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Robust Decision Making in Aerial and Marine Vehicles Optimization: a Designer's Viewpoint

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Abstract

The paper presents a formulation for robust optimization of aerial and marine vehicles design. The general framework is that of optimal design under uncertainty, also referred as Robust Design Optimization (RDO). Specifically, statistical decision theory concepts are used to formulate the design decision problem under uncertain operating conditions. The design specifications are given in terms of probability density function of different operating parameters and the optimal design configuration is that which maximizes the performance expectation. Applications to the conceptual design of civil aircraft and vessels are shown.

Keywords: Robust Design Optimization (RDO), Aircraft Design, Ship Design.

1. Introduction

In the standard approach to design optimization, all the relevant quantities are addressed from a deterministic viewpoint and the overall analysis disregards any kind of uncertainty involved in the process. In this context, the final solution of the optimal design process is (very) specialized for the deterministic conditions assumed, and, apparently, depends on the deterministic models adopted. Nevertheless, in most cases the final products operate in off-design conditions. This is because of the unavoidable deviations from the theoretical design due to the manufacturing tolerance, and/or to the variety of environmental conditions and operational constraints the designed system is subject to, during its every day exercise. In these conditions, the performances might significantly drop, limiting the effectiveness and the productivity of the final product. Marczyk (2000) stresses the latter limitation stating that, in a deterministic engineering context, optimization is synonymous of specialization and, therefore, is the opposite of robustness and flexibility about uncertainties.

The aim of the present work is to reformulate the problem of optimal design, taking into account the uncertainty and redefining optimality in terms of robustness of the final solution. Specifically, the final goal is that of identifying a final solution able to keep a good performance in the whole uncertain scenario under analysis. The general framework is that of Robust Design Optimization (RDO) in which optimality criteria from statistical decision theory are assessed from the designer’s viewpoint.

Theory and tools of RDO have been developed to improve product quality and reliability in industrial engineering. Specifically, the uncertain parameters are taken into account by means of their probabilistic distribution and included, some how, in the definition of the optimality criteria used for the design optimization – see, e.g., Beyer and Sendhoff (2007), Park et al. (2006) and Zang et al. (2005).

Generally, the source of uncertainty may be categorized into two main types: external and internal (Du and Chen, 2000). External uncertainties are related to the analysis models input, such as design variables tolerance or uncertain usage and operating conditions. Internal uncertainties are related to the system output and may be associated to the accuracy in computing. In other words, internal sources of uncertainty are related to those stochastic variations that are not conditional on the input uncertainties. In the context of optimal design and from the designer’s viewpoint, we may consider the uncertainty related to the definition of the design variables (tolerance or actuators precision), of the environmental and operating conditions, and to the evaluation of the relevant functions (inaccuracy in computing).

The tools of statistical decision theory, specifically Bayes criteria (De Groot, 1970), may provide the designer with a sound framework to manage the above uncertainties and formulate the problem for RDO (Trosset et al., 2003). Specifically, the expectation of the merit factors (with respect to the stochastic variations involved in the analysis) may be taken as the objective of the optimization procedure. In addition, the standard deviation of the relevant quantities may be also taken into account to improve the insensitiveness of the final solution to the uncertain parameters variation (Zang et al., 2005).

In this work, particular attention will be paid to the uncertainty related to the environmental and operating conditions of the final product. It may be noted that, in aerial and marine vehicle design (Padula et al., 2006, Diez and Iemma, 2007, Torenbeek et al., 2004, Diez and Peri, 2009 and 2010), operating and environmental conditions may be considered as "intrinsic" stochastic functions, whose expected values and standard deviations can neither be influenced by the designer nor by the manufacturer. Conversely, the uncertainties related to the design variables and to the functions evaluation are connected to the available knowledge and technology, and – theoretically – may be reduced by improving modeling, computing and manufacturing processes. The final goal here is that of minimizing the effects of the uncertainties involved in the system design, without suppressing their causes. The tools used for the definition of the decision problem are that of statistical decision theory, properly translated in the context of optimal design.

The next section presents the general problem of design optimization subject to uncertainty. In Section 3 the formulation for robust decision making in optimal design is given, whereas numerical example of conceptual design of aircraft and vessels are shown in Section 4. Specifically, an application of robust design optimization aimed at minimum life-cycle cost of a mid range civil aircraft will be shown as well as a robust decision making process for optimal design of a bulk carrier. Moreover, Appendices 1 and 2 present a brief overview of the models used for the conceptual design of the above aerial and marine vehicles.

