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Multidisciplinary Design Optimization of UAV Under Uncertainty

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ABSTRACT: Uncertainty-based multidisciplinary design optimization considers probabilistic variables and parameters and provides an approach to account for sources of uncertainty in design optimization. The aim of this study was to apply a decoupling uncertainty-based multidisciplinary design optimization method without any dependence on probability mathematics. Existing approaches of uncertainty-based multidisciplinary design optimization are based on probability mathematics (transformation to standard space), calculating an approximation of the constraint functions in standard space and finding the most probable point, which is the best possible one. The current approach used in this paper was inspired on interval modeling, so it is good when there is insufficient data to develop a good estimate of the probability density function shape or parameters. This approach has been implemented for an existing Unmanned Aerial Vehicle (UAV, Global Hawk) designed for purposes of comparison and validation. The advantages of the provided approach are independence of probability mathematics, appropriate when there is insufficient data to approximate the uncertainties variables, appropriate speed to calculate the best reliable response, and proper success rate in the presence of uncertainties.

KEYWORDS: Uncertainty-based multidisciplinary design optimization, MDO, Systemic design, Unmanned Aerial Vehicles design.

INTRODUCTION

Uncertainty existing at the early phases of the design process influences the system reliability. It is important to manage error early in the design process to decrease the redesign likelihood. Designing complicated and large systems such as aerospace vehicles requires appropriate compromise for gaining balance between multiple coupled targets. The targets include high performance and low costs. The sooner these compromises are understood in design process, the more technology, programming, and cost-related risks can be minimized. There are complicated relationships existing between assignment requirements, constraints, design sub-systems and contradicted targets, which could be coordinated using a suitable strategy of optimization. Multidisciplinary design optimization (MDO) or coordination between multidisciplinary analyses makes understandable more effective solutions during design and optimization of complicated systems. This allows system engineers to look for a vast scope of compromise in a systematic and thoughtful way and to consider more structures in conceptual design phase and before concentrating on final design.

Preliminary application of optimization in aerospace industries is accompanied by optimization of sub-systems or components such as aerodynamic shape, orbital path, as well as optimization of sub-systems altogether. Anyway, an optimized systemic compound will not be always created through optimization of sub-systems. In aerospace engineering, MDO was first applied in design of airplanes and to date the method has been used in academic papers and manufactured airplanes (Geethaikrishnan 2003).

In Olds (1993), González *et al.* (2005), Morris and Kroo (1990), Raymer (2002), Çavuş (2009), Neufeld (2010), Hendrich

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(2011), Giunta (1997), Buonanno (2005), Iqbal (2009), Mattos and Secco (2013), Eisler (2003), Rowell *et al.* (1999), Goraj (2005), Lee *et al.* (2007), Tianyuan and Xiongqing (2009), Jaeger *et al.* (2013), Ahn *et al.* (2002), Perez *et al.* (2004), Sóbester and Keane (2006), Lee *et al.* (2009), Choi *et al.* (2010), Zill *et al.* (2011), and Tekinlap and Cavus (2012), the airplane conceptual designing is done by taking advantage of MDO. In these references, all fighter, passenger, and conventional planes, as well as Unmanned Aerial Vehicles (blended wing body and conventional) are considered. In a systemic attitude towards previous studies, the applied design algorithms are: MDOs in different frameworks, such as All at Once (AAO), Multiple Discipline Feasible (MDF), Collaborative (CO), and Bi-level Integrated System Synthesis (BLISS), which are made compatible to different optimization methods like evolutionary algorithms and Steepest Descent. Mostly, design criteria are minimum-cost, minimum-weight, and minimum-drag under constraints of scenario performance and functional capability. New researches started to study and develop novel design methods, applying optimized and efficient frameworks in various fields. Aerospace science is included in a way that the application of MDO methods with various single- or multi-level frameworks in aerospace vehicles — such as airplane, launch vehicles, and satellites — is seen referring to reliable papers, being considered as a current theme up to date. Aircraft design under uncertainty has been the subject of some recent studies too. In Ahn and Kwon (2006), it was introduced a BLISS based on Reliability-Based Design Optimization (RBDO) framework to design a simplified supersonic transport problem (Ahn and Kwon 2006; Sobieszczanski-Sobieski *et al.* 2000). The study assumed normal distributions with coefficients of variation equal to 0.3 (the ratio of the mean to standard deviation) on each of the 10 design variables considered such as wing area, span, and others describing aircraft geometry. In Smith and Mahadevan (2003), it was solved a spacecraft conceptual optimization problem using RBDO to consider uncertain design variables, reflecting the possibility of minor design changes later in the design process. Probabilistic error terms were added to the responses of the aerodynamics and structural analysis output with assumed values of 10%. The optimization problems were solved with several MDO architectures and First-Order Reliability Method (FORM) based reliability analysis methods. The aforementioned studies consider uncertainties in the design variables or parameters such as atmospheric conditions or material properties.

