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# Aircraft derivative design optimization considering global sensitivity and uncertainty of analysis models

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## Abstract

Aircraft manufacturing companies have to consider multiple derivatives to satisfy various market requirements. They modify or extend an existing aircraft to meet new market demands while keeping the development time and cost to a minimum. Many researchers have studied the derivative design process, but these research efforts consider baseline and derivative designs together, while using the whole set of design variables. Therefore, an efficient process that can reduce cost and time for aircraft derivative design is needed. In this research, a more efficient design process is proposed which obtains global changes from local changes in aircraft design in order to develop aircraft derivatives efficiently. Sensitivity analysis was introduced to remove unnecessary design variables that have a low impact on the objective function. This prevented wasting computational effort and time on low priority variables for design requirements and objectives. Additionally, uncertainty from the fidelity of analysis tools was considered in design optimization to increase the probability of optimization results. The Reliability Based Design Optimization (RBDO) and Possibility Based Design Optimization (PBDO) methods were proposed to handle the uncertainty in aircraft conceptual design optimization. In this paper, Collaborative Optimization (CO) based framework with RBDO and PBDO was implemented to consider uncertainty. The proposed method was applied for civil jet aircraft derivative design that increases cruise range and the number of passengers. The proposed process provided deterministic design optimization, RBDO, and PBDO results for given requirements.

**Key words:** Reliability Based Design Optimization, Possibility Based Design Optimization, Aircraft Conceptual Design, Derivative Design

## 1. Introduction

A family of military/civil aircraft generally has multiple derivatives to satisfy diverse requirements. Aircraft manufacturers develop new aircraft models as modifications or extensions of existing aircraft in order to meet new market demands while keeping the development time and cost to a minimum [1]. The commonality of the aircraft as well as its family has advantages to both the airliner and the manufacturer. These include simplification of maintenance procedures, flexibility in scheduling and reduced spare-parts inventory [1]. Additionally, airlines that operate several derivative aircraft types can reduce the pilot training time between different types. However, the redesign for derivatives of existing aircraft does require additional development resources and time. Many researchers studied techniques for derivative design. These research efforts considered the whole set of design variables and designed the baseline and derivatives simultaneously [1-10]. Richard et al., Robert et al., and Deepak et al. identified the important parameters for the family design by applying the market requirement analysis [1, 2, and 3]. Jonathan et al. utilized the generation of a Pareto



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frontier to identify the candidates of product family members [4]. Timothy et al. and Rajesh et al. applied a Multi-Objective Genetic Algorithm (MOGA) for derivative design. A genetic algorithm with the considerations of different platform levels was employed to optimize the product baseline and its family [5, 6, and 7]. A Multi-Objective Particle Swarm Optimization (MOPSO) method was proposed by Seng Ki et al. [8]. Moreover, James et al. and Dongwook et al. suggested an evolutionary method and data mining technique for a family of aircraft design [9, 10]. They assumed values for the requirements needed for the market purposes, which often differed from actual market requirements. A more efficient design process for aircraft derivative design is needed to properly handle the ever changing market demands.

The aircraft conceptual design utilizes many types of low fidelity analysis tools because of their fast computation time. However, comparably low accuracy of these analysis tools makes an error and it can cause the optimization results to violate active constraints. This error can be handled as uncertainty. Uncertainty is inherent in any form of simulation-based design. Recently, handling uncertainty in design optimization has been studied in order to increase the probability of optimized solutions. The Reliability Based Design Optimization (RBDO) method has been developed to enforce probabilistic constraints in optimization problems involving uncertainty [11]. The RBDO method is used when the information concerning uncertain parameter is sufficient to generate accurate input of statistical distribution functions. However, the probabilistic method cannot be used for reliability analysis when a sufficient amount of uncertain data cannot be obtained. The Possibility Based Design Optimization (PBDO) method is proposed to overcome this disadvantage of the RBDO method [12]. The PBDO method uses a fuzzy membership function for uncertain parameter modeling and is useful when it has insufficient data for producing probability density functions.

In this research, an efficient derivative design process was studied to develop aircraft derivatives. Sensitivity analysis and an aircraft database were used to identify important design variables for objectives and requirements. Furthermore, uncertainty of low fidelity analysis tools was considered in order to increase the reliability of optimized design results. The RBDO and PBDO algorithms were developed to deal with uncertainty connected to the traditional low fidelity analysis used in aircraft conceptual design. Error terms were derived from comparing analysis results of low fidelity tools and a database of existing aircraft.

