A Multidisciplinary Robust Optimization Framework for UAV Conceptual Design

Nhu Van Nguyen[1], Tyan Maxim[1], Hyeong-Uk Park[2], SangHo Kim[1], and Jae-Woo Lee[1]

[1]Aerospace Information Eng. Dept., Konkuk University, Seoul, 143-701, Korea
[2]Department of Aerospace Eng., Ryerson University, Toronto, Canada

Abstract

This paper describes a multidisciplinary robust optimization framework for UAV conceptual design. An in-house configuration designer system is implemented to generate the full sets of configuration data for a well-developed advanced UAV® analysis tool. Fully integrating configuration designer along with the UAV analysis tool ensures that full sets of configuration data is provided simultaneously while the UAV configuration changes during optimization. A robust design process is formulated as defining a new objective function which consists of adjusted mean and variance function, then integrated into UAV analysis tool and optimizer. The computational strategy for probabilistic analysis is proposed by implementing a central difference method and fitting distribution for a less Monte Carlo Simulation sampling points. The minimization of a new robust design objective function helps to enhance the reliability while other UAV performance criteria are satisfied. The robust framework provides a robust optimal UAV configuration. In addition, the fully integrated process and a probabilistic analysis strategy method demonstrate reduction in the failure probability under noise factors without any noticeable increase in design turnaround time. The proposed robust optimization framework for UAV conceptual design case study yields a more trustworthy prediction of the optimal configuration and is preferable to the traditional deterministic design approach.

Keywords: *Robust Design Optimization (RDO), Uncertainty Design, Multidisciplinary Design Optimization (MDO), Unmanned Aerial Vehicles (UAVs), Sensitivity analysis*

Nomenclature

η_{prop}	=	Propeller efficiency
$\sigma^2_{\hat{y}}$	=	Adjusted variance
$\mu_{\hat{y}}$	=	Adjusted mean function
β	=	Propeller pitch angle
ΔC_{df}	=	Increase drag due to flap deflection
C_L	=	Lift coefficient
C_{Lmax}	=	Maximum lift coefficient
C_{Do}	=	Parasite drag coefficient
C_{Di}	=	Induced drag coefficient
C_{β}	=	Static lateral derivative
$C_{n\beta}$	=	Static directional derivative
$C_{m\alpha}$	=	Static pitching derivative
C_T	=	Thrust coefficient
k	=	Induced drag factor
J	=	Propeller advanced ratio
L/D	=	Lift to drag ratio
R/C	=	Rate of climb
SM	=	Static Margin
S_{to}	=	Takeoff distance
S_{land}	=	Landing distance
S_W	=	Wing area
PCT	=	Power Setting
T_{var}	=	Target variance
T_{μ_y}	=	Target mean value
V_{stall}	=	Stall speed
V_{max}	=	Maximum speed
V_{design}	=	Design flight speed
W_e	=	Empty weight
W_o	=	Takeoff gross weight
MALE	=	Medium Altitude Long Endurance
MCS	=	Monte Carlo Simulation
UAV	=	Unmanned Aerial Vehicle
z_i	=	Noise factors
WOT	=	Wide Open Throttle

1. Introduction

A recent trend in aircraft conceptual design activity is to develop or to implement the quick and accurate design analysis tools for seeking the deterministic optimal design solutions by compromising many complex and highly-coupled subsystems and disciplines [1] with the help of optimization algorithms. The optimal results from conceptual design stage play an extremely important role to the next preliminary and detailed design stage. However, the nondeterministic nature of the complex aircraft design problem and the importance of the modeling the human designer's decision making activities have been largely neglected [2] at the conceptual design stage. For example, the design flight speed is required as a design variable to maximize the aircraft critical performance features at conceptual design of Medium Altitude Long Endurance (MALE) UAV. The design flight speed might be slightly changeable during very long endurance or it might be affected by the wind. In addition, the round off of main geometry parameters during constructing the mathematical models or manufacturing stage and the lack of knowledge might lead to the variations in the conceptual optimal design solutions. These sources are called the uncertainty or unexpected derivations. The robust design is applied to prevent such phenomena [3]. The robust design has been recognized and applied in control system design and structural design as the state-of-the-art for those particular fields. Doltsinis et al. applied the robust design to minimize the expected value and standard derivation of the objective function in structure design [4]. The Dimitri N. Mavris et al. implements the Robust Design Simulation (RDS) in the high-speed civil transportation to show why a probabilistic approach to aircraft design is preferable over the traditional deterministic approaches [2]. H.U Park et al. applied the robust design process for the Very Light Jet (VLJ) design optimization [5] that improves VLJ performance quality while considering the noise factors of aircraft speed and flight altitude. Wet Chen et al. applies the robust design for improving vehicle handling performance. The proposed process using robust design is effective for preventing the worst maneuver condition and a range of maneuver inputs as well [6]. In addition, Wet Chen et al. presents a flexibility for robust design process to provide more freedom to the discipline that takes the role of follower [7]. Xiaoping Du et al. evaluated an efficient uncertainty analysis methods for multidisciplinary robust design comparing with conventional Monte Carlo simulation approach [8]. The system uncertainty analysis (SUA) method and the concurrent subsystem uncertainty analysis (CSSUA) method are proposed and developed to estimate the mean and variance of system performance subject to uncertainties or noise factor [7] under multidisciplinary design optimization (MDO) environment. The robust design is also applied in structure design problem. Doltsinis et al. introduces a robust design framework for multi-criteria structure design problem in which the sensitivities of mean values and the variance of structural performance function according to design variable are calculated in optimization task [9]. Eric Sandgren et al. presents an optimal structure design with load, material properties, and geometry uncertainty consideration [10]. The Monte Carlo simulation is embedded with a genetic algorithm for outputs distribution simulation. The optimal structure design shows the better map with designer's intent [10].

In this study, a MALE UAV is considered as a design application. There are several uncertainty parameters affected to UAV performance, especially to endurance such as a flight altitude, speed, wind effect, and propeller efficiency during cruise condition. Therefore, the multidisciplinary robust optimization framework for Unmanned Aerial Vehicles (UAVs) conceptual design is developed and proposed to enhance UAV performance result quality that is less sensitive to UAV performance variations while minimizing the effects of noise factor. The deterministic and robust optimum configuration with probabilistic analysis results are presented to demonstrate a robustness and more trustworthy UAV performance improvement compared with a traditional deterministic optimization approach without considering noise factors.