This study aimed to introduce the decoupling of Uncertainty-based Multidisciplinary Design Optimization (UMDO) method, applying it to design UAVs as a case study. The following section introduces UMDO methods. Then, it is developed UAV decoupling UMDO algorithm, based on MDO method in single-level frameworks (MDF), using genetic algorithm optimization and sequential quadratic programming (SQP). In the section "Implementation of Uncertainty-Based Multidisciplinary Design Optimization Methods and Their Comparison", the redesign of Global Hawk UAV was made using prepared algorithm, and the comparison was carried out between MDO and UMDO while validating the results.

UMDO METHODS

MDO is a branch of engineering science that applies optimization methods for solving design problems with multiple contexts and themes with coupled parameters. The method is called multidisciplinary optimization or Multidisciplinary System Design Optimization (MSDO). The method allows designers to consider related themes simultaneously (Olds 1993). Any deviation in the designer's assumptions (*i.e.*, the material strength or the manufacturing precision of a structural member) or approximate analysis methods may result in the failure of the optimized design because the results take place in feasibility bound.

Any design variable, parameter, or any output from analysis codes in a given optimization problem can be considered as uncertain quantities provided that the uncertainty can be mathematically represented. Uncertainty at the early phases of the development exists due to the limited knowledge concerning the system characteristics and due to the low-fidelity simulations and analyses performed. UMDO methods are recent, still under development, and partially applied in conceptual phases. Many methods currently exist for quantifying the behavior of aleatory and epistemic uncertainty. The methods most often applied in design optimization are interval analysis, fuzzy numbers, and probability theory. The choice of the method is driven by the quantity of information available to the designer about the source of uncertainty. In general, sources of uncertainty in which there is insufficient data to accurately estimate a probability density function (PDF), interval analysis or fuzzy numbers are preferred (Hu and Qiu 2010; Schueller and Jensen 2008; Hajela 2002; Vittal and Hajela 2003). UMDO process relies on 2 steps (Fig. 1): uncertain system modeling and UMDO procedure.

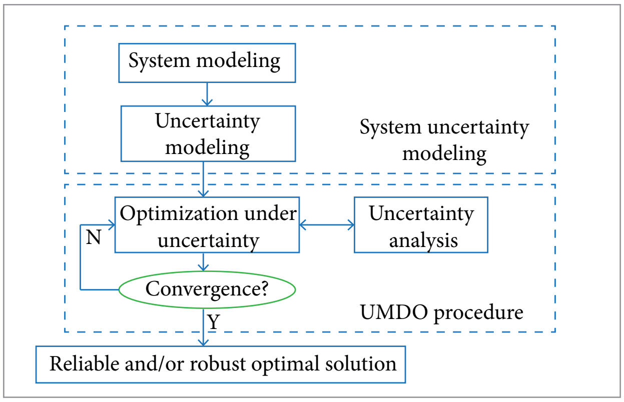

Figure 1. UMDO process (Yao *et al.* 2011).

The first phase of the process consists on desired system and mathematical uncertainty modeling; the second phase includes optimization in the presence of uncertainty, resistance, and uncertainty analysis, as well as the reliability of the answer. UMDO should match the mathematical uncertainty modeling (probability theory, possibility, etc.) and type of design algorithm (AAO, MDF, CO, etc.). In an optimum problem designing, the failure of the plan will be determined by the problem constraints. If these constraints are identified by uncertainty variable, the output of the constraints will have some uncertainty. There are 2 ways to resolve the issue through reliability strategies: nested and decoupling approaches.