The proposed derivative design process was applied to B737-300 aircraft to design the aircraft that is comparable to B737-900. The design variables for derivative design were selected from GSA result. The comparison between B737-800 and different cases with different number of design variables was performed to select design variables. The target aircraft was optimized using the selected design variables.

## 2. Derivative design process

The proposed design process selected design variables and obtained derivative designs based on changes in requirements. The global sensitivity analysis method was implemented to enhance efficiency of the derivative design optimization process. The sensitivity analysis result demonstrated the most necessary design variables that need to be altered to satisfy the new requirements. This information was used to reduce the scope of the derivative design optimization problem. The reduction of the number of design variables increased the computational efficiency of the Multidisciplinary Design Optimization (MDO) problem.

When the new requirements have emerged, the designer has to analyze these requirements and establishes the design problem. From the problem definition, design requirements and objectives are specified and qualitative and quantitative properties are derived. A fuzzy expert system is used to identify the feasible range of design variables in order to satisfy the new demand. A database within the aircraft and their derivatives is used for the criteria of the inference engine in the expert system. The first phase of the process specifies the range of design variables to satisfying the new demands. The derived boundaries of design variables are utilized in the sensitivity analysis for the next phase.

Using the results of the baseline aircraft analysis, sensitivity analysis is carried out to identify which design variables are important for complying with the new design requirements. The sensitivity analysis is used for various applications such as ranking the individual parameters in order of their relative importance to the objective and assessing changes in the response due to parameter variations. The sensitivity analysis is implemented to select the important design variables for local derivative design changes.

When uncertain parameters are considered, RBDO and PBDO methods are employed. RBDO and PBDO are the methods to overcome the drawbacks of deterministic optimization. They have been developed to improve product reliability in industrial engineering. To apply RBDO and PBDO with MDO, a distribution of the uncertain parameters is developed. Subsequently, RBDO and PBDO are prepared to derive the reliable solution when uncertainty from low fidelity analysis tools are considered. Fig. 1 shows the concept of the proposed design process.

## 2.1 Expert system

The database is categorized by aircraft type and arranged by the parts that are considered to fulfill each additional requirement. The database then provides guidance in selecting the design variables for local design changes. The first phase of the design process specifies the design variables relevant to the new demands. The fuzzy expert system is then used to establish the feasible region of design variables that comply with the new demands. The feasible region for each design variable is utilized in the sensitivity analysis for the next phase [13, 14]. Fig. 2 shows the process of the expert system in this research.

The expert system consists of the design variables, rules, and results. A fuzzy function is applied to design variables for input into the expert system and the values are normalized between 0 and 1 based on the information in the database.

## 2.2 Global sensitivity analysis: extended Fourier Amplitude Sensitivity Test (e-FAST) method

The e-FAST method was implemented in this research to determine the global sensitivity indices [15]. This method is based on the original Fourier Amplitude Sensitivity Test (FAST) method. The FAST method is more efficient than the Monte Carlo Simulation method when estimating value, variance and contribution of individual inputs to the sensitivity of the function output [15-18].

The e-FAST method computes the main contribution of each input to the variance of the output. A sinusoidal function of a particular frequency for each input is implemented in the sampling procedure in e-FAST method. The frequencies assigned to the parameters must meet several criteria so that they can be distinguished within a Fourier analysis. Due to the symmetry properties of trigonometric functions, the sinusoidal function will repeat the same samples, so a re-sampling scheme is implemented to avoid this inefficiency. The e-FAST method is robust at low sample sizes and computationally efficient [19]. In this research, the e-FAST module was developed using the Visual Fortran language. Fig. 3 describes the application of the global sensitivity analysis method in this research.