2. Robust Design Optimization (RDO) Framework

Robust design optimization framework is presented in Figure 1 which includes a deterministic, RDO formulation, analysis & optimizer, and probabilistic analysis block. The RDO framework is developed and integrated under ModelCenter 10.1 software [11] to apply for improving the product's quality and to minimize the effects of noise factors while considering uncertainty parameters in aerospace vehicle design application. The framework starts with a deterministic and RDO formulation in block 1 and block 2, respectively. Then, analysis and optimizer are implemented to figure out deterministic and RDO optimum configuration after block 3 termination. Monte-Carlo Simulation (MCS® solver) [11] is applied to perform a probabilistic analysis for both deterministic and RDO optimum results in block 4: Probabilistic analysis. The probabilistic results are analyzed to demonstrate an improvement of aircraft performance comparing with a traditional deterministic optimization approach.

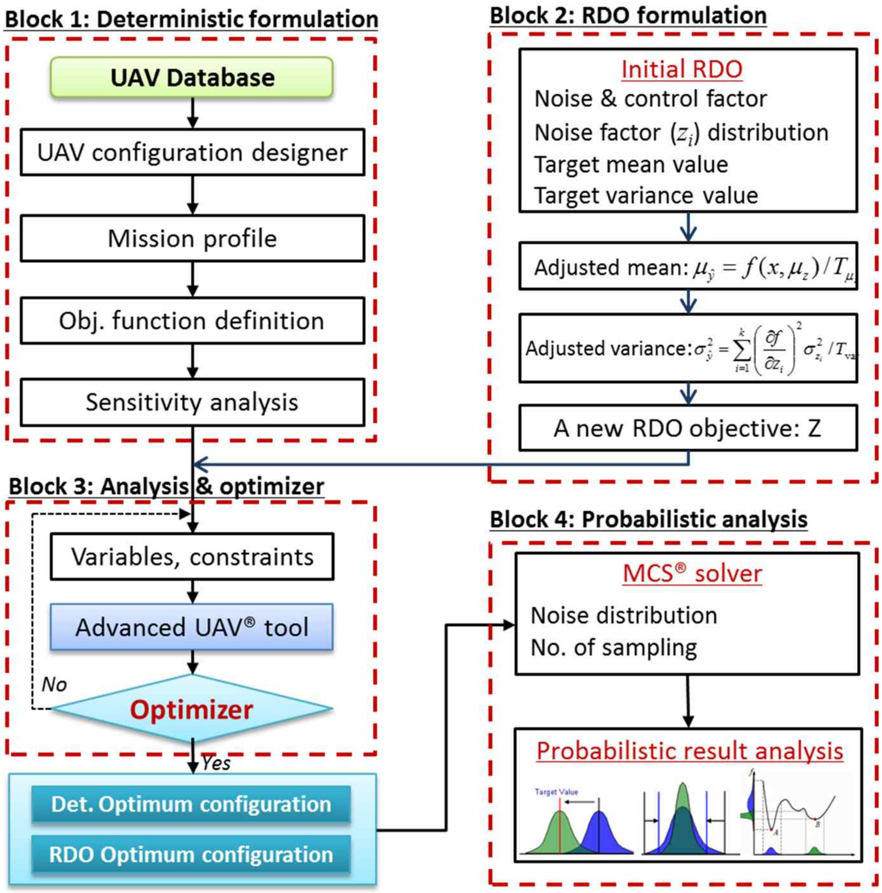


Figure 1 Robust Design Optimization (RDO) process

2.1. Robust Design Optimization (RDO) introduction

Robust Design Optimization is implemented to substantially reduce the variability of aircraft quality that minimizes the effects of uncertainty than by removing the source of noise or uncertainty parameter effects on vehicle performance parameters. The example of robustness result is shown in Figure 2 in which result point B presents a higher objective value but a low variance with more trustworthy and robust result.

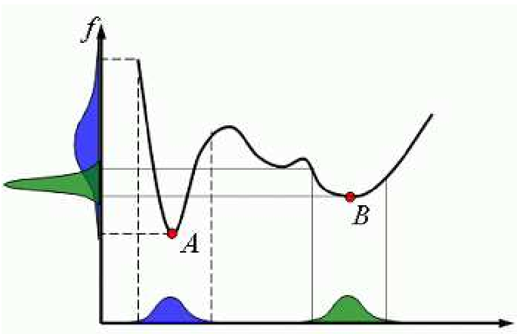


Figure 2 Comparison of two design points in robustness of objective function [12]

2.2. Block 1: Deterministic formulation

Block 1 starts to create UAV configuration from a database for fuselage, wing, horizontal tail and vertical geometry data by applying an in-house UAV configuration designer [13]. The outputs of UAV configuration designer provides a full sets of configuration data including a fuselage cross section, wetted area, airfoil data, horizontal, wing, and vertical geometry for Advanced UAV® analysis tool in Block 3 as shown in Figure 1. A mission profile and an objective function definition are required to define in Block 1 to perform a sensitivity analysis which helps to remove design variables which have a small effects on the selected objective function and other UAV performances.

2.3. Block 2: RDO formulation

RDO formulation is to establish a new RDO objective function based on a set of target mean (T_{μ_y}) and target variance (T_{var}) value according to noise factors. The new RDO objective function (Z) is a summation of adjusted mean and variance function as shown in Figure 1. The adjusted mean function consists of noise and control factor in equation (1). The adjusted variance is a summation of an objective function differentiation according to noise factors (z_i) shown in equation (2). The new problem is to minimize the new objective function as shown in equation (3) [12].

Adjusted mean value of response: $$\mu_{\hat{y}} = f(x, \mu_z) / T_{\mu_y} \tag{1}$$

Adjusted variance of response: $$\sigma_{\hat{y}}^2 = \sum_{i=1}^{k} \left(\frac{\partial f}{\partial z_i} \right)^2 \sigma_{z_i}^2 / T_{\text{var}} \tag{2}$$

Minimize: Z = *(adjusted mean value) + (adjusted variance)* (3)

The central numerical difference is applied for determining an adjusted variance of response to noise factors as shown in equation (2).

2.4 Block 3: Analysis and Optimizer

Block 3 is composed of Advanced UAV® analysis tool and optimizer to generate deterministic and RDO optimum configuration. In-house Advanced UAV® Tool is an integrated design and analysis tool. It is developed and validated by authors for various types of aircrafts such as UAVs, UCAVs [14, 15]. The analysis module is composed of the aerodynamics and stability & control, mission, propulsion, weight, and performance discipline as shown in Figure 3.