In the first method (nested approach), reliability analysis is carried out through optimization cycles for feasibility in the presence of uncertainty. For this purpose, at each iteration of optimizer, reliability analysis is carried out through uncertainty modeling in the parameters in mind. One of the theories available can be used for uncertainty modeling (probability theory, possibility, etc.). Depending on the use of existing theories for uncertainty modeling, there are 2 cases (Rao and Cao 2002):

- RBDO: in this method, the probability theory is used for uncertainty modeling. This technique allows the propagation of uncertainty (given probability density function of variables) in the design process to determine their influence on the final answer (Rao 1992). For uncertainty analysis in RBDO strategy, there are various methods such as first- and second-order analysis (first-order reliability method — FORM and second-order reliability method — SORM). In this method, all design variables are mapped to normal distribution space, then the minimum distance between the design point and feasibility boundary is calculated. The point in the border of feasibility nearest to the design point is known as MPP. The distance between the design point and MPP is called reliability (β) of the desirable value which is determined by the designer and must have a minimum value. Several methods are used to calculate the MPP and β such as performance measure approach (PMA) and reliability index approach (RIA). These methods are based on FORM but differ in methods of finding MPP (Yu *et al.* 1997; Tu *et al.* 1999).
- Possibility-Based Design Optimization (PBDO): when there is not enough information about the uncertainty of design variables, PBDO is appropriate. In this method, the interval or fuzzy theory is used for uncertainty modeling, and interval or FORM-based optimization methods are applied. In general, the results of this method compared to RBDO are the more stable (Du *et al.* 2006).

Finally, to check the reliability of the obtained optimal solution, uncertainty analysis can be used.

In the second method (decoupling approach), optimization cycles and reliability analysis are separated. For this purpose, 4 steps are carried out:

1. Optimization without uncertainty.
2. Uncertainty analysis on the found answer from step 1 by applying the uncertainty on the desired parameters of the issue.
3. Convergence: if the uncertainties violate the possibility of the answer, a reliable optimal solution is obtained.
4. Lack of convergence: if the uncertainties violate the possibility of the answer, a shifting vector of the answers must be found for feasibility. Then step 3 is carried out again.

The important thing in this method is finding the shifting vector of answers in a way that the least number of repetitions are needed. One of the ways to find shifting vector is using PMA method to find MPP for each constraint. In this case, the difference between optimal solution without uncertainty and the answer located at the MPP is considered as a shifting vector, and this cycle continues to achieve reliable optimal solution (Du and Chen 2004). In finding shifting vector, the designer's experience can be very effective.

UAV DECOUPLING UMDO ALGORITHM

Before presenting the design algorithm, it is necessary that various parts of the UAV design be identified, modeled, and transformed into a software code. Other subjects involved in design are: aerodynamic, structure, propulsion, and path simulation.

INTEGRATED DESIGN ALGORITHM WITH UMDO METHOD

UAV design includes, respectively, 11, 15, and 11 common, uncommon, and coupled parameters (a total of 37) in addition to 33 constraints. The above design algorithm, mission definition, and flight scenario exist within which the following parameters are determined: payload geometrical specification and mass; cruise phase speed, altitude, and range; loiter phase speed, altitude, and duration; in addition to stall speed. Optimization methods applied in system level is a combination of genetic algorithm and SQP, taking the number of design parameters and related constraints into consideration. Combining these 2 methods makes the optimized point resulted from genetic algorithm using SQP method more accurate.

Figure 2 presents UAV's multidisciplinary design optimization algorithm in MDF structure, in which an optimizer is located at system level within which UAV design parameters (a total of 37) are achieved in a way that, observing the problem's constraints (a total of 33), optimization criterion (overall mass of the UAV) becomes minimum.

In order to expedite design algorithm and maintain a better convergence, constraints are prioritized, and a certain value is added to the criterion function against any of these priorities not being observed. This way, optimization algorithm will satisfy constraints while minimizing criterion function. Constraints are prioritized according to their importance: 1) geometrical constraints; 2) constraints related to minimum required thrust; 3) constraints related to minimum require lift; 4) static stability constraints; 5) load coefficient constraints; 6) propulsion mass constraints; and 7) constraints related to performing an mission.

In this framework, disciplines would be feasible through multidisciplinary analyses and internal cycles between coupled sub-systems. In other words, internal cycles between coupled sub-systems are continued till all disciplines are feasible in each optimizer evaluation.

The uncertainty of some of these parameters, such as the aerodynamic ones, according to the theory used, is available in the references; however, for the rest of the parameters, there is no authoritative reference. Thus, according to the authors' experience, sources of uncertainty and their values (3σ) are considered in this work as follows:

- Environmental uncertainties include gravity (5% of nominal value) and density (5% of nominal value).
- Uncertainties of the appliance model include mass (5% of nominal value), fuel consumption (5% of nominal value), aerodynamic coefficients (10% of nominal value [5, 17]), and thrust (5% of nominal value).