## 2.3 Design optimization with uncertainty

This research examined the implementation of the RBDO and PBDO methods considering uncertainty from low fidelity analysis methods. Low fidelity analysis tools create

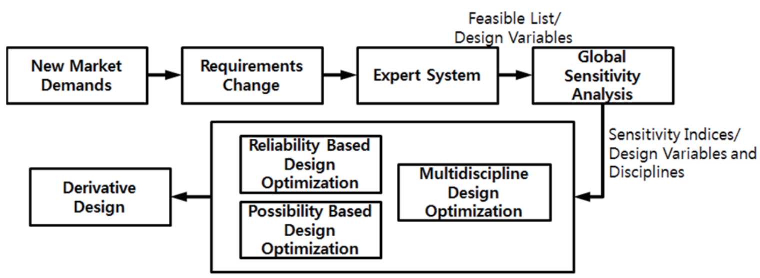


Fig. 1. The proposed aircraft derivative design process

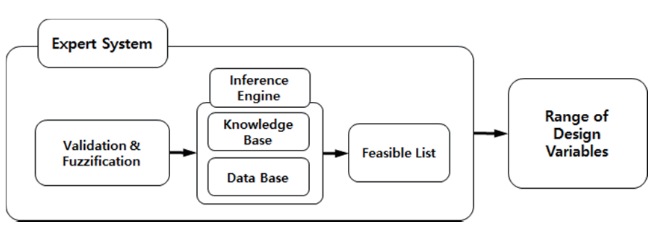


Fig. 2. Process of the expert system

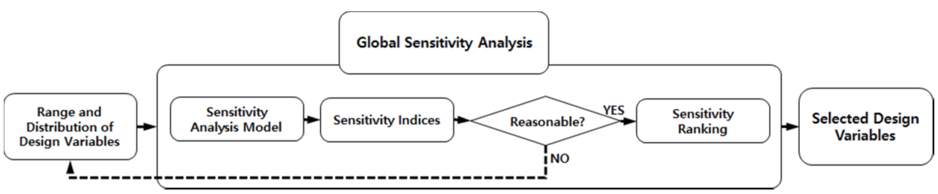


Fig. 3. Process of global sensitivity analysis

uncertainty and this can cause the optimization results to violate certain constraints.

### 2.3.1 Uncertainty

Figure 4 shows uncertainty sources in a simulation-based design process. It is difficult to simulate natural phenomena exactly, thus simulation models apply many assumptions and simplifications, which generate errors in the model. In addition, uncertainty can exist due to uncontrollable variations in the external environment or an inadequate unified modeling technique. This uncertainty is researched and suitable methods are applied to handle different types of uncertainty [27-30].

### 2.3.2 Reliability Based Design Optimization (RBDO)

The basic idea of the RBDO is implementing numerical optimization algorithms to achieve a reliable optimal design while considering the associated uncertainty [11, 21]. Active constraints for the deterministic solution may lead to a system failure when an optimization is carried out with uncertainty. The reliable solution is placed farther inside the feasible design region than the deterministic optimization result to achieve the targeted reliability level. In the RBDO, probability theory is applied to model uncertainty and the Probability Density Function (PDF) is used to obtain probability distributions of the random variables. The probability of failure corresponding to a particular failure mode can be obtained or posed as a constraint in the optimization problem in order to obtain the reliability target [22, 26, and 27]. The RBDO model can generally be defined as [11]

$$\begin{aligned} &min.\ f(\boldsymbol{d}) \\ &subject\ to\ P(G_i(\boldsymbol{X}) \le 0) - \Phi(-\beta_t) \le 0, \qquad i = 1, 2, \cdots, np \\ &\qquad d^L \le \boldsymbol{d} \le d^U,\ d \in R^{ndv},\quad \mathrm{X} \in R^{nrv} \end{aligned} \tag{1}$$

where $d$, $d^L$, and $d^U$ are the design variable vector, the lower design variable boundary, and the upper design variable boundary respectively. $G_i(X)$ is the $i^{th}$ constraint function and $X$ is the random vector. $P(\bullet)$ is the probability measure and $np$ is the number of possible constraints. The variables $ndv$ and $nrv$ are the number of design vectors and random vectors respectively. $\Phi(\bullet)$ is the standard normal Cumulative Distribution Function (CDF) and $\beta_t$ represents the probability distributions and their prescribed reliability target.

### 2.3.3 Possibility Based Design Optimization (PBDO)

When an uncertainty parameter has an insufficient amount of information to generate PDF for RBDO, the possibility-based design optimization method has been proposed for design optimization. The possibility-based method gives a more conservative design result than the probabilistic design when information regarding uncertain parameters is inadequate [12, 20, 22, and 23]. The general formula of PBDO is shown below [12].

$$\begin{aligned} &min.\ f(\boldsymbol{d}) \\ &subject\ to\ \ \Pi\big(G_i(\boldsymbol{X})\big) > 0\ \le\ \alpha_t,\ \ i = 1, 2, \cdots, np \\ &\qquad d^L \le \boldsymbol{d} \le d^U \end{aligned} \tag{2}$$

$\Pi(\bullet)$ is the possibility measure, $X$ is the random vector and $\alpha_t$ is the target possibility of failure.