2. Design optimization subject to uncertainty

The present Section deals with the general description of a design optimization problem subject to uncertainty. Depending on the application, different kind of uncertainties may be addressed. A comprehensive overview of design optimization under uncertain conditions may be found in Beyer (2007), Park et al. (2006), Zang et al. (2005). In order to define the context of the present work, we may formulate the following optimization problem,

$$\begin{array}{lll} \text{minimize w.r.t. } x \in A, & f(x,y) & \text{for a given } y = \hat{y} \in B \\ \text{subject to} & g_n(x,\hat{y}) \le 0 & \text{for } n = 1,\dots,N \\ \text{and to} & h_m(x,\hat{y}) = 0 & \text{for } m = 1,\dots,M \end{array} \qquad (1)$$

where $x \in A$ is the design variables vector (which represents the designer choice), $y \in B$ is the design parameters vector (which collects those parameters independent of the designer choice, like, e.g., environmental or usage conditions, defining the operating point of the final product), and f, g_n, h_m: $\mathrm{R}^k \to \mathrm{R}$, are the optimization objective, the inequality and equality constraints functions, respectively. While handling the above problem, the following uncertainties may occur (the present classification may be found in Diez and Peri, 2010, and the interested reader is referred to their work).

a) Uncertain design variable vector. When translating the designer choice into the "real world," the design variables are likely affected by uncertainty due to manufacturing tolerance and/or actuators precision. Assume a specific designer choice x^* and define $\xi \in \Xi$ the error or

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tolerance related to this choice.[1] Assume then ξ as a stochastic process with probability density function[2] $p(\xi)$. The expected value of x^* is, by definition,

$$\bar{x}^* := \mu(x^* + \xi) = \int_{\Xi} (x^* + \xi) p(\xi) d\xi$$

It is apparent that, if the stochastic process ξ has zero expectation, i.e.

$$\bar{\xi} := \mu(\xi) = \int_{\Xi} \xi p(\xi) d\xi = 0$$

we obtain $\bar{x}^* = x^*$. It may be noted that, in general, the probability density function $p(\xi)$ depends on the specific designer choice x^*.

b) Uncertain environmental and usage conditions. In real life applications, environmental and operational parameters may differ from the given guess $\hat{y}$, made during the design phase (see problem 1). The design parameters vector may be assumed as a stochastic process with probability density function $p(y)$ and expected value or mean

$$\bar{y} := \mu(y) = \int_{B} y\, p(y) dy$$

Note that, in this formulation, the uncertainty on the usage conditions is not related to the definition of a specific design point. Environmental and operating conditions are treated as "intrinsic" stochastic processes in the whole domain of variation B, and the designer is not requested to pick a specific design point in the usage parameters space. For this reason, we do not define an "error" in the identification of the usage conditions, preferring the present approach, which addresses the environmental and operational parameters in terms of their probabilistic distributions in the whole domain of variation.

c) Uncertain evaluation of the function of interest. The evaluation of the functions of interest (objectives and constraints) may be affected by uncertainty due to inaccuracy in computing. Collect objective and constraints in a vector $\varphi := [f, g_1, \ldots, g_N, h_1, \ldots, h_M]^T$, and assume that the assessment of φ for a specific "deterministic" design point, $\varphi^* := \varphi(x^*, \hat{y})$, is affected by a stochastic error $\omega \in \Omega$. Accordingly, the expected value of φ^* is

$$\bar{\varphi}^* := \mu(\varphi^* + \omega) = \int_{\Omega} (\varphi^* + \omega) p(\omega) d\omega$$

Note that, in general, the probability density function of ω, $p(\omega)$, depends on φ^* and, therefore, on the design point $(x^*, \hat{y})$.

Combining the above uncertainties, we may define the expected value of φ as

[1] The symbol * is used in the present formulation to denote a specific designer choice. While $\boldsymbol{x}$ represents all the possible choices in A, x^* defines a specific one.

[2] It is, by definition, $\int_{\Xi} p(\xi) d\xi = 1$.

$$\overline{\varphi} := \mu(\varphi) = \iiint_{\Xi B \Omega} [\varphi(x^* + \xi, y) + \omega] p(\xi, y, \omega,) d\xi dy d\omega \tag{2}$$

where $p(\xi, y, \omega)$ is the joint probability density function associated to ξ, y, and ω. It is apparent that $\overline{\varphi} = \overline{\varphi}(x^*)$; in other words, the expectation of φ is a function of only the designer choice. Moreover, the variance of φ with respect to the variation of ξ, y, and ω, is

$$V(\varphi) := \sigma^2(\varphi) = \iiint_{\Xi B \Omega} \{[\varphi(x^* + \xi, y) + \omega] - \overline{\varphi}(x^*)\}^2 p(\xi, y, \omega,) d\xi dy d\omega \tag{3}$$

resulting, again, a function of only the designer choice x^*. Equations 2 and 3 give the general framework of the present work. Specifically, we concentrate on the stochastic variation of the operating and environmental conditions, thus referring to uncertainties of the *b* type.

3. Robust decision making for optimal design subject to uncertain environmental and operating conditions

In this section, the formulation for robust design optimization subject to uncertain environmental and operating conditions is presented. Assume that the optimization objective in problem 1 is associated to a general loss (like, for instance, the performance loss with respect to a given target). Under the hypothesis of uncertain environmental and operating conditions, we may refer to $f(x,y)$ as the loss associated to the designer choice x, when the condition y occurs. Therefore, the expectation of the loss f, evaluated through the integral of Eq. 2 (limited to uncertain y), may be defined as the risk associated to the decision x under the distribution $p(y)$ (De Groot, 1970). It follows that the designer should choose, if possible, a decision x which minimizes the risk (expected loss).