To provide design algorithm in the presence of uncertainties, it is necessary to identify the sources of the uncertainty. According to the given description, all design methods are based on reliability on

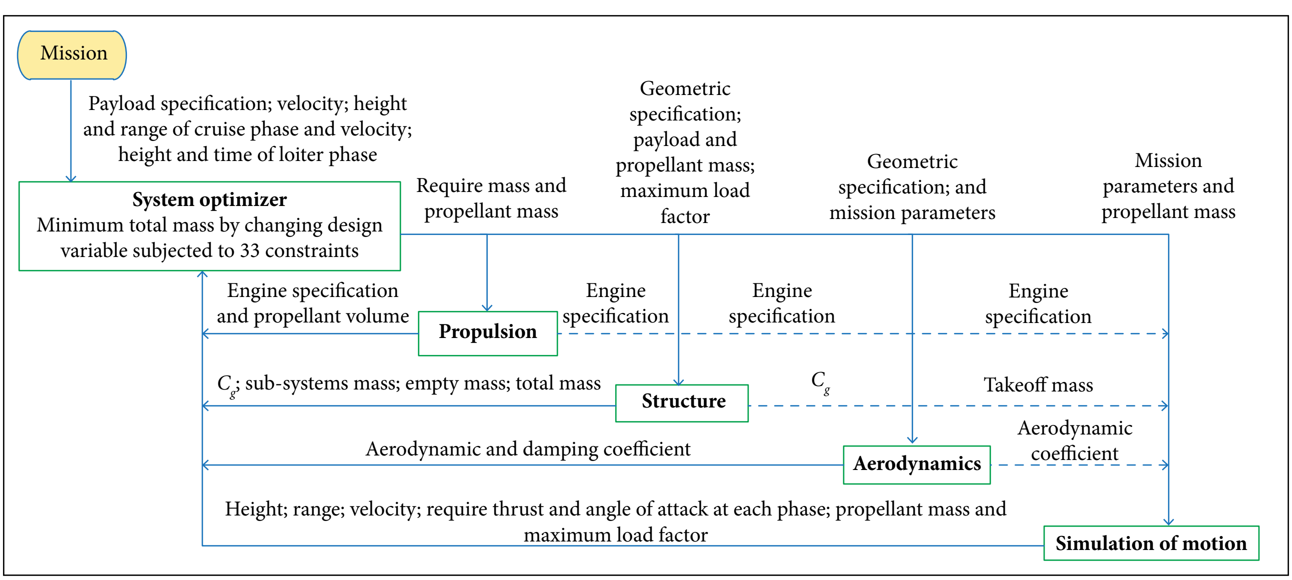

Figure 2. Multidisciplinary design optimization of UAV.

the basis of the mathematics of uncertainty (mapping to a normal distribution space), calculating the border of feasibility and the nearest point from it with a point (MPP). Since the constraints defined in the current problem of UAV are in a way that there is no clear feasibility border, using such methods is very difficult. Here it is presented the method for UAV multidisciplinary optimal design in the presence of uncertainties, which is based on the evolutionary algorithm. The advantage of this method compared to introduction ones is its independence from mathematics of uncertainty and no need for calculating the feasibility border. To perform the design in the presence of uncertainties, the following steps should be taken separately:

1. Optimization without uncertainty (Table 1-3).
2. Uncertainty modeling by the found answer from step 1 as follows: the worst case of uncertainty in a definite range for any constraint is calculated by an optimization algorithm as below. The parameters of optimization algorithm are uncertainty values, and optimization criteria maximize the impossibility of any constraint (for example, minimizing the duration of the flight or an increase in instability). The optimization algorithm in this method, like the original optimization algorithm, is a combination of genetic algorithm and SQP. Therefore, its output will be the set of the worst uncertainties for each constraint):
Maximize constraint(i), (i = No. of constraints)
By changing (7 parameters): U_T, U_{SFC}, U_{We}, U_{CD}, U_{CL}, U_g, U_ρ
3. Convergence: uncertainty analysis by applying the set of the worst uncertainties on the parameters of the problem. If the uncertainties do not violate the possibility of the answer, a reliable optimal solution is obtained.

Table 1. Optimization without uncertainty (step 1). Fitness function.