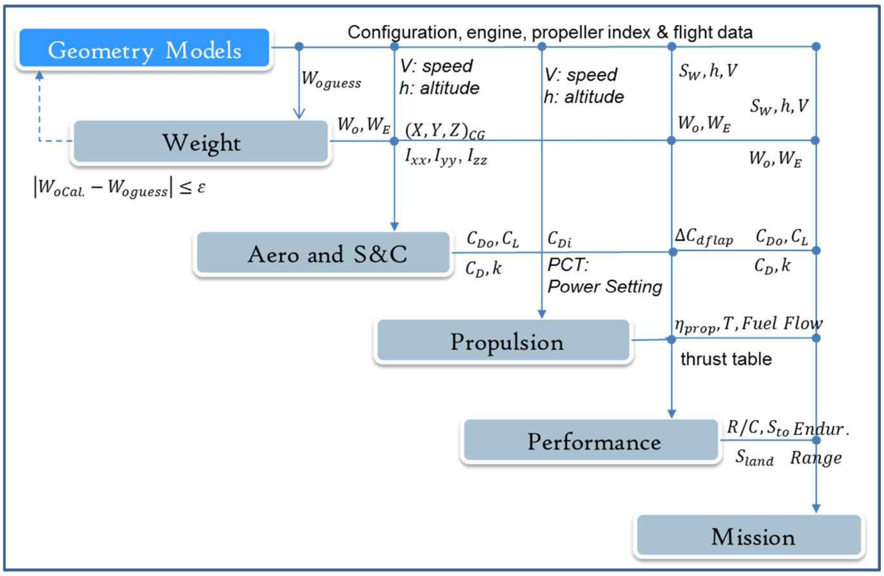


Figure 3 Advanced UAV® analysis dataflow

Design Explorer (DE) algorithm, which developed by Boeing and integrated into PHX ModelCenter 10.1 [11], helps to search on an entire design space by surrogate models with sequential optimization algorithm (SEOPT) [16]. The Design Explorer has been implemented and validated in many Boeing design applications such as high lift aerodynamics, multidisciplinary wing planform design, forming of aircraft wing skin, engine duct seal, and other produces [16]. Therefore, Design Explorer is selected as an optimizer in framework.

2.5 Block 4: Probabilistic analysis

Monte Carlo Simulation (MCS) is used for probabilistic analysis to both deterministic and RDO optimum configuration as shown in Figure 1. The distribution for noise factors are considered and assigned in Block 4. The sampling points are set to 1500 runs for MCS. The fitting methods are applied after 1500 sampling points are run from MCS to reduce the computation burden in MCS.

3. Verification for Advanced UAV® analysis tool

3.1. Aerodynamics and S&C Analysis Module

The Predator A configuration [17] is selected as the baseline for the tool validation. The analysis results from the Advanced UAV® analysis tool is compared with the Predator A published data and Computational Fluid Dynamics (CFD) Fluent result [18] in the Figure 4. The L/D is predicted for the wing only for different angle of attack (AoA). The Predator A reaches L/D at 22.8 with AoA around 2~3 deg. The L/D is calculated by using the Advance UAV® tool for whole aircraft at 22.2, as shown in the Figure 4. The slight difference is caused by the most of wing lift contribution on Predator A. The horizontal stabilizer and fuselage have small contribution on whole aircraft configuration.

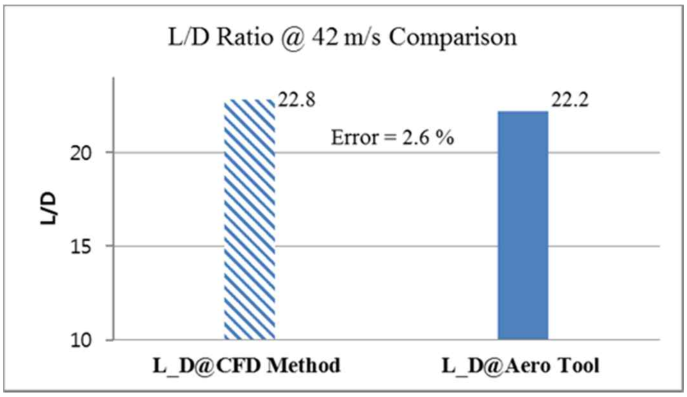


Figure 4 Lift to Drag (L/D) ratio comparison at speed of 42 m/s

3.2. Weight Analysis Module

The estimated weight components comparison is shown in the Figure 5. The estimated weight components show relatively good agreement with the reference weight component [17] as shown in the Table 1. The maximum error is around 6% at the subsystem weight component. While the published empty and weight data for Predator A are 350 kg and 1020 kg, respectively. Therefore, it concludes that the weight analysis module is well-developed for UAV configuration.

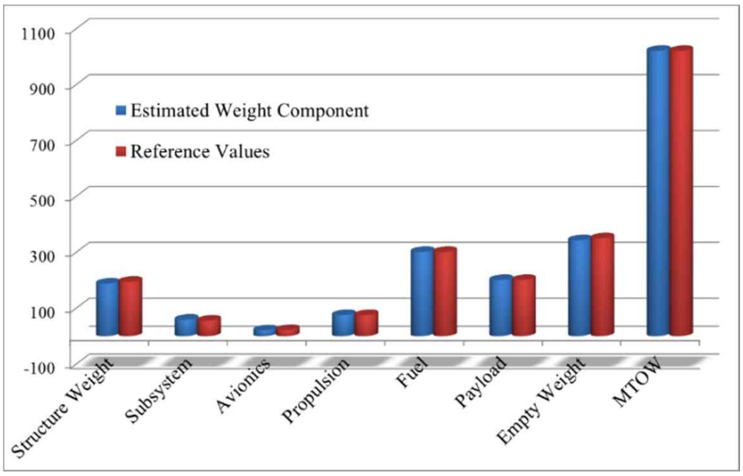


Figure 5 The weight analysis discipline validation

Table 1 The Weight Component Comparison for Predator A

	Estimated Weight (kg)	Reference [17] (kg)	Error (%)
Avionics	20.58	21.80	5.58
Structure Weight	188.11	194.74	3.41
Subsystem	59.08	55.60	6.26
Empty Weight	343.28	350.17	1.97
MTOW	1011.70	1020.60	0.87

3.3. Propeller analysis module

The validation on propeller analysis code is performed on the 2 blades propeller [19]. The results show the relatively good agreement with the experimental data at three different propeller pitch angles (β) for thrust coefficients versus to advanced ratio (J).

