local derivation at an unknown point x is established via stochastic processes. This involves the generation of multiple design points as sampling points, followed by the construction of a surrogate model. This model utilizes a Gaussian random function as the correlation function to estimate the trend through the stochastic process.

B. *Expected Improvement (EI)*

The Expected Improvement (EI) [12], denoted as $\mathrm{E}[\mathrm{I}(\mathrm{x})]$, at a point x can be expressed as

$$I(x) = \max\left[f_{ref} - \hat{y}(x), 0\right], \tag{4}$$

$$E[I(x)] = \int_{\infty}^{f_{ref}} \left(f_{ref} - \hat{y}(x)\right)\phi(\hat{y}(x))\,dy, \tag{5}$$

Continuously leveraging the probability density function ϕ, which encapsulates uncertainty regarding $\hat{y}(\mathrm{x})$, which is the predicted function value from the surrogate model, the process iterates, adding sampling points guided by the EI. This iterative addition of sampling points persists until convergence of the objective function is achieved.

C. *Genetic Algorithm (GA)*

Genetic Algorithms (GA) represent a stochastic search methodology rooted in the principles of natural selection, pioneered by Holland [13] at the University of Michigan. Renowned as an Evolution Algorithms method, GA stands out for its versatility and applicability to optimization problems, often regarded as a black box method due to its ease of implementation. Initially adapted for single-objective optimization, the original GA formulation remains a fundamental framework in the domain of evolutionary computation.

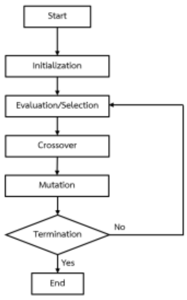


Fig. 3. Flowchart of GA.

III. WING DESIGN PROBLEM

In this study, the primary aim within the wing design problem is to maximize the lift per drag ratio (L/D) specifically at a Mach speed of 0.054286 (19 m/s) and Reynolds number of 1.57×10^6. The following equation illustrates the expression of the optimization problem.

$$\text{Maximize}: \; L/D \;\; \text{at} \;\; Re = 1.57\times10^6 \tag{6}$$

The initial design, created with Airfoil S8036, exhibited an initial L/D value of 18.5476, featuring a wing length of 0.9 meters and no wing sweep angle. For this study, the NACA series 6 airfoil was specifically selected and designed to achieve a lift coefficient of 0.5. The involves the adjustment of three design parameters, specifically focusing on the airfoil's maximum thickness per chord length (t/c), half wing span ($b/2$), and wing sweep angle (Λ), encompassing upper and lower limits as specified in Table 1.

TABLE I
THE RANGE OF DESIGN PARAMETERS

Design parameter	Design range
Maximum thickness per chord length, t/c	0.08 to 0.24
Half wing span, $b/2$ (m)	0.9 to 1.035
Wing sweep angle, Λ $(°)$	0 to 30

These design variables are optimized using Latin Hypercube Sampling (LHS) while adhering to constraints—a fixed wing area of 0.504 m^2 and a root chord size of 0.28 m. The initial number of samples is set to 30. Furthermore, this optimization process by add a single sample iterates through a total of 30 rounds, ensuring a comprehensive exploration and refinement of the design space to achieve the desired objective of maximizing the lift per drag ratio (L/D). The most suitable values for optimization are calculated using Genetic Algorithms (GA), configuring generation = 100 and population = 100 for each iteration calculation.

IV. AERODYNAMIC EVOLUTIONS

VSPAERO [14] was employed to evaluate the aircraft aerodynamics performance for this work. The VSPAERO is the software based on the vortex lattice method. The advantage of the vortex lattice aerodynamic evaluation based is it required for low computation time. The rapid computation times facilitate handling numerous estimations, providing the advantage of grasping the evolving trend for each variable. The first step involves creating a UAV model based on the specifications outlined in Table 2.

TABLE II
UAV SPECIFICATION AND FLIGHT CONDITIONS

Parameters	Value
Wing area (m^2)	0.504
Root chord (m)	0.28
Wing dihedral $(°)$	2.2
Fuselage (m)	1.33
Center of gravity (% Chord)	30
Mach speed	0.054286
Reynolds number	1.57×10^6

This entails adjusting the design variable sizes within the parameters established in Table 1 using LHS, with visual representations provided in Figures 4 and 5. Subsequently, a Computational Fluid Dynamics (CFD) mesh is generated to facilitate data preparation for result evaluation. The next phase tackles problem-solving using VSPAERO, configured as depicted in Figure 6. Finally, solution data is systematically collected for subsequent comparative analysis.