Fitness function	Function name
Minimize takeoff weight in order to below mission parameters	
V_{Cruise}	Cruise velocity
H_{Cruise}	Cruise height
R	Range
V_{Loiter}	Loiter velocity
H_{Loiter}	Loiter height
E	Endurance
Payload specifications	
V_S	Stall speed
R_N	Nose radius

Calculate & check constraint(i), (i = No. of constraints)
in order to mission parameters (V_{Cruise}, H_{Cruise}, R, V_{Loiter}, H_{Loiter}, E, Payload Specifications, V_S, R_N)
& Uncertainty value ($U_i = [U_T, U_{SFC}, U_{We}, U_{CD}, U_{CL}, U_g, U_\rho]$) for $i = 1, 2, \ldots, n_c$
& Optimum design variable: X_W, C_{rW}, C_{tW}, b_W, R_B, L_B, Λ_W, C_{rH}, C_{tH}, b_H, Λ_H, C_{rV}, C_{tV}, b_V, Λ_V, i_P, Z_W, i_W, i_H, L_N, L_A, Θ_W, Γ_W, Θ_H, Γ_H, Z_{CG}, W_F, T, n

Table 2. Optimization without uncertainty (step 1). Design variable.

Design variable	Variable name
C_{rW}	Wing root chord
C_{tW}	Wing tip chord
b_W	Wing span
R_B	Body radius
L_B	Body length
Λ_W	Wing sweep
C_{rH}	Horizontal tail root chord
C_{tH}	Horizontal tail tip chord
b_H	Horizontal tail span
Λ_H	Horizontal tail sweep
C_{rV}	Vertical tail root chord
C_{tV}	Vertical tail tip chord
b_V	Vertical tail span
Λ_V	Vertical tail sweep
i_P	Propulsion system incidence
Z_W	Wing vertical position
i_W	Wing incidence
i_H	Horizontal tail incidence
L_N	Nose body length
L_A	Aft body length
Θ_W	Wing twist
Γ_W	Wing dihedral
Θ_H	Horizontal tail twist
Γ_H	Horizontal tail dihedral
Z_{CG}	Vertical position of gravity center
W_F	Fuel weight
T	Thrust
N	Load factor

4. Lack of convergence: if the uncertainties violate the possibility of the answer, a shifting vector of the answers, appropriate for the violated constraint, must be found for feasibility — for example, if the constraints related to flight time requirements is not met. The difference between the required fuel and the available one will be added to the latter (required fuel is the output of movement simulation), then step 3 is carried out again.

After designing in the presence of uncertainty, its analysis using the Monte Carlo method is performed to check the final answer. The UAV multidisciplinary optimal design algorithm in the presence of uncertainties is presented in Fig. 3.

UAV design algorithm in the presence of uncertainties was transformed into a software code; through it, the results of re-designing UAV — Global Hawk (RQ-4B) — in the presence of the uncertainties are presented. The results of UAV design have been compared without the presence of uncertainties.

Table 3. Optimization without uncertainty (step 1). Constraints.

Constraints
$V_{PL} + V_F < V_W + V_b$
$b_W > 2R_B$
$b_H > 2R_B$
$b_V > 2R_B$
$C_{tW} < C_{rW}$
$C_{tH} < C_{rH}$
$C_{tV} < C_{rV}$
$Z_W < R_B$
$X_W + C_{rW} < 0.8L_B$
$L_N < 0.5L_B$
$L_A < 0.5L_B$
$C_{m_\alpha} < 0$ without fuel and external payload
$C_{n_\beta} > 0$ without fuel and external payload
$C_{m_\alpha} < 0$ without fuel and with external payload
$C_{n_\beta} > 0$ without fuel and with external payload
$C_{m_\alpha} < 0$ with fuel and without external payload
$C_{n_\beta} > 0$ with fuel and without external payload
$C_{m_\alpha} < 0$ with fuel and external payload
$C_{n_\beta} > 0$ with fuel and external payload
$W_{F\,Opt} > W_{F\,Required}$
$n_{Opt} > n_{Calculated}$
Lift > W_{TO} in stall speed
Lift > W_{TO} in cruise speed
Lift > $W_{TO\text{ in loiter speed}}$
$T > T_{\text{Calculated in stall speed}}$
$T > T_{\text{Calculated in cruise speed}}$
$T > T_{\text{Calculated in loiter speed}}$
$V_{Cruise} = V_{Cruise\text{ calculated in simulation}}$
$H_{Cruise} = H_{Cruise\text{ calculated in simulation}}$
$R = R_{\text{Calculated in Simulation}}$
$V_{Loiter} = V_{Loiter\text{ calculated in simulation}}$
$H_{Loiter} = H_{Loiter\text{ calculated in simulation}}$
$E = E_{\text{Calculated in simulation}}$