Specifically, if we consider the Bayes risk, i.e. the lower bound of the expected loss for all the possible choices in A,

$$\bar{f}^* := \inf_{x \in A} \bar{f}$$

we look for the Bayes decision of the problem against the distribution $p(y)$, for which the risk equals the Bayes risk.

The Bayes approach to the designer decision problem may be formulated as follows.

$$\begin{array}{lll} \text{minimize w.r.t. } x \in A, & \bar{f}(x) := \int_B f(x,y) p(y) dy & \\ \text{subject to} & \sup_{y \in B} \{g_n(x,y)\} \le 0 & \text{for } n = 1,\ldots,N \\ \text{and to} & \bar{h}_m := \int_B h_m(x,y) p(y) dy = 0 & \text{for } m = 1,\ldots,M \end{array} \tag{4}$$

In the present formulation, the inequality constraints are treated in the worst case, following a conservative approach. An alternative method is that of considering the inequality constraints as probabilistic inequalities, and assessing the reliability of the design with respect to the constraints violation. The latter approach is the main idea behind Reliability-Based Design Optimization (RBDO - see, e.g., Tu et. al, 1999, Agarwal, 2004, and Agarwal and Renaud, 2004) and is beyond the scopes of the present work and, therefore, not further addressed here.

The optimal designer choice $x = x^*$ of the problem of Eq. 4 is that which minimize the expected loss of the system performances with respect to the stochastic variation of the environmental and operating conditions collected in y. It may be noted that in the present context, the design specifications, are not longer given in terms of a single operating design point, but in terms of probability density function of the operating scenario.

The problem of Eq. 4 may be enriched by considering the standard deviation of f, with respect to the operating conditions variation, as a second objective function. The latter approach improves the insensitiveness of the final design to the operating conditions variation.

4. Numerical results

In this section we present an example of application of robust design optimization aimed at minimum life-cycle cost of a short-mid range civil aircraft, as well as a robust decision making process for optimal design of a bulk carrier, aimed at minimum unit transportation cost.

4.1 Optimal aircraft conceptual design aimed at minimum life-cycle cost

The formulation presented in Morino et al. (2004) and its extension to take into account the community-noise cost (Iemma et al., 2006 and Iemma and Diez, 2005), are used here for estimating the life-cycle cost of the aircraft in the context of Multidisciplinary Design Optimization (MDO, see also Appendix 1). Specifically, the total aircraft life-cycle cost (*TALC*) is modeled as a linear function[3] of empty weight W, useful fuel weight F and noise emission N,

$$TALC = C_0 + C_W W + C_F F + C_N N \qquad (5)$$

where C_0 is the portion of the cost that is independent of W, F and N, whereas C_W, C_F and C_N are the cost increases per unit W, F and N, respectively. The second and the third term of the right-hand side of Eq. 5 are representative of research, development, test, evaluation and manufacturing costs as well as direct operating costs of flying (fuel and oil cost) and direct operating costs of maintenance (labor and spare parts for airframe and engines). The cost of the noise is expressed as a cost per dB and included in the last term of Eq. 5. The cost of crew, depreciation, take-off, landing and navigation fees (independent of noise emissions), registry taxes and cost of financing, are included in the term C_0. Specifically, the latter includes all those contribution to the *TALC* insensitive to the aircraft-designer choice. The objective function of the optimization process may be written as (note that the "insensitive" part of the

[3] Note that in the context of design optimization, we look for a model able to relate the designer choice to the life-cycle costs. Although the relation used here doesn't constitute an exhaustive modeling of all the issues connected to the total aircraft life-cycle cost estimate, we believe that this simple relation fits well the requirements of the problem at hand, emphasizing the "designer's contribution" to the total cost.

cost, C_0 , is inessential in the optimization)

$$f = (C_W W + C_F F + C_N N) Q_0^{-1}$$

where, again, C_W , C_F and C_N are respectively the cost per unit empty-weight, fuel-weight and noise. Q_0 is a reference value used to normalize f . Finally, we may write

$$f = \alpha_W \frac{W}{W_0} + \alpha_F \frac{F}{F_0} + \alpha_N \frac{N}{N_0} \tag{6}$$

where the quantities with subscript 0 denote reference values and $\alpha_W := C_W W_0/Q_0$ and $\alpha_F := C_F F_0/Q_0$ are known constants (in this work, they are calculated using the values of C_W and C_F from Morino et al., 2004); $\alpha_N := C_N/Q_0$ is the relative cost of noise. For details on life-cycle cost multidisciplinary optimization, the reader is referred to Morino et al. (2004).