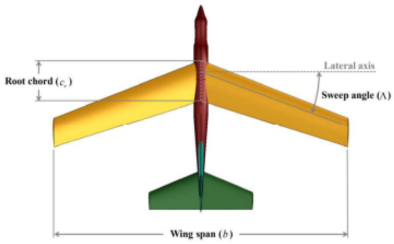


Fig. 4. Wing span and sweep angle of UAV

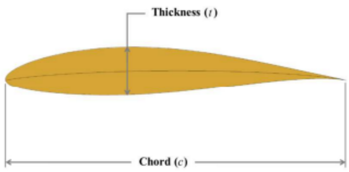


Fig. 5. Thickness and chord of UAV

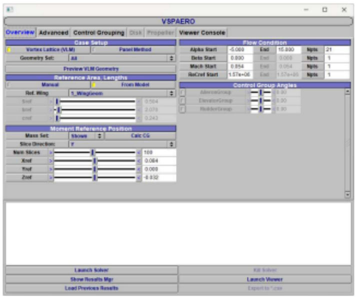


Fig. 6. Thickness and chord of UAV

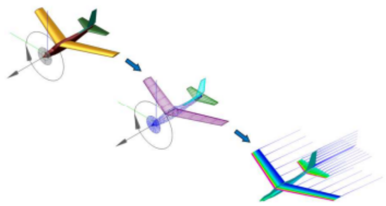


Fig. 7. The process of evaluating with VSPAERO

Figure 7 shown the attributes and features of the evaluation process with VSPAERO from CAD modeling, CFD mesh to the obtained solution results.

V. PARALLEL COORDINATE PLOT (PCP)

The Parallel Coordinate Plot (PCP), a statistical visualization method used to represent high-dimensional data in a 2D graph. This technique involves arranging multiple numerical variables along parallel axes to facilitate comparison and analysis of the data's patterns and relationships. Each axis represents a different variable, and lines connecting these axes create a profile for each data point, allowing analysts to visualize and explore complex data sets efficiently. In this study, the expression for the normalization value p_i derived from the design variable dv is provided as follows:

$$p_i = \frac{dv_i - dv\min_i}{dv_i \max_i - dv\min_i} \tag{7}$$

This expression utilizes $dv\min_i$ to indicate the lower boundary of the i^{th} design variable and $dv\max_i$ to represent the upper limit of the i^{th} design variable.

VI. RESULTS

Figure 8 depicts the results derived from EGO alongside EGO's initial sampling. This comparison showcases that EGO successfully acquired a UAV wing shape with superior aerodynamic efficiency compared to the initial sampling. Additionally, Figure 9 illustrates a comparative analysis between the chosen optimal design and the initial design. Remarkably, the selected optimal design demonstrates the potential to enhance the L/D by approximately 16.56% compared to the initial design, maintaining an equal wing area. Figure 9, the results displayed in the PCP format exhibit the relationship between input and output. The data, normalized and visualized in a graph, incorporates gray lines representing the initial sampling data and red lines indicating additional sampling points. This visualization suggests that wing span exerts the most significant impact on aircraft performance. Additionally, the blue line represents optimal design information, potentially applicable to the actual aircraft as demonstrated in Figure 10 b.

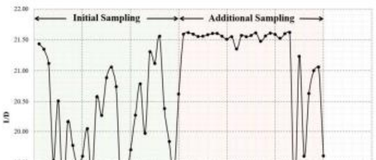


Fig. 8. Wing design solution

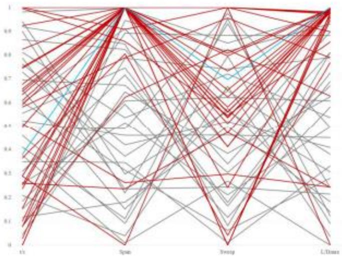
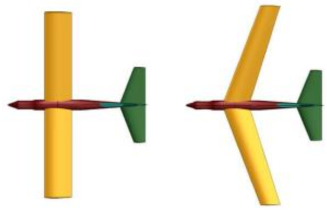


Fig. 9. PCP of the sampling in the EGO process



a. initial design b. selected optimum design

Fig. 10. Comparisons of the selected optimum design and initial design

VII. CONCLUSION

In this study, the combination of Efficient Global Optimization (EGO) alongside Latin Hypercube Sampling (LHS) and Expected Improvement (EI) methodologies was utilized to address the UAV wing design challenge with the objective of augmenting the L/D ratio. Employing with thorough iterations and strategic sampling based on LHS coupled with the evaluative power of EI, the optimization process efficiently traversed the design space. EGO's iterative refinement of the wing shape led to the identification of an optimal design, markedly enhancing the L/D ratio. The selected optimal design demonstrated a remarkable improvement of approximately 16.56% in L/D when compared to the initial design, highlighting the effectiveness of this integrated approach. This study underscores the potential and efficacy of harnessing EGO, LHS, and EI methodologies in optimizing UAV wing designs, ultimately achieving significant enhancements in aerodynamic performance.

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