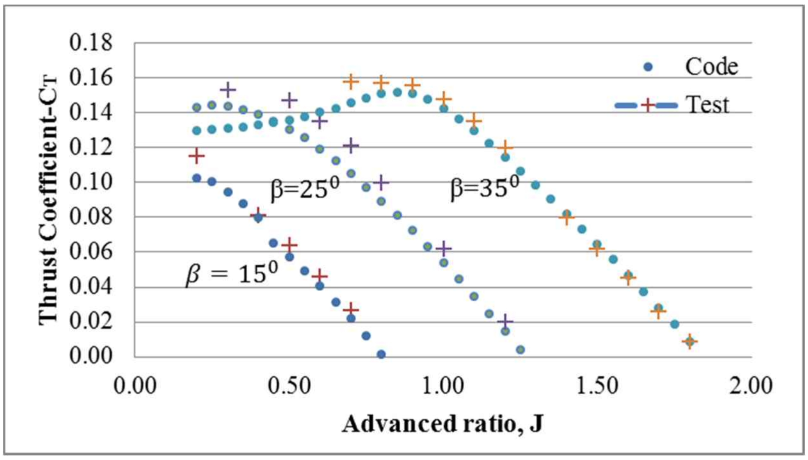


Figure 6 Two blades propeller analysis validation

3.4. Performance Analysis Module

The performance validation is performed on the Predator A configuration in the Table 2. The published data are given for detailed takeoff, landing condition, and endurance. The comparison results show the good agreement with published data of Predator A. The maximum takeoff and landing lift coefficient is assumed by 1.8 and 2.1 respectively. The engine is Rotax Turbo Charge 914 [20]. The friction coefficient for landing and takeoff condition are assumed from D. Raymer [21]. The performance validation results show a maximum error at 9.26% for takeoff ground roll distance as shown in Table 3. The landing and takeoff field distance, and endurance of Predator A are validated within less than 6.3% error comparing with a published data in Table 3.

Table 2 Assumptions for Performance Validations

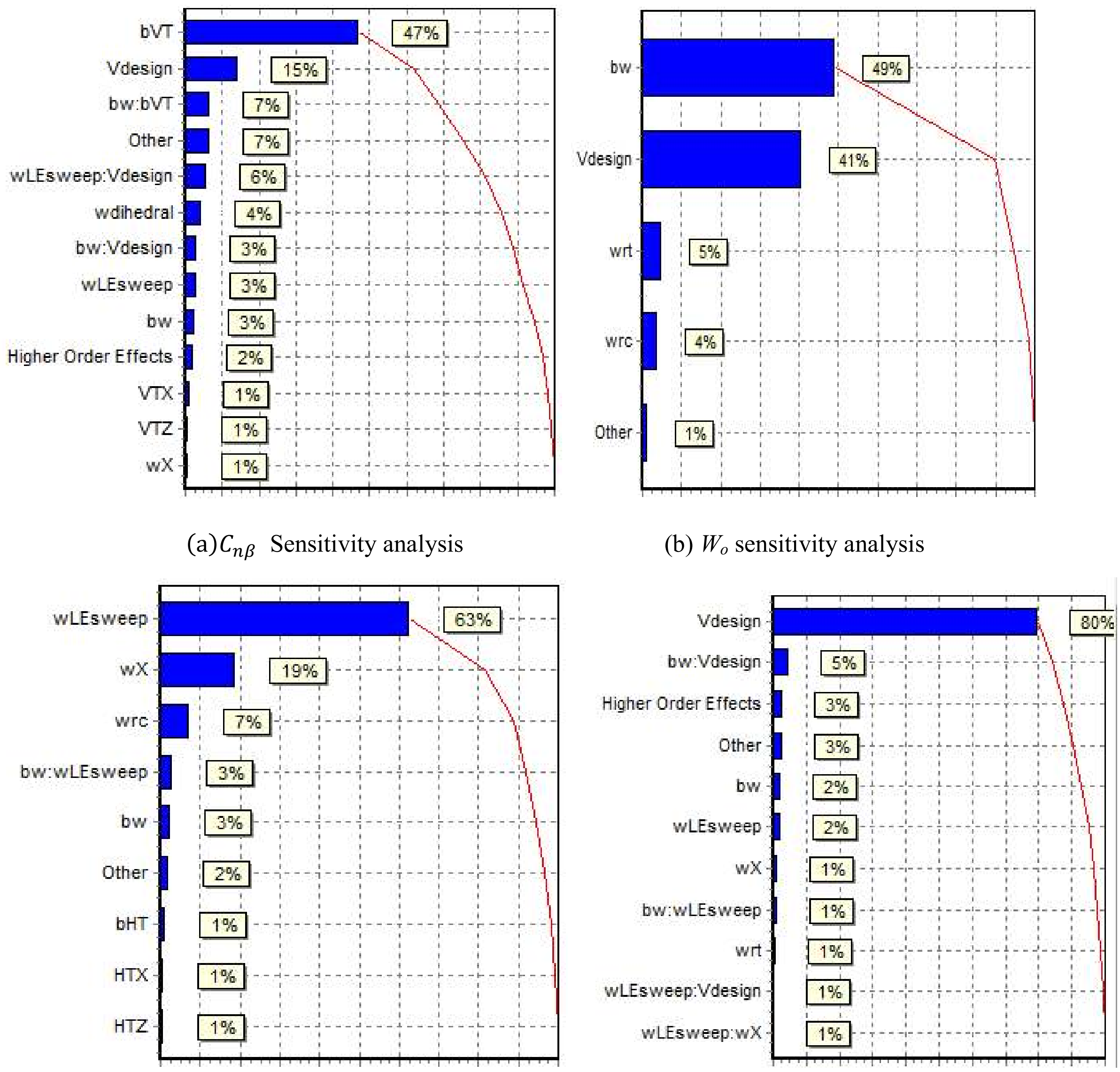
Parameters	**Assumed Value**	**Note**
C_{Lmax} at takeoff condition	1.8	Assumption
C_{Lmax} at landing condition	2.1	Assumption
μ takeoff friction coefficient	0.025	Raymer for Military Aircraft [21]
Friction coefficient including brake	0.3	Raymer for Military Aircraft [21]
Takeoff and landing altitude	0	at Sea Level
Obstacle height	50 (ft)	
Engine	Rotax 914/Turbo Charge	