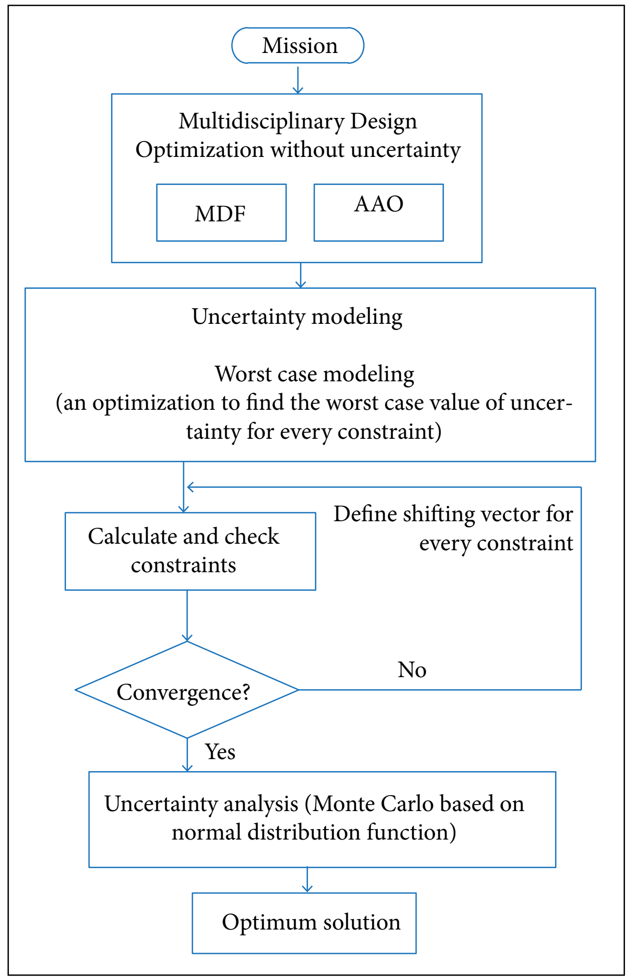

Figure 3. UAV MDO algorithm in the presence of uncertainties.

IMPLEMENTATION OF UMDO METHODS AND THEIR COMPARISON

The results of the MDO algorithm in MDF structure and decoupled method are provided for Global Hawk UAV in the rest of the paper, and parameters such as total mass, runtime code, and the percentage of success have been compared.

To do so, mission information of this UAV was considered as design code input and the output extracted. Then, outputs were compared to real UAV information. Code inputs for Global Hawk redesign are: 575 km/h of velocity cruise, 28 h of flight endurance, maximum altitude of 18 km, and payload mass of 1,360 kg.

In Table 4, by the percentage of success, we wonder what is the percentage of likelihood of fulfillment of all constraints (as explained in previous seasons) in the presence of uncertainty for the final design. As seen in this table, result differences in MDF method with existing information from Global Hawk are between 13 – 23% in mass and less than 9% in geometrical specifications. The following points could be referred to as the reasons for these differences:

- Lack of sufficient information about Global Hawk flight scenario.
- Lack of information about airfoil and lifting instruments at the time of takeoff and landing.
- Lack of information about accurate stall speed and some of functional parameters.
- Lack of information about payload geometric specifications, sub-systems layout, and fuel.
- Lack of consideration of uncertainties.

Convergence procedure in MDF frameworks is shown in Fig. 4. As can be seen, the success rate of optimal response from MDF algorithm (without uncertainty) is 51 and 100% for decoupled method. The run time of this code in decoupled method is 1,600 s more than the MDF algorithm (without uncertainty). The total mass obtained from the decoupled method is 1,974 kg more than that of the MDF algorithm.

Table 4. Outputs of design code for Global Hawk redesign in presence of uncertainty.

Section	Value		
	Real value	MDF	Decoupling approach
Wing span (m)	39.9	39	39
Wing area (m²)	63.02	68.2	68.25
Body diameter (m)	1.42	1.28	1.3
Body length (m)	14.5	14.5	14.5
Empty mass (kg)	5,868	5,229	5,538
Takeoff mass (kg)	14,628	12,159	14,133
Propellant mass (kg)	7,400	5,570	7,235
Time of optimization(s)	-	21,507	23,107
Percentage of success	-	51	100

The total mass obtained from the optimal design algorithm in the presence of uncertainties in decoupled method is 14.1 t. This means that, to compensate the failure probability in multidisciplinary optimal algorithm without uncertainties, the mass is increased in order to increase the success chance from 51 to 100%, considering that the uncertainties have also resulted in less difference between the obtained responses and the real values. Regarding the obtained result, although designing without uncertainties in a more optimal way, it is not reliable.

In Figs. 5 and 6, the results of the Monte Carlo analysis are presented for thousands of performances. In Fig. 7, it is observed the 3-D view; in Fig. 8, the presented charts resulted from redesigned UAV simulation of motion.