In the following, we present the numerical results obtained applying the formulation to the optimization of the wing system of a mid range aircraft (the interested reader may found more details in Diez and Iemma, 2007, AIAA paper 2007-3668). The aircraft major specifications are shown in Tab. 1, whereas the designer-choice variables are listed in Tab. 2. The design constraints are given in Tab. 3. As probabilistic parameters we take into account the relative cost of the noise introduced above, α_N, and the cruise Mach number, M_∞. Note that the first parameter depends upon Governments and Authorities regulations and significantly increased in the last decade. The cruise Mach number depends on the air traffic in a specific sector (especially for short-mid range missions in high density flights regions) and can vary upon air traffic control decisions. For the sake of simplicity and without loss of generality, the probability density function for both parameters (p_1 and p_2 respectively) is taken as a constant function in the variation domain (uniform distribution). Specifically, $0.4 \leq \alpha_N \leq 1.2$ and $p_1(\alpha_N) = 1/0.8$, whereas $0.7 \leq M_\infty \leq 0.9$ with $p_2(M_\infty) = 1/0.2$; the joint probability density function is set to $p(\alpha_N,M_\infty) := p_1(\alpha_N)\, p_2(M_\infty)$.

Table 1. Design specifications.

number of seats	150
payload, kg	16,600
max. range, nm	3,000
max. cruise Mach no.	0.9
number of engines	2
max thrust per engine, lb	25,000

Table 2. Design variables vector (designer choices).

variable	lower b.	upper b.
span, m	28.00	40.00
root chord, m	2.00	12.00
tip chord, m	0.50	2.00

root panel thickness, mm	1.0	15.00
tip panel thickness, mm	1.0	15.00
root spar thickness, mm	10.0	100.00
tip spar thickness, mm	10.0	100.00
root built-in angle of attack, deg	-5.00	12.00
tip built-in angle of attack, deg	-5.00	12.00
sweep angle, deg	0.00	50.00

Table 3. Design constraints.

Maximum normal stress	100 MPa
Maximum shear stress	100 MPa
Minimum flutter speed	280 m/s
Minimum divergence speed	280 m/s

The noise emission has been evaluated in terms of SEL (dB) for an observer situated 1,000 m from the aircraft in the final approach phase and at flight Mach number equal to 0.3, with a sloope angle of 3 degrees.

The objective of the optimization process is the expected value of the total aircraft life-cycle cost according to Eqs. 4 and 6, whereas the constraints for the aircraft configuration are shown in Tab. 3. The constrained minimization problem is solved using an evolutionary algorithm (see Goldberg, 1989) coupled with a penalty function method. In order to evaluate the reference parameters used in Eq. 3, a preliminary robust analysis has been performed, setting the cost of the noise equal to zero. The minimum noise configuration has been also identified for further comparisons.

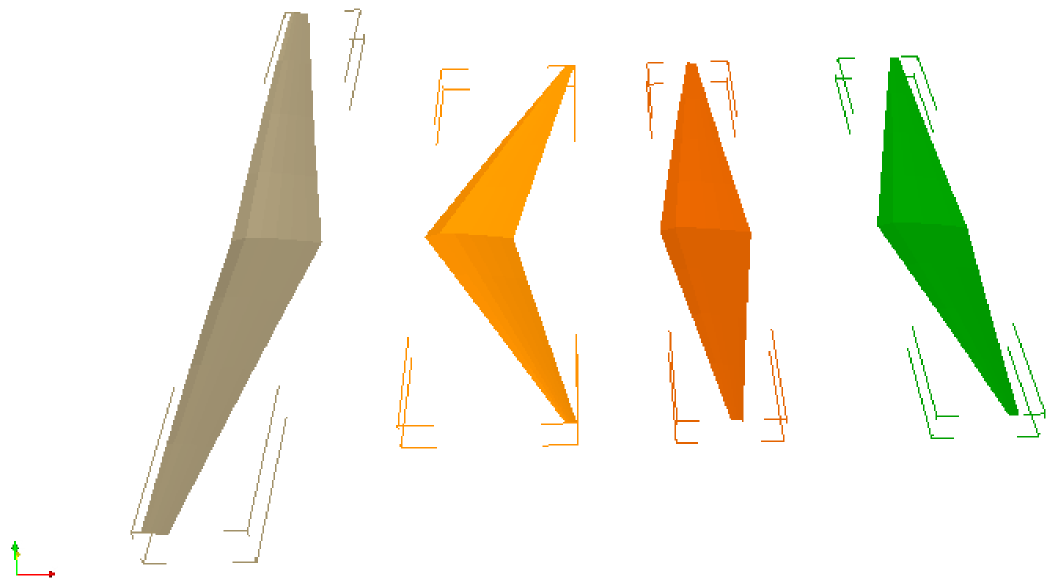

Figure 1. Wing optimized configurations.