Table 3 The Predator A Performance Validation

Performance Parameters	Predator A	Advanced UAV tool	Error (%)	Unit
Take-off Ground Roll	1440	1306.59	9.26 %	ft
Take-off field length (50ft)	2000	1922.48	3.88 %	ft
Landing field length (50 ft)	1700	1731.82	1.87 %	ft
Endurance (full payload)	18	19.23	6.83 %	hours

4. Implementations of RDO framework for multidisciplinary UAV design

4.1. Sensitivity analysis



(a) $C_{n\beta}$ Sensitivity analysis (b) W_o sensitivity analysis

(c) SM sensitivity analysis (d) Endurance sensitivity analysis

Figure 7 Sensitivity analysis for a multidisciplinary UAV design

Sensitivity analysis is performed on 21 variables of MALE UAV configuration including wing, horizontal tail, vertical tail, and their location to 18 constraints and endurance shown in Table 4. 500 design points are selected by implementing Latin Hyper-cube and orthogonal method [11] to execute Advanced UAV analysis program.

Four sensitivity analysis results for directional stability derivatives, gross weight, static margin (SM), and endurance are shown in Figure 7. The main effects for directional stability derivatives are vertical span (*bVT*), design speed (*Vdesign*), and wing geometry as shown Figure 7a which agree with aircraft stability characteristics. Similarly, main effects for static margin are wing sweep angle (*wSweep*) (63%), wing location (*wX*), and wing root chord (*wrc*) as shown in Figure 7b. Wing span (*bw*), design speed (*Vdesign*), wing tip (*wrt*), and wing root (*wrc*) are a main effect to gross weight due to small weight contribution of horizontal and vertical tail shown in Figure 7c. The endurance parameters is mainly affected by design speed (80%) due to gross weight kept a constant for an electric-powered UAV. If UAVs flight at a lower speed, the endurance increases with flight speed. Other effects on endurance are a combination of wing span and speed relating to aerodynamics parameters and other wing geometry parameters as shown in Figure 7c. The higher order effects of design variables are neglected during sensitivity analysis.

Therefore, the main effective variables for UAV endurance and 17 constraints are kept as Table 7. The vertical location of wing, horizontal, and vertical tail are neglected for design formulation which are slightly affected to endurance and constraints

4.2. MALE UAV design formulation

a) Deterministic optimization formulation

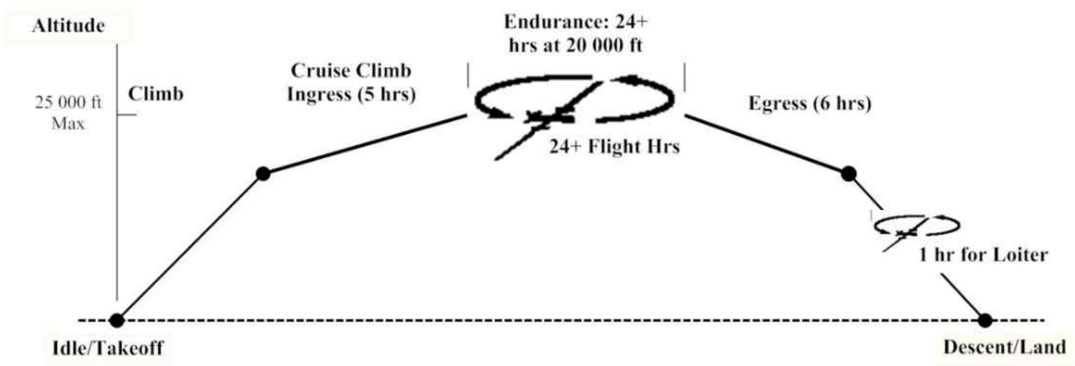


Figure 8 Predator A missile profile [17]

The mission profile of Predator A is shown in the Figure 8. The Predator A design optimization is performed to increase the endurance time at the cruise flight condition with a full payload condition.

- ✓ The climb and ingress is designed for 5 hours.
- ✓ Egress and descent/land stage is designed for 6 hours.
- ✓ Loiter time condition is designed for as 1 hour.

The design condition is considered at cruise condition with no payload and full payload condition 18 and 24 hours, respectively [17]. The designed condition is a cruise condition with full payload aimed for Predator A. The 18 design variables including wing, horizontal, and vertical tail geometry, and flight condition are listed in Table 4 after a sensitivity analysis step.

The endurance of MALE UAVs is a main factor for surveillance and other mission. Therefore, it is selected as an objective function to maximize for MALE UAV.

$$\text{Maximize } Endurance = Endur\ (\vec{x_i})\ \ j = 1, 18 \quad (4)$$

$$\text{Subject to: } \Pi(\mathrm{G_i}(X)) > 0,\quad \mathrm{i} = 1, \ldots, 17 \quad (5)$$

Table 4 Design variables for multidisciplinary UAV design optimization

	Baseline	Lower Bounds	Upper Bounds	Unit
Wing span	14.8	10	20	m
Wing root chord	1.24	1.0	1.4	m
Wing tip chord	0.5	0.3	0.7	m
Wing sweep	5	0	10	*deg.*
Wing dihedral	0	0	5	*deg.*
Wing X location	3.59	3	4	m
HT span	4	3.5	4.5	m
HT root chord	0.742	0.4	1	m
HT tip chord	0.742	0.4	1	m
HT sweep	0	0	10	*deg.*
HT X location	6.82	5.8	7.8	m
VT span	1.14	0.7	1.5	m
VT tip chord	0.742	0.4	1	m
VT root chord	0.742	0.4	1	m
VT LE sweep	0	0	60	*deg.*
VT X location	6.82	5.8	7.8	m
V_{design}	42	27.78 (V_{stall})	64	m/s
h altitude	3000	2000	4000	m