## 2.4 Multidisciplinary Design Optimization (MDO): Collaborative Optimization (CO) method

The Collaborative Optimization (CO) method was developed as a decomposed and decentralized bi-level optimization method [33]. A system level optimizer provides target values for global design variables $z$ and system responses $y$. Local disciplinary level optimizers assure that the discrepancies between disciplines vanish by enforcing compatibility constraints. It is modeled to minimize the interdisciplinary discrepancies while satisfying specific local constraints. The CO formulation can be stated at the system level as [33]

$$\begin{aligned} &min.\ f(z_{SL}, y_{SL}) \\ &\text{subject to}\ J_i\left(z_{SL}, z_i^*, y_{SL}, y_i^*(x_i^*, y_j, z_i^*)\right) = 0, \\ &\qquad j = 1, 2, \cdots, n,\quad j \ne i \end{aligned} \tag{3}$$

where $J$ is the compatibility constraints (one for each discipline), subscript $SL$ is system level and $z^*$, $y^*$ and $x^*$ are the optimal disciplinary optimization level results. The $i^{th}$ disciplinary level optimization problem is formulated as

$$\begin{aligned} &min.\ J_i = \sum (z_{SL} - z_i)^2 + \sum (y_{SL} - y_i)^2 \\ &subject\ to\ \ g_i\big(x_i, z_i, y_i(x_i, y_j, z_i)\big) \le 0 \end{aligned} \tag{4}$$

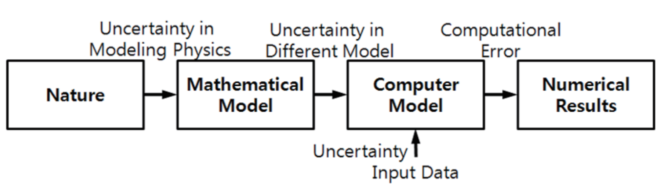


Fig. 4. Sources of uncertainty in simulation based design process

where $g_i$ is the $i^{th}$ disciplinary constraint.

### 2.5 RBDO/PBDO with MDO

Many research of reliability based MDO methods and various RBDO techniques was studied [34-40]. In this research, the CO method was implemented and combined with RBDO and PBDO methods [41]. The system level objective function was unchanged from the deterministic optimization. On the other hand, constraints were updated from the RBDO and PBDO results to incorporate the uncertainty associated with various parameters. Since compatibility between disciplines was carried out by the objective function of each local optimization, auxiliary constraints did not appear in the local optimization problem statements. Therefore, modification of the reliability analysis with coupling variables and compatibility constraints was unnecessary. In this paper, two modules: the CO with RBDO and the CO with PBDO were developed and their results were compared with each other.

The system level optimization of the CO with RBDO was derived from Eq. (3) and is given in Eq. (5) [41].

$$\begin{aligned}&min.\, f(z_{SL}, y_{SL}, \bar{p})\\&\text{subject to } J_i(z_{SL}, z_i^*, y_{SL}, y_i^*(x_i^*, y_j, z_i^*), \bar{p}) = 0,\\&\qquad j = 1, 2, \cdots, n, \quad j \neq i\end{aligned} \tag{5}$$

where $\bar{p}$ is the uncertain parameters. The formulation of $i^{th}$ disciplinary level optimization problem in Eq. (4) changes to [41]

$$\begin{aligned}&min.\, J_i = \sum (z_{SL} - z_i)^2 + \sum (y_{SL} - y_i)^2\\&subject\ to\ \ P\big(\, g_i(x_i, z_i, y_i(x_i, y_j, z_i), p) \leq 0\big) \geq P_t\end{aligned} \tag{6}$$

$P$ is the set of probabilities of feasibility for each problem constraint and $P_t$ is the target probability of feasibility. The CO with the PBDO method formulation of the system level changed from Eq. (3) [41].

$$\begin{aligned}&min.\, f(z_{SL}, y_{SL}, \bar{X})\\&\text{subject to } J_i(z_{SL}, z_i^*, y_{SL}, y_i^*(x_i^*, y_j, z_i^*), \bar{X}) = 0,\\&\qquad j = 1, 2, \cdots, n, \quad j \neq i\end{aligned} \tag{7}$$