Figure 1 presents (from the left to the right) the minimum-noise solution, the reference configuration (minimum life-cycle cost with a cost of the noise equal to zero), the optimal solution found performing a "deterministic" analysis with all the probabilistic parameters equal to their expectations and, finally, the robust solution which takes in to account the stochastic variation of the uncertain parameters. The optimal configurations are summarized in Tab. 4. It is worth noting that (at least) one of the structural constraints is always critical.

It may be noted how the minimum-noise solution has a very high aerodynamic efficiency in the final approach condition and how the aerodynamic efficiency drops down for the cruise condition (increasing the overall life-cycle cost). The noise emission in terms of SEL is, as expected, the lowest. The reference configuration has the greater efficiency in cruise condition and the greater value of the noise emission in the approach phase; the configurations optimized taking into account the cost of the noise present closer values for the aerodynamic efficiency for the two conditions, cruise and approach respectively.

Figure 2 depicts the variation of the total aircraft life-cycle cost depending on the operating cruise Mach number for the optimal "deterministic" solution (standard deterministic problem) and for the "robust" solution. As apparent, the configuration optimized using the present approach for robust design optimization has a lower average cost and a greater "robustness" with respect to the variation of the operating conditions.

Table 4. Optimized parameters.

variable/function	min. noise	reference	MDO	MRDO
span, m	39.98	28.00	28.00	28.00
root chord, m	4.66	4.54	4.65	4.56
tip chord, m	1.06	0.5	0.54	0.50
root panel thickness, mm	1.55	1.53	1.60	1.63
tip panel thickness, mm	1.04	1.92	1.00	1.08
root spar thickness, mm	21.30	10.00	10.01	10.45
tip spar thickness, mm	10.01	10.00	10.01	10.38
root built-in angle of attack, deg	2.59	4.70	3.63	3.90
tip built-in angle of attack, deg	8.41	8.59	10.33	10.50
sweep angle, deg	0.20	26.95	8.43	11.30
wing structural weight, kg	10,842	9,044	8,737	8,757
fuel burn for target mission (1,000 nm), kg	13,572	3,294	3,712	3,660
Noise at 1,000 m, SEL[dB]	66.41	67.00	66.71	66.73
aerodynamic efficiency (cruise, $M_\infty = 0.8$)	4.86	19.48	17.15	17.40
aerodynamic efficiency (approach, $M_\infty = 0.3$)	25.21	15.74	18.49	18.23
max. normal stress, MPa	98.65	89.97	74.93	76.34
max. shear stress, Mpa	98.63	99.91	99.96	99.79
futter speed, m/s	327	>400	>400	>400
divergence speed	348	>400	>400	>400

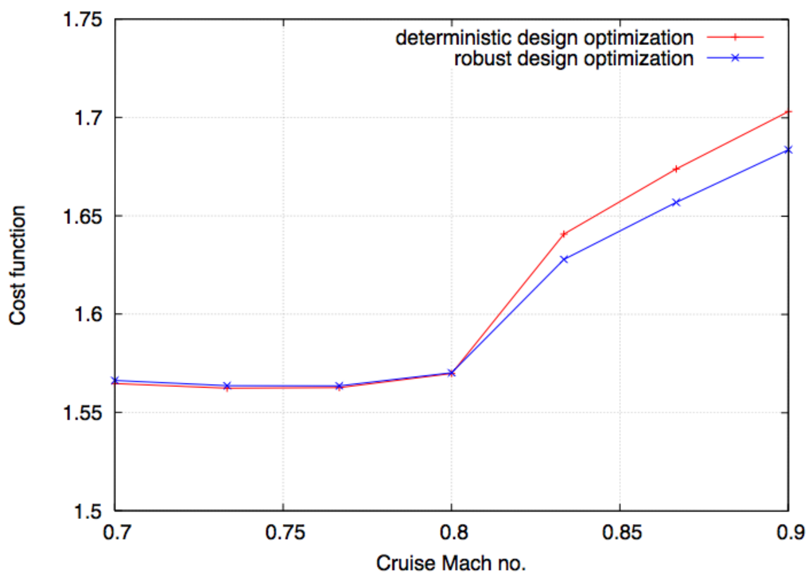

Figure 2. Variation of aircraft life-cycle costs with respect to operating conditions.

4.1 Optimal design of a bulk carrier aimed at minimum unit transportation cost

In this section, the formulation for robust optimization is applied to the conceptual design of a bulk carrier, subject to uncertain operating conditions (for more details on the topic, the interested reader is referred to Diez and Peri, 2009 and 2010). Specifically, the port handling rate (i.e., the capacity of loading and unloading goods, due to harbor facilities) is taken as a probabilistic parameter. Moreover, a uniform distribution from 1,000 ton/day per ship to 11,000 ton/day per ship is assumed. The design variables used in the present application are indicated in Table 5.