Table 5 Design constraints for multidisciplinary UAV design optimization

Constraints	Description	Discipline
G(1,2)	Static Margin: $0.05 \leq SM \leq 0.2$	S&C (@V_{design})
G(3)	Take-off field length ≤ 670 (m) (2200 ft)	Perf. (50 ft) (WOT)
G(4)	Lateral stability derivative: $C_{l\beta} \leq -0.03$	S&C (@V_{design})
G(5)	Gross weight: MTOW ≤ 1020 (kg)	Weight
G(6)	Pitching moment der. $C_{ma} \leq 0$	S&C (@V_{design})
G(7)	Landing distance ≤ 518 (m) (1700 ft)	Performance (perf.)
G(8)	Wing weight: $W_{wing} \leq W_{baseline}$ (kg)	Weight
G(9)	Lift over drag ratio: $L/D \geq L/D_{baseline}$	Aeros (@V_{design})
G(10)	Wing Taper ≥ 0.4	Geometry
G(11)	Take-off Ground Roll ≤ 438 (m) (1440 ft)	Perf. (@WOT)
G(12)	Maximum speed (V_{max}) ≥ 60.3 m/s	Perf. (@WOT)
G(13)	Stall speed (V_{stall}) ≤ 27.8 m/s	Perf. (Clean)
G(14)	Service ceiling ≥ 25 000 (ft)	Perf. (@WOT)
G(15,16)	Directional derivatives coefficient $0.08 \leq C_{n\beta} \leq 0.28$	S&C (@V_{design})
G(17)	Empty weight: $W_e \leq W_{e\_Baseline}$(kg)	Weight

b) RDO formulation

The altitude (h) and flight speed (V) are considered as noise factors for MALE UAV cruise design condition. The adjusted variance function is calculated by implementing a central difference method as following equation (6).

$$\sigma_{\hat{y}}^2 = \left[\left(\frac{f(V+\Delta V) - f(V-\Delta V)}{2\Delta V} \right)^2 + \left(\frac{f(h+\Delta h) - f(h-\Delta h)}{2\Delta h} \right)^2 \right] \times \left(\frac{1}{3} \right)^2 \times \frac{1}{T_{\text{var}}} \tag{6}$$

Where ΔV and Δh are flight speed and altitude step.

A new objective function for RDO is defined by equation (3) with altitude and speed noise factor consideration in equation (6).

4.3. Deterministic and robust design optimum results

The deterministic and robust design optimum configuration results for multidisciplinary UAV design optimization are presented in Table 6 comparing with a baseline - Predator A configuration. The endurance objective function shows an improvement in both deterministic and RDO UAV results from 19.23 hours to 21.13 and 22.26 hours for deterministic and robust design results respectively by the helps of Design Explorer algorithm. The objective convergent history and maximum violation constraints for a deterministic formulation are shown in Figure 9. The endurance objective function converges at 21.13 hours with 1% constraints violation in Figure 9b. The new objective function for RDO includes an adjusted endurance mean function and adjusted variance which converges to 1 with no constraints violation shown in Figure 10a and 10b. The wing weight and directional derivatives coefficient constraints are active. Hence, the design formulation problem for deterministic and robust design process are converged and strictly formulated. The maximum constraints violation graphs are also shown that if designers are accepted for more risk in constraints violation, the endurance objective value is also increased shown in Figure 9b and 10b.

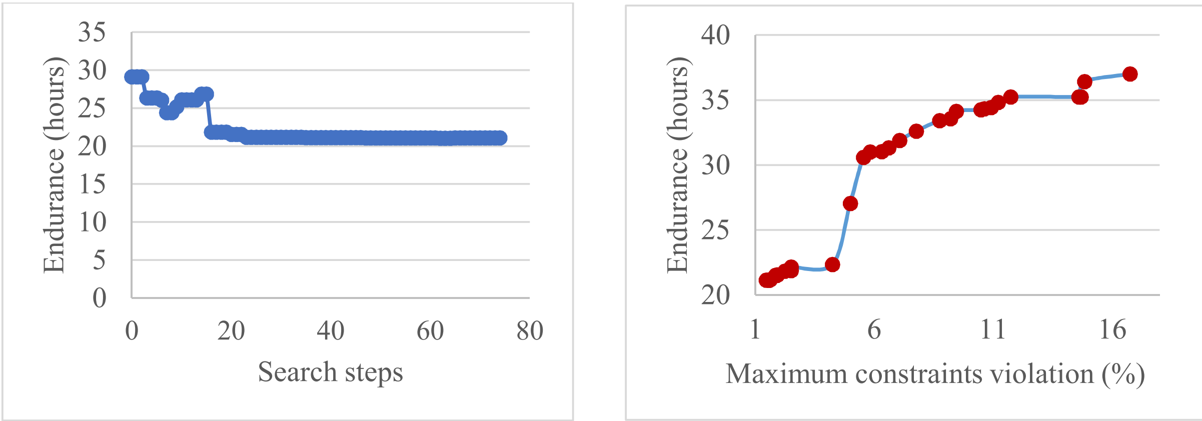
The horizontal tail root chord and sweep angle variables are hit upper bound for robust design results due to increment in wing area and wing sweep angle and reduction in wing location. Hence, the horizontal tail is required to increase a span to satisfy static stability conditions such as static margin and pitching moment coefficient. The vertical tail geometry and its location optimum results are also satisfied the directional and lateral constraints as shown in Table 6. The optimum results are also recommended to flight at lower speed and higher altitude to improve an endurance as shown in RDO UAV results column. Other performance constraints such as takeoff, landing distance, stall speed, maximum speed, and lift over drag ratio are satisfied for design requirements. The UAV gross, empty, and wing weight are satisfied for constraints which are set by following a baseline value.

The probabilistic analysis are performed on deterministic and RDO results with considering flight speed and altitude as noise factor. The probabilistic analysis results are shown in Figure 11 and Table 7. The 1500 sampling points are used for MCS, then the distribution are fitted as shown in Figure 11. The reason are a central difference method directly used into establishing a new RDO objective which requires a four times running Advanced UAV to complete one iteration. In addition, MCS is normally required at least on millions sampling points to obtain a simulation results. Therefore, the fitting method is applied to generate a fit distribution curve in Figure 11 while still maintaining an accuracy of probabilistic analysis results and saving MCS run. The target endurance mean value and target variance value is set 21 hours and 1.5 hours respectively. The comparison are presented in Table 7 with a small improvement in an endurance objective function at 3.46%. However, the variance reduces from 9.57 hours to 1.5 hours with 84.33% improvement which is also seen by Figure 11 while the RDO fitting distribution provides a narrow and more reliable results comparing with a deterministic UAV results. The reliability is also increased by 55.56% comparing with a deterministic results due to RDO process that reduces less sensitivities of noise factor to an endurance objective function. Therefore, RDO process demonstrates the improvement of reliability UAV performance results while considering uncertainty parameters and provides trustworthy design results comparing with a traditional deterministic design optimization approach at the conceptual design stage.

