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# 3 An efficient aerodynamic shape optimization of blended wing body UAV using multi-fidelity models

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## 10 **KEYWORDS**

- 12 Adaptive filter sequential 13 quadratic programing 14 (AFSQP); 15 Adaptive robust meta-model; 16 Aerodynamic shape opti-17 mization; 18 Blended wing body (BWB); 19 Move limit strategy;
- 20 Unmanned aerial vehicle 21 (UAV)

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Abstract This paper presents a novel optimization technique for an efficient multi-fidelity model building approach to reduce computational costs for handling aerodynamic shape optimization based on high-fidelity simulation models. The wing aerodynamic shape optimization problem is solved by dividing optimization into three steps—modeling 3D (high-fidelity) and 2D (lowfidelity) models, building global meta-models from prominent instead of all variables, and determining robust optimizing shape associated with tuning local meta-models. The adaptive robust design optimization aims to modify the shape optimization process. The sufficient infilling strategy known as adaptive uniform infilling strategy—determines search space dimensions based on the last optimization results or initial point. Following this, 3D model simulations are used to tune local meta-models. Finally, the global optimization gradient-based method—Adaptive Filter Sequential Quadratic Programing (AFSQP) is utilized to search the neighborhood for a probable optimum point. The effectiveness of the proposed method is investigated by applying it, along with conventional optimization approach-based meta-models, to a Blended Wing Body (BWB) Unmanned Aerial Vehicle (UAV). The drag coefficient is defined as the objective function, which is subjected to minimum lift coefficient bounds and stability constraints. The simulation results indicate improvement in meta-model accuracy and reduction in computational time of the method introduced in this paper.

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> an effort. In addition to the elimination of the tail for this par- 28 ticular kind of UAV and the significant reduction in equivalent 29 weight, drag force, and radar cross-section, the available space 30 for installing equipment inside the wing and the effective range 31

### 1. Introduction 23

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## CJA 1034<br>16 April 2018 10:00 10:00 No. of Pages 16

2 P. MOHAMMAD ZADEH, M. SAYADI

 have also been increased. Despite all these mentioned advan- tages, instability is the negative outcome of eliminating the tail. Correcting this flaw requires designing a combination of con- trol surfaces and reflexed wing sections and using sophisticated computer control systems. Therefore, the aerodynamic shape design optimization of BWBs, along with the need to meet the design requirements, has inspired several researchers to overcome its challenges.

 However, BWB and pure flying wing have some differences in definition; their optimization design approaches and some principles of aerodynamic design are practical for each other. The BWB design challenges along with necessity of developing aircraft efficiency impose more computational effort on the preliminary design process.

 Various objectives and different constraints in the design of BWB make them a proper candidate for the application of multi-objective and multi-disciplinary design optimization 49 techniques.<sup>[1,2](#page--1-0)</sup> The characteristics of their shape makes their geometry parameterization easier. A study on improving the Concurrent Subspace Optimization (CSSO) structure on the basis of response surface and Monte Carlo analysis for the robust, single-objective optimization of the flying wing was 54 conducted in this field.<sup>[3](#page--1-0)</sup> Multidisciplinary Design Optimization (MDO) architecture of aerodynamic shape optimization was developed for battery-powered composite BWB with Delta wing[.4](#page--1-0) The results of implementing this architecture and con- ventional optimization process were compared to demonstrate 9 the presented formulation. Pan et al.<sup>5</sup> presented a systematic technique in aerodynamic and stealthy MDO issue for double-sweep flying wing. They utilized the hybrid structure of global optimization and gradient algorithm as an optimiza-3 tion strategy in conceptual design. Morris et al.<sup>6</sup> devoted atten- tion to multi-disciplinary multi-level optimization for the simultaneous optimization of aerodynamic shape and structure.

 The mere design of the aerodynamic shape was the main objective of optimization in certain studies, while only the air-69 foil cross-section was the focus in some others.<sup>[7,8](#page--1-0)</sup> The defini- tion of geometry and surface meshing was investigated by 71 Truong et al. $\frac{9}{2}$  $\frac{9}{2}$  $\frac{9}{2}$  to enhance the quality of the mesh modified dur- ing optimization. The robust design of airfoil shape optimiza- tion is investigated to reduce the sensitivity of small random geometry perturbations and uncertain operational condi- tions.[10](#page--1-0) The construction of meta-models based on Kriging and gradient-enhanced Kriging is based on a relatively small number of CFD evaluations. Since the optimization of the fixed geometry aircraft demands satisfying conflicted con- straints in various flight conditions, aerodynamic shape opti- mization of morphing wing is the subject of the study by 81 Hunsaker et al.<sup>[11](#page--1-0)</sup> This method increases allowable wingspan with induced drag reduction for a given structural weight.