Table 5: Design variables vector (designer choices).

variable	lower bound	upper bound
length, m	100.00	600.00
beam, m	10.00	100.00
depth, m	5.00	30.00
draft, m	5.00	30.00
block coefficient	0.63	0.75
cruise speed, kts	14.00	18.00

The model used for the bulk carrier conceptual design analysis is that used by Parsons and Scott (2004). The cost function addressed in this work is the unit transportation cost, whereas the design constraints pertain geometry, static stability, and model validity. The dimension constraints refer to the Capesize category (see again Table 5). The analysis model by Parsons and Scott (2004) is briefly recalled in Appendix 2.

A deterministic particle swarm optimization (DPSO, see Campana et al., 2009, Pinto et al., 2004, Kennedy and Eberhart, 1995) algorithm coupled with a penalty function method is used to solve the constrained minimization problem, minimizing the expected value of the unit transportation cost. The solution is compared with that obtained trough a "deterministic" standard approach (for which the uncertain parameter is taken equal to its mean value). Table 6 contains the optimal solutions, whereas Figure 3 depicts the non-dimensional optimal variables (normalized so as -1 represents the variables lower bound and +1 the upper bound). Figure 4 presents a comparison between the "robust" and the "deterministic" solution performance in terms of unit transportation cost as a function of the uncertain parameter (port handling rate). Moreover, Figure 5 shows the difference between the "robust" and the "deterministic" solution performance, as a function of the port handling rate. It may be noted that, as the uncertain parameter has a uniform density function, the integral of the latter function represents the difference between "robust" and "deterministic" solution expectation of the transportation cost. It may be also noted how the robust configuration has a better overall behavior with respect to the deterministic (specialized) solution. The interested reader may found more results on Diez and Peri (2009 and 2010).

Table 6: Optimal parameters.

variable/function	deterministic solution	robust solution
length, m	182.79	165.70
beam, m	30.60	27.75
depth, m	15.89	14.25
draft, m	11.90	10.76
block coefficient	0.67	0.65
cruise speed, kts	14.00	14.00
Cost for expected port handl. rate	**7.22**	7.31
Expected cost	8.63	**8.50**
Cost standard deviation	3.47	2.93

(optimization objectives highlighted in bold)

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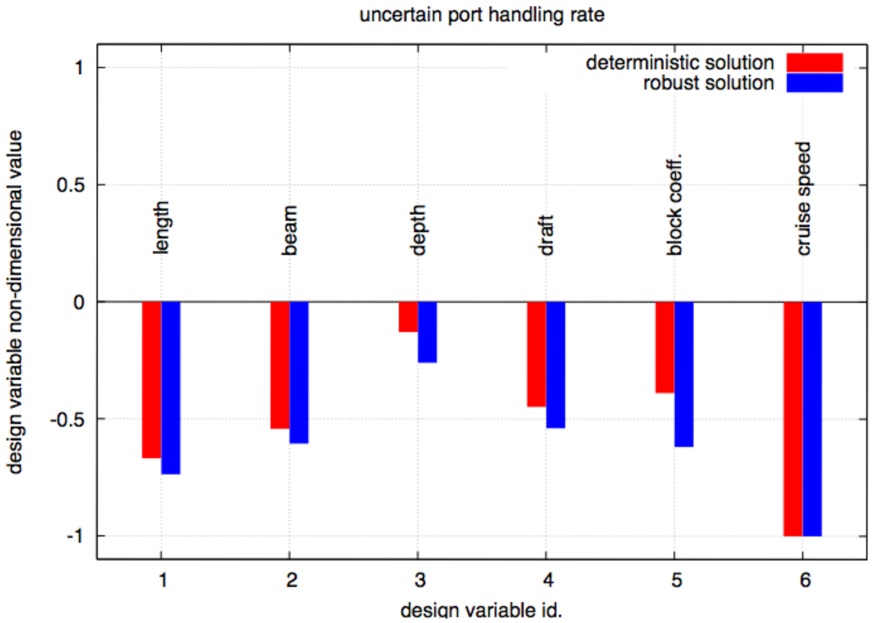

Figure 3. Adimensional optimal variables for standard-deterministic and robust optimization