The computational strategy for a proposed robust UAV design implements a central difference method and fitting distribution for 1500 sampling points of MCS which shows extremely computational time savings comparing with normal RDO method required at least 1 million sampling points shown in Table 8. The computer performance configuration is i7, 3.07 GHz and 16GB of RAM with a parallel computing set for 4 CPUs. The proposed UAV RDO framework is only required almost 21 hours to obtain a probabilistic analysis results comparing with 116 days expected by a normal RDO approach. Therefore, the computational strategy for UAV RDO framework is extremely efficient than a normal RDO approach.

Table 6 MALE UAVs deterministic and RDO design results comparison

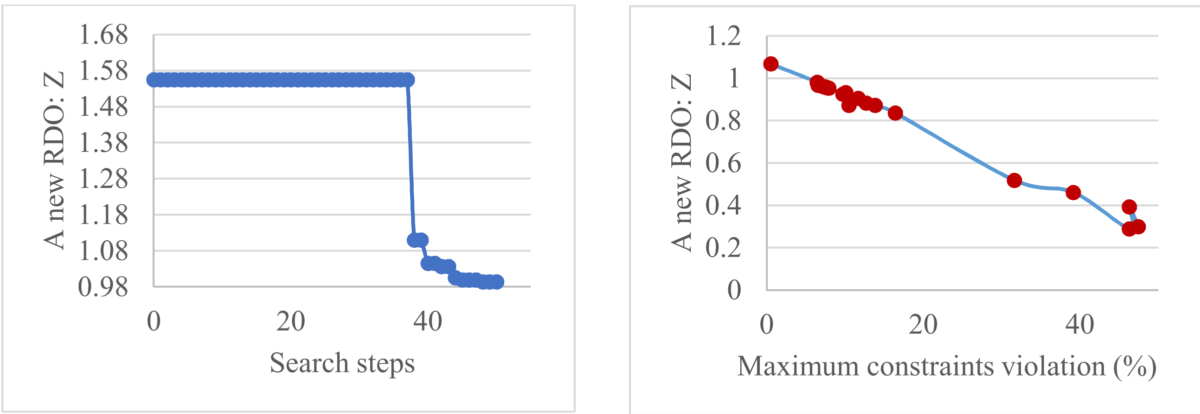
		Baseline	**Deterministic UAV result**	**RDO UAV result**	**Unit**
Objective function	Endurance	19.23	21.13	**22.26**	hours
Design Variables	Wing span	14.8	15.01	**13.2**	m
	Wing root chord	1.24	1.23	**1.31**	m
	Wing tip chord	0.5	0.52	**0.67**	m
	Wing sweep	5	7.85	**7.97**	deg.
	Wing dihedral	0	0	**1.5**	deg.
	Wing location	3.59	3.43	**3.28**	m
	HT span	4	3.51	**3.95**	m
	HT root chord	0.742	0.743	**1**	m
	HT tip chord	0.742	0.695	**0.56**	m
	HT sweep	0	10	**10**	deg.
	HT location	6.82	6.24	**6.78**	m
	VT span	1.14	1.6	**1.48**	m
	VT tip chord	0.742	0.958	**0.84**	m
	VT root chord	0.742	0.77	**0.84**	m
	VT LE sweep	0	6.44	**3.75**	deg.
	VT location	6.82	7.8	**6.38**	m
	V_{design}	42	38	**32.1**	m/s
	Flight altitude	3000	2754	**3793**	m
Constraints	Wing taper ratio	0.4	0.42	**0.511**	
	Lift to drag ratio	21.3	21.55	**22.11**	
	Maximum speed	64.35	64	**66**	m/s
	Stall speed	24.48	24.27	**24.23**	m/s
	Takeoff ground roll	387.6	381	**377.95**	m
	Takeoff field length	651.7	647.6	**651.7**	m
	Landing distance	402.7	397.8	**395.6**	m
	C_{lb}	0.0069	-0.123	**-0.208**	
	C_{nb}	0.0055	0.05	**0.049**	
	$C_{m\alpha}$	-1.074	-1.46	**-1.14**	
	Static Margin	0.156	0.15	**0.179**	
	Wing weight	91	91	**91**	kg
	MTOW	1011.7	1010	**1006.4**	kg
	Empty weight	334.7	333.2	**329.34**	kg



(a) Convergent history

(b) Constraints violation for UAV endurance

Figure 9 Deterministic optimization results for MALE UAV



(a) Convergent history

(b) Constraints violation for UAV endurance

Figure 10 Robust design optimization results for MALE UAV

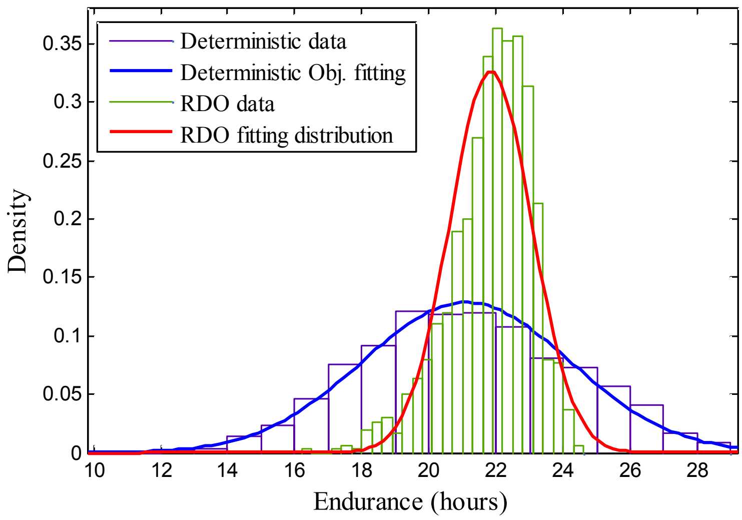


Figure 11 MCS and fitting distribution deterministic results and RDO comparison

Table 7 Deterministic and robust design results probabilistic analysis comparison

	Deterministic results	**Robust design results**	**Improvement (%)**	**Unit**
Endurance	21.11	21.84	3.46	hours
Variance	9.57	1.5	84.33	hours
Probability ($P_r \geq 21\ hr$)	0.504	0.784	55.56	

Table 8 Computational strategy of probabilistic analysis for UAV robust framework comparison

	Normal RDO (Estimated)	**UAV RDO framework**
No. of calls: Advanced UAV®	1	5
Execution time (s): Advanced UAV®	40	40
Monte Carlo Simulation (MCS)	1000000	1500
Total computation time (hours)	2778	20.75
Total computation (days)	116	3/4

5. Conclusion

A multidisciplinary robust optimization framework for UAV conceptual design is developed and applied successfully for improving a Predator A endurance with a trustworthy optimum configuration with a 55.56% improvement in reliability and 84.33% improvement of variance reduction comparing with a traditional deterministic approach. The robust optimization framework demonstrates an effectiveness of reducing less sensitivity of noise factors to an endurance objective function in UAV conceptual design case study. Especially, the computational strategy for probabilistic analysis shows extremely computational time saving comparing with an expected normal RDO approach with a same computer performance.