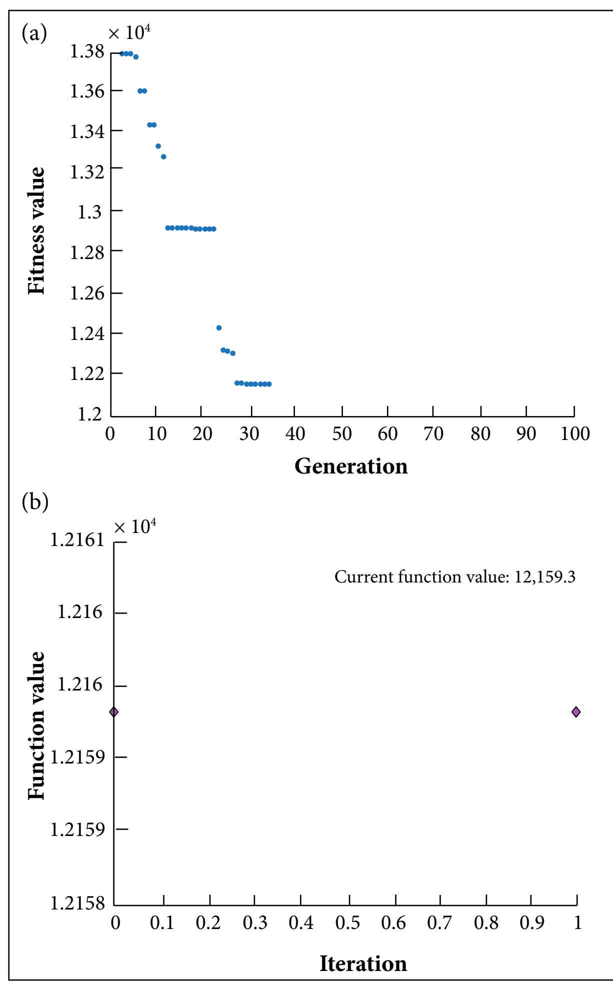

Figure 4. (a) Convergence trend in GA algorithm ; (b) SQP.

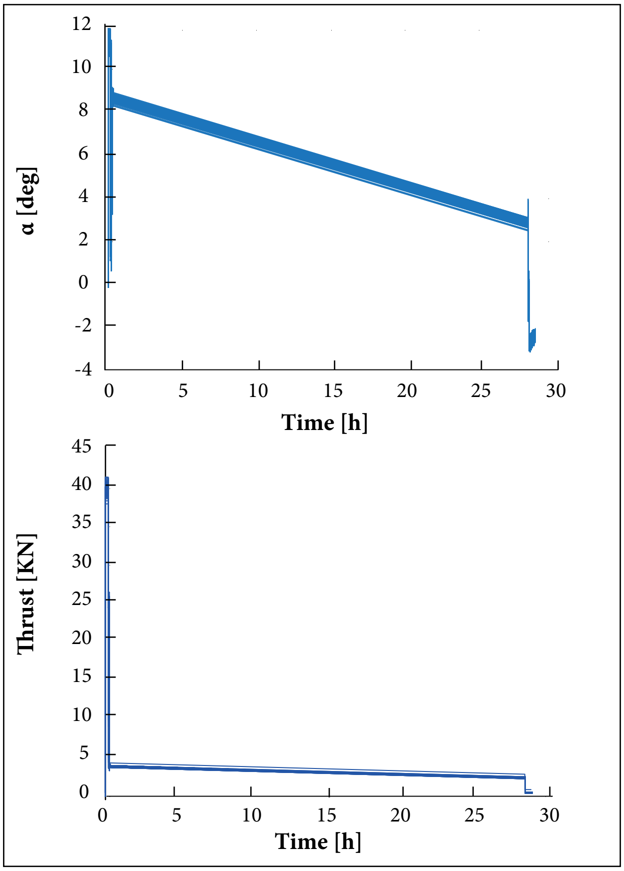

Figure 5. Monte Carlo analysis: angle of attack and thrust *versus* time.