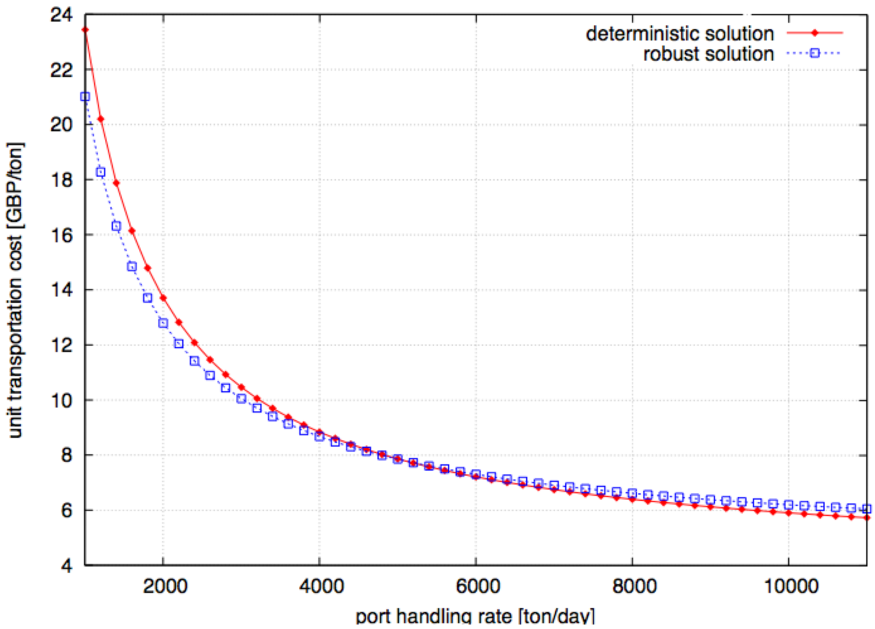

Figure 4. Comparison between deterministic and robust optimal solution permormances (unit transportation cost) as a function of the uncertain parameter (port handling rate).

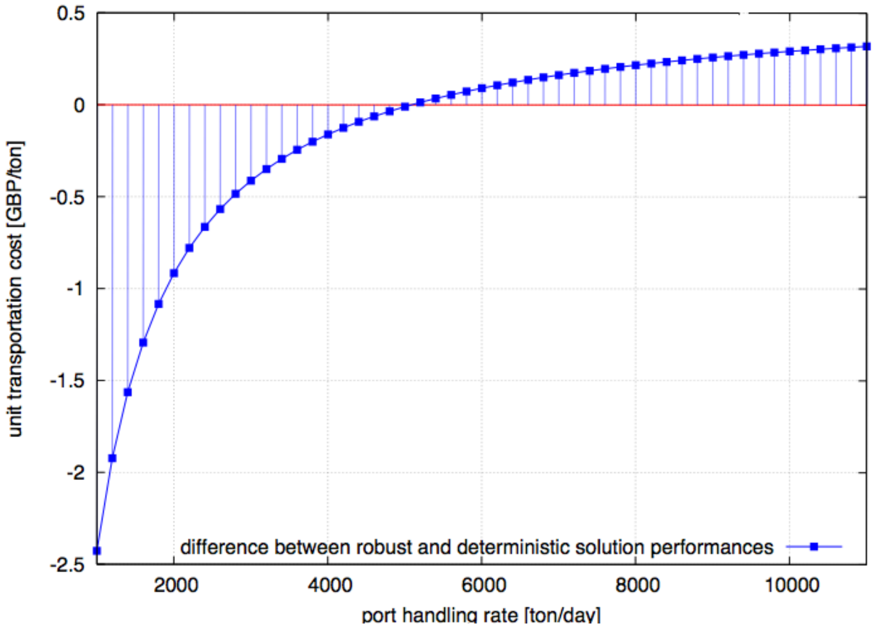

Figure 5. Difference between robust and deterministic unit transportation cost as a function of the port handling rate.

Concluding remarks

A formulation for robust decision-making in optimal design subject to uncertainty has been presented and discussed. The decision problem is formulated so as to look for the Bayesian solution to the design problem. The design requirements are given, in the present formulation, in terms of probabilistic distribution of the operating scenario. Applications to the conceptual design of a mid range civil aircraft and of a bulk carrier, both under uncertain operating conditions, have been shown. The numerical results show how the present approach may increase the robustness of the overall performance when the uncertainty is taken into account in the design process. It is also shown how the robust formulation for optimal design leads to final solutions with minimum value for the expected loss or, in other words, minimum risk in a Bayesian sense.

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Glossary

RDO: Robust design optimization.

RBDO: Reliability based design optimization.

MDO: Multidisciplinary design optimization.

MRDO: Multidisciplinary robust design optimization.

TALC: Total aircraft life-cycle cost.

DPSO: Deterministic particle swarm optimization.

Appendix

Appendix 1. Multidisciplinary analysis tool for aircraft conceptual design

In this appendix, we provide the reader with an idea of the overall algorithm used for the aircraft design optimization. The analysis modules included in the MDO to describe the complete mechanics of the aircraft deal with the structural dynamics, the aerodynamics, the aeroelasticity and the mechanics of flight. For the sake of compactness, the theoretical models underlying the algorithms implemented are only briefly outlined, and the interested reader is addressed to Morino et al. (2003), Morino et al. (2004), Iemma et al. (2005), and Iemma and Diez (2005).

The model used for the structural analysis of the wing is that of a three-dimensional bending-torsional beam, with geometric and structural parameters varying in the spanwise direction. These include structural element geometric dimensions (rib area, spar and skin panel thickness, etc.), wing twist, mass properties plus bending and torsional moments of inertia. Clamped boundary conditions have been considered at root in order to take into account the wing-fuselage juncture.