Advanced UAV® analysis tool is well-developed for a multidisciplinary UAV conceptual design and integrated into a robust optimization framework. Aerodynamics, propeller, weight, and performance analysis are validated for a baseline Predator A with a maximum error at 9.28% which is acceptance for a conceptual design stage.

A multidisciplinary UAV design formulation is successfully made for a robust framework which provides a robust optimum UAV configuration without any noticeable increase in design turnaround time under multidisciplinary design optimization environment.

6. Future works

- ✓ The Computational Fluid Dynamics (CFD) using ANSYS Fluent is going to perform on entire MALE UAV configuration for both deterministic and robust UAV configuration results
- ✓ The validation of ANSYS fluent on both configuration are addressed and discussed

Acknowledgments

The authors would like to acknowledge that this research was supported by Ministry of Education Science and Technology (MEST), Space Core Technology Development Program-a grant number 2012033521.

References

[1] J. Sobieszczanski-Sobieski and R. T. Haftka, Multidisciplinary aerospace design optimization: survey of recent developments, *Structural and Multidisciplinary Optimization*, vol. 14, no. 1, pp. 1-23, 1997.
[2] Dimitri N Mavris, Oliver Bandte, and Daniel A DeLaurentis, Robust Design Simulation : A Probabilistic

Approach to Multidisciplinary Design, *Journal of Aircraft*, vol. 36, no. 1, pp. 298-307, 1999.
[3] Gyung-Jin Park, Tae-Hee Lee, Kwon Hee Lee, and Kwang-Hyeon Hwang, Robust Design: An Overview, *AIAA Journal*, vol. 44, no. 1, pp. 181-191, 2006.
[4] I. Doltsinis and Z. Kang, Robust design of structures using optimization methods, *Computer Methods in Applied Mechanics and Engineering*, vol. 193, no. 23–26, pp. 2221-2237, Jun. 2004.
[5] Hyeong-Uk Park, Sang-Ho Kim, Jae-Woo Lee, and Yung-Hwan Byun, Design of Very Light Jet (VLJ) Aircraft Using Robust Design Optimization Approach, in *CJK 5th Proceedings*, Jeju, Korea, 2008.
[6] W. Chen, R. Garimella, and N. Michelena, Robust design for improved vehicle handling under a range of maneuver conditions, *Engineering Optimization*, vol. 33, no. 3, pp. 303-326, Feb. 2001
[7] Wei Chen and Kemper Lewis, Robust design approach for achieving flexibility in multidisciplinary design, *AIAA Journal*, Vol. 37, No. 8, August 1999
[8] Xiaoping Du and Wei Chen, Efficient uncertainty analysis methods for multidisciplinary robust design, *AIAA Journal*, Vol. 40, No. 3, March 2002.
[9] Ioannis Doltsinis and Zhan Kang, Robust design of structures using optimization methods, *Computational Methods Applied Mechanics and Engineering.* 193 (2004) p. 2221-2237, Elsevier
[10] Eric Sandgren and T.M. Cameron, Robust design optimization of structures through consideration of variation, *Computers and structures* 80 (2002) p. 1605-1613, Pergamon, Elsevier
[11] ModelCenter 10.1, PHX ModelCenter®: http://www.phoenix-int.com/software/phx-modelcenter.php
[12] Hyeong-Uk Park, Jae-Woo Lee, and Yung-Hwan Byun, Development of the Robust Aerospace System Design Process, *21st Canadian Congress of Applied Mechanics*, Department of Mechanical & Industrial Engineering, Ryerson University, Toronto, Ontario, CANADA, 3-7 June 2007
[13] Abdulaziz Azamatov, Jae-Woo Lee, and Yung-Hwan Byun, Comprehensive aircraft configuration design tool for Integrated Product and Process Development, *Advances in Engineering Software*, vol. 42, no. 1–2, Jan. 2011.
[14] Nhu-Van Nguyen, An Efficient Multi-Fidelity Approach for the Multi-Disciplinary Aerospace System Design and Optimization, Ph.D thesis, Konkuk University, Seoul, Korea, 2011.
[15] Nhu-Van Nguyen, Seok-Min Choi, Wan-Sub Kim, Sangho Kim, Jae-Woo Lee, and Yung-Hwan Byun, Multidisciplinary Unmanned Combat Air Vehicle (UCAV) System Design Implementing Multi-Fidelity Models, *Aerospace Science & Technology*, Vol. 26, Issue 1, p. 200-210, 2012, Elsevier Publisher.
[16] Andrew J. Booker, Martin Meckesheimer, and Tony Torng, Reliability Based Design Optimization Using Design Explorer, *Optimization and Engineering*, June 2004, Volume 5, Issue 2, pp 179-205
[17] J. F. Gundlach IV, Multi-disciplinary design optimization of subsonic fixed-wing unmanned aerial vehicles projected through 2025, Virginia Polytechnic Institute and State University, 2004.
[18] FLUENT 6.0 User's Guide. http://202.118.250.111:8080/fluent/Fluent60_help/html/ug/main_pre.htm.
[19] Hartman, Edwin P Biermann, and David, The aerodynamic characteristics of full-scale propellers having 2, 3, and 4 blades of Clark y and R.A.F. 6 airfoil sections, *NACA-TR-640*, USA,
[20] Rotax Turbo Charge 914. http://www.rotaxparts.net/scripts/prodView.asp?idproduct=39.
[21] Daniel P. Raymer, *Aircraft Design: A Conceptual Approach,* 5th Edition, AIAA, 2012.