 In addition to putting forward an optimal Lifting-Fuselage Configuration (LFC) shape for BWB in the research by Reist 85 and Zingg, $12$  the aerodynamic shape was optimized for the best cruise altitude and reduced fuel consumption. In another study, the hybrid design of the aerodynamic shape and struc- ture of the flying wing was optimized by combining the multi-bump method with automatic optimization and flow control to increase the lift-to-drag ratio and improve longitu-91 dinal static stability.<sup>[13](#page--1-0)</sup> The presented approaches differ mainly in the definition of the geometry of the problem, objective

functions, optimization constraints,  $\frac{14}{4}$  $\frac{14}{4}$  $\frac{14}{4}$  and finally, the accuracy 93 of the adopted models.  $15 \times 94$  $15 \times 94$ 

In complicated engineering design problems such as BWB, 95 Surrogate-Assisted Optimization (SAO) methods have been 96 developed to enhance the accuracy and reliability of optimiza- 97 tion process.<sup>[16](#page--1-0)</sup> In particular, due to the high computational  $\frac{98}{100}$ cost of solving the CFD models, the researchers use the 99 meta-model in aerodynamic optimizations.  $14,17,18$  However, 100 constructing accurate meta-model would still be time- 101 consuming and is often associated with insufficient accuracy 102 in order to ensure a great degree of change in variables and 103 the presence of local extrema for the objective and constraint 104 functions. 105

The concept of sequential approximation method is intro-<br>106 duced to overcome the mentioned limitations of the meta- 107 models imposed by large-scale and complex design space.  $\frac{19}{108}$  $\frac{19}{108}$  $\frac{19}{108}$  108 The simulation outcomes show that building appropriate 109 low-fidelity model reduces the computation costs and improves 110 model accuracy. Using the response correction techniques for 111 aerodynamic shape optimization introduced by Koziela et al.<sup>[7](#page--1-0)</sup>,  $\qquad$  112 the precision of the alternative models derived from low- 113 accuracy models is improved. An automated selection of 114 low-fidelity model for aerodynamic shape optimization is pro-<br>115 posed in another study.<sup>[20](#page--1-0)</sup> This approach utilizes low- and high-<br>116 fidelity model misalignment. 117

In the variable-fidelity shape optimization, the hierarchical 118 kriging technique is utilized for modifying low-fidelity kriging 119 model. $^{21}$  $^{21}$  $^{21}$  Since the low-fidelity model is constructed based on a 120 single design point, some weighted aerodynamic data correct 121 the meta-model as high-fidelity data. Other studies consider 122 the effects of boundary layer transition for optimizing the 123 shape of a lifting body with adjustment of the meta- 124 models. $^{22}$  $^{22}$  $^{22}$  The sample selection method for correcting the 125 model plays a key role in such architectures.<sup>[23](#page--1-0)</sup> Maximizing 126 the Expected Improvement function  $(EI)$ ,  $^{24}$  $^{24}$  $^{24}$  Probability of 127 Improvement function (PI), and the Mean Squared Error 128  $(MSE)^{25}$  $(MSE)^{25}$  $(MSE)^{25}$  and minimizing the Lower Confidence Bound 129  $(LCB)^{26}$  $(LCB)^{26}$  $(LCB)^{26}$  are some examples of these methods—known as infill-<br>130 ing strategies. 131

K-means algorithm classifies the solutions for selecting 132 points and modifying the database of the meta-model, whereas 133 genetic algorithm is tasked with optimization of the aerody- 134 namic shape.<sup>[27](#page--1-0)</sup> The application of the parallel processing capa- $135$ bilities to the optimization of aerodynamic problems is 136 facilitated by combining these techniques in order to mitigate 137 the defects of each. $23,28$  138

The other method for reclaiming local adaptive meta-model 139 building is the move-limit strategy. The main merit key of these 140 approaches is the suppression off design space in the current 141 optimum point neighborhood and refining of the model in this 142 space. The vital importance of selecting the move limit strategy 143 is controlling optimization performance. These strategies— 144 both fixed<sup>[29](#page--1-0)</sup> and adaptive<sup>30</sup>—differ from one another by differ-<br>145 ent bound-adjustment methods. $31$  Among them, the global  $146$ convergence can be achieved by utilizing the trust-region 147 method.  $32 \times 148$  $32 \times 148$ 

On the other hand, the selection of design variables in shape 149 optimization has an important effect on the appropriate cover- 150 ing design space and reduction of computational cost. Poole 151 et al. $33$  proposed a novel method for the proper orthogonal  $152$ decomposing set of training airfoils, which increase the num- 153 Download English Version:

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