The solution of the structural problem is obtained using the modal approach. The approximate modes of vibration are evaluated by a finite-element model of the wing, and used to express the displacement field. The physical model used for the aerodynamics is that of compressible quasi-potential flows, enriched by a boundary-layer integral model to take into account the effects of viscosity, and provide an adequate estimate of the viscous drag. Under the assumption that the wake geometry remains fixed in a frame of reference connected with the wing, the numerical solution is obtained through a boundary elements method (BEM, see Morino, 1993, for details). The aeroelastic feedback generated by the interaction between unsteady aerodynamics and structural dynamics is also taken into account in the MDO formulation, through a suitable reduced order model (ROM). The aeroelastic stability analysis is reduced to the study of a root locus (see Morino et al., 1995, for details). The static longitudinal stability, an essential issue for aircraft, is satisfied by imposing that the derivative with respect to the angle of attack of pitch moment coefficient (evaluated with respect to the center of mass G) be less than zero. In order to evaluate fuel consumption, the mission profile considered in this work consists of: (i) take-off, (ii) climb, (iii) cruise, (iv) descent, and (v) landing. The relation between fuel burn, aircraft weight and range is addressed through the Breguet equation (see, e.g., Mair and Birdsall, 1992, and Raymer, 2006).

The approach used for the aeroacoustic simulation is chosen taking into account several concurring factors. An accurate evaluation of the noise perceived at a specified location requires a prime-principle-based accurate modeling of several physical phenomena, which are extremely expensive to simulate (turbulence, shock waves, unsteady wakes, etc.). Considering that each analysis module can be called thousands of times during a complete optimization process, it is apparent that a prime-principle-based simulation of the noise generation mechanisms would make the computational burden too heavy even for the most powerful computer systems. In addition, the noise prediction is not directly related to critical design issues such as safety, reliability, and performance. Moreover, in the formulation used, the optimization process is driven by the trend of the noise as a function of the design variables, rather than by its absolute value. For all these considerations, we can conclude that the requisite of high accuracy in noise prediction does not represent a critical issue, at least considering the aims of this work. Thus, within the optimization framework, we have preferred here to use efficient, well assessed algorithms based on empirical (or semi-empirical) models. Accordingly, the algorithm used for the evaluation of the noise emission is based on a Noise-Power-Distance table obtained from experimental data.

Appendix 2. Bulk carrier conceptual design tool

In this Appendix, the bulk carrier analysis tool used by Parsons and Scott (2004) is briefly recalled.

Independent variables:
L = length [m], B = beam [m], D = depth [m], T = draft [m], C_B = block coefficient, V_k = speed [knots].

Model:
annual cost = capital costs + running costs + voyage costs
capital costs = 0.2 ship cost
ship cost = 1.3 (2,000 $Ws^{0.85}$ + 3,500 Wo + 2,400 $P^{0.8}$)
steel weight = Ws = 0.034 $L^{1.7}$ $B^{0.7}$ $D^{0.4}$ $C_B^{0.5}$
outfit weight = Wo = $L^{0.8}$ $B^{0.6}$ $D^{0.3}$ $C_B^{0.1}$
machinery weight = Wm = 0.17 $P^{0.9}$
displacement = 1.025 L B T C_B
power = P = $\text{displacement}^{2/3}$ V_k^3/(a + b Fn)
Froude number = Fn = $V/(gL)^{0.5}$
V = 0.5144 V_k m/s; g = 9.8065 m/s^2
a = 4,977.06 C_B^2 - 8,105.61 C_B + 4,456.51
b = - 10,847.2 C_B^2 + 12,817 C_B - 6,960.32
running costs = 40,000 $DWT^{0.3}$
deadweight = DWT = displacement - light ship weight
light ship weight = Ws + Wo + Wm
voyage costs = (fuel cost + port cost) RTPA
fuel cost = 1.05 daily consumption * sea days * fuel price
daily consumption = 0.19 P 24/1,000 + 0.2
sea days = round trip miles/24 V_k
round trip miles = 5,000 (nm)
fuel price = 100 (£/t)
port cost = 6.3 $DWT^{0.8}$

round trips per year = RTPA = 350/(sea days + port days)
port days = 2[(cargo deadweight/handling rate) + 0.5]
cargo deadweight = DWT - fuel carried - miscellaneous DWT
fuel carried = daily consumption (sea days + 5)
miscellaneous DWT = 2.0 $DWT^{0.5}$
handling rate = 6,000 (t/day)
annual cargo capacity = DWT * round trips per year
unit transportation cost = annual cost / annual cargo capacity
vertical center of buoyancy = KB = 0.53 T
metacentric radius = BMT =$(0.085\ C_B - 0.002)\ B^2/(T\ C_B)$
vertical center of gravity = KG = 1.0 + 0.52 D

Constraints used in this work:
$L/B \geq 6$
$L/D \leq 15$
$L/T \leq 19$
$T \leq 0.45\ DWT^{0.31}$
$T \leq 0.7\ D + 0.7$
$25{,}000 \leq DWT \leq 500{,}000$
$Fn \leq 0.32$
$GMT = KB + BMT - KG \geq 0.07\ B$