$\tilde{X}$ is the fuzzy parameters. The formulation of $i^{th}$ disciplinary level optimization changes to [41]

$$\begin{aligned}&min.\, J_i = \sum (z_{SL} - z_i)^2 + \sum (y_{SL} - y_i)^2\\&subject\ to\ \ \Pi\big(\, g_i(x_i, z_i, y_i(x_i, y_j, z_i), X) \leq 0\big) \leq \alpha_t\end{aligned} \tag{8}$$

$\Pi(\bullet)$ is a possibility measure and $\alpha_t$ represents the target possibility of failure.

## 3. Aircraft derivative design

GSA method was performed to find the important design variables for the new requirements [42]. Moreover, RBDO and PBDO were implemented to consider errors associated with low fidelity analysis tools of aircraft conceptual design [41-46]. Nuefeld et al. (2011) and Jaeger et al. (2013) implemented RBDO to handle uncertainty from the fidelity of the analysis model [43, 45]. In this research, analysis results using the low fidelity analysis tools and a historical database were compared to derive error terms for uncertainty-based design optimization methods. Additionally, RBDO and PBDO results were compared with each other. RBDO and PBDO targeted only active constraints, adjusting designs away from the active constraints within the optimization scheme.

In this work, the B737-300 was selected as the baseline for derivative design since it has many types of derivative. The solution procedure is described as below and is shown in Fig. 5.

(1) Input baseline aircraft parameters.

(2) Determine important design variables to achieve new

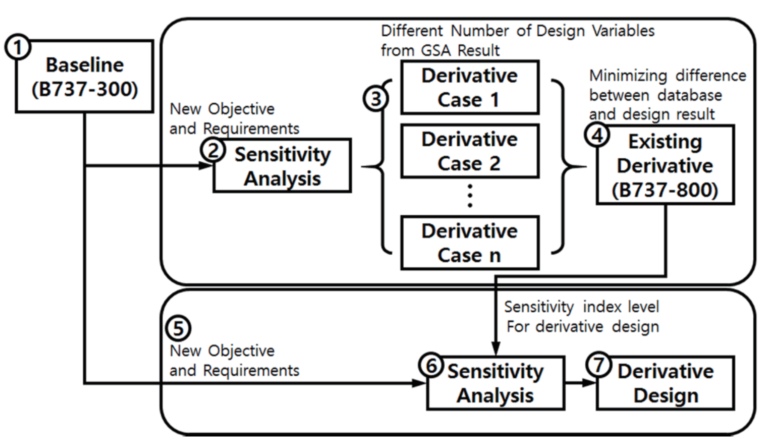


Fig. 5. Derivative design process

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requirements using Global Sensitivity Analysis (GSA).

(3) Obtain derivative design optimization cases (various numbers of design variables) from the GSA result.

(4) Compare optimization cases with the baseline aircraft and its known derivative and minimize the difference.

(5) Input requirements (modelled after the B737-900 for comparison).

(6) Implement a GSA method to identify important design variables to satisfy the new design requirements.

(7) Run optimization and solve for the derivative aircraft configuration.

The design requirements shown in Table 1 were compatible with the B737-900. The analysis method consisted of four discipline groups: weight, performance, aerodynamics and stability.

### 3.1 Expert system

In this research, a database was developed by collecting data from forty different types of civil jet aircraft [47-57]. Table 2 shows the design variables and their fuzzy input range from the database. The design variables and rules for the expert system were extracted from the database. When derivatives were considered, these design variables were changed to satisfy new requirements [46].

The responses shown in Fig. 6 were derived from the expert system based on the B737-300 aircraft, which has been adopted as a baseline concept for this research. Fig. 6 shows the feasible region for new requirements with normalized values, and the results show various aircraft trends when the design variables were changed. Fig. 6. a) presents the trend of the wingspan with respect to the number of passengers of B737-800 (dotted line, 0.228) and B737-900 (solid line, 0.238) on the target cruise range as 2,000 NM (normalized value is 0.1). In this figure, the shading region represented the feasible space. From this figure, the corresponding required range for the wing span was found to be 0.02~0.52 (normalized value).