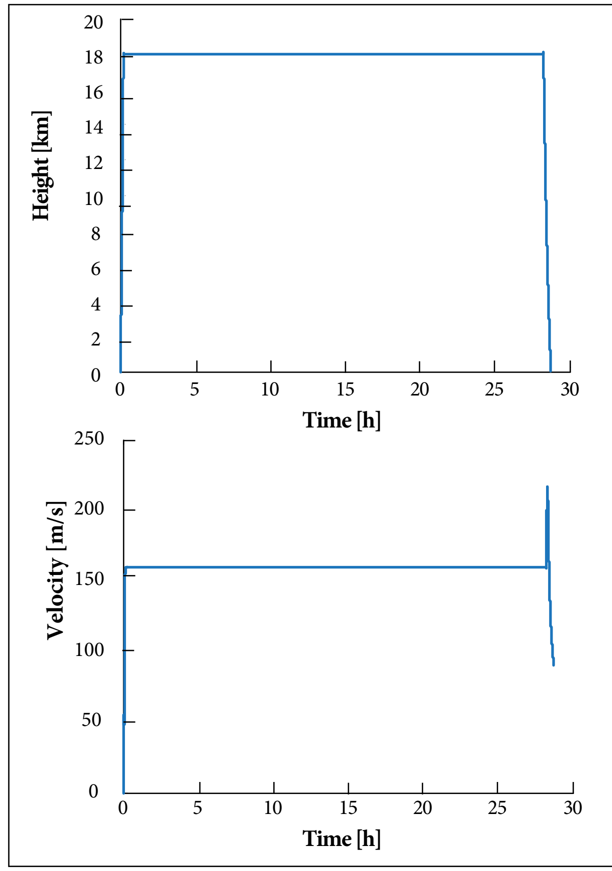

Figure 8. Height and velocity *versus* time.

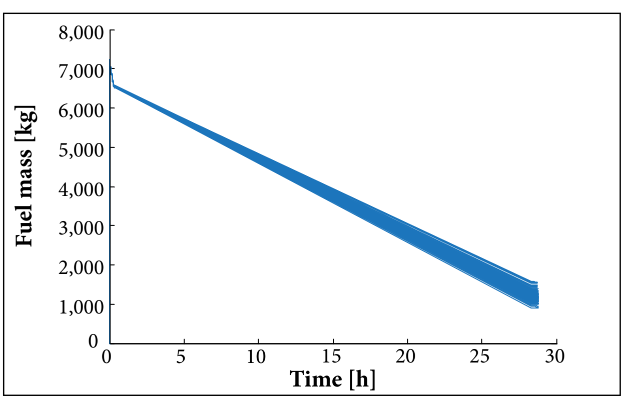

Figure 6. Monte Carlo analysis: fuel consumption *versus* time.

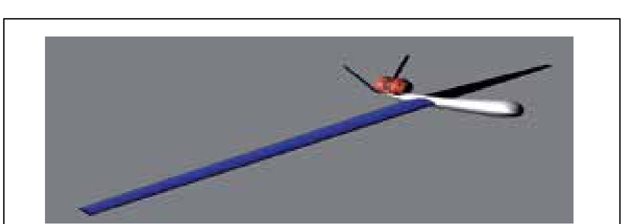

Figure 7. 3-D view of the redesigned UAV.

CONCLUSION

The present study introduced MDO and UMDO frameworks in UAVs, implemented and compared as a case study. To this aim, sub-systems and disciplines involved in design were modeled, and a proposed algorithm for conceptual design of UAV was developed based on multidisciplinary optimization method in MDF framework, using genetic algorithm optimization method and SQP. This algorithm includes 11 common parameters, 15 uncommon parameters, 11 coupled parameters (a total of 37) and 33 constraints.

Regarding the results achieved from MDO in the presence of uncertainties for operational UAV, the results are explained as:

- The comparison of the code outputs, results of the movement simulation, and Monte Carlo analysis for multidisciplinary optimal design code output in the presence of uncertainties indicates the correctness and reliability of results of the proposed algorithm.

- To compensate the failure probability in multidisciplinary optimal algorithm without uncertainties, the mass is increased in order to increase the success chance to 100%.

The advantages of the provided approach are: independence from probability mathematics, appropriate when there is insufficient data to approximate the uncertainties variables or develop a good estimate of the probability density function shape, appropriate speed to calculate the best reliable response, and proper success rate in the presence of uncertainties.

Totally, regarding the presence of the uncertainties in the real world, it is better to consider the mass increase penalty in order to increase the reliability of the design. With the help of this algorithm, we can, according to the defined operation for the UAV and the level of uncertainties of the proposed models in the design, achieve a reliable and optimal answer in the conceptual design phase with the least time and highest accuracy.

AUTHOR'S CONTRIBUTION

Hosseini M and Nosratollahi M, conceived the idea and co-wrote the main text; Hosseini M, prepared the tables and figures. All authors discussed the results and commented on the manuscript.

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