Table 1. Design requirements of aircraft derivative design [47]

| Requirement | Target Value |
|---|---|
| Number of Passengers | $N_{pax} = 189$ |
| Payload Mass | $M_{pl} = 45{,}720\ lb$ |
| Range (with 200 *NM* reserve) | $R \geq 2{,}060\ NM$ |
| Cruise Mach Number | $M_{cr} = 0.785$ |
| Cruise Altitude | $h_{cr} = 36{,}000\ ft$ |
| Empty Weight | $W_e \leq 93{,}655\ lb$ |
| Approach Speed | $V_a \leq 140\ kts$ |

Table 2. Design variables and its range for fuzzy function

| | Very Low | Low | Medium | High | Very High |
|---|---|---|---|---|---|
| Wing Span (*ft*) | 85 | 110 | 135 | 160 | 185 |
| Wing Aspect Ratio | 6.8 | 7.5 | 8.1 | 8.7 | 9.3 |
| Wing Taper Ratio | 0.15 | 0.2 | 0.25 | 0.29 | 0.35 |
| Horizontal Tail Span (*ft*) | 32 | 41.3 | 49.8 | 58.3 | 66.8 |
| Vertical Tail Span (*ft*) | 14 | 18.4 | 22.8 | 27.2 | 31.6 |
| Length of Fuselage (*ft*) | 93.1 | 123.7 | 154.3 | 184.9 | 215.5 |
| Number of Passengers | 76 | 170 | 265 | 360 | 455 |
| Range (*NM*) | 1,298 | 2,768 | 4,238 | 5,709 | 7,179 |

Similarly, Fig. 6. b) ~ 6. f) indicate the trends of other design variables with respect to the target cruise range and the number of passengers. Table 3 shows normalized values and real values regarding cruise range related trends for B737-800 and B737-900. Table 4 shows the feasible range of design variables from the expert system results.

## 3.2 Analysis modules

### 3.2.1 Aerodynamics

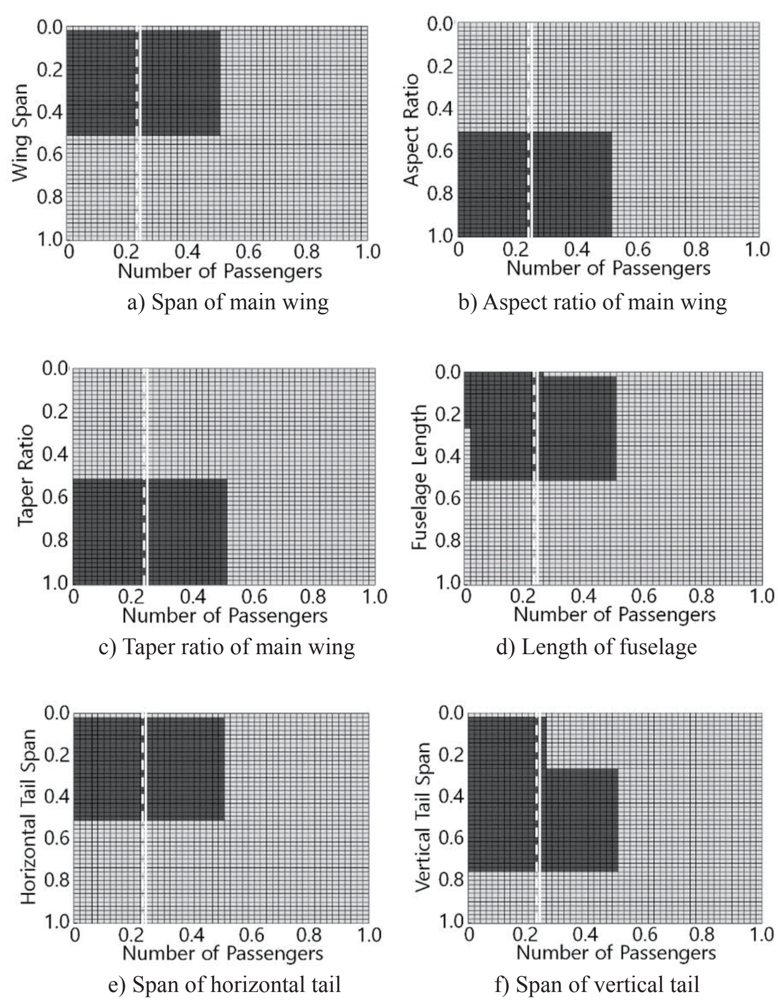
The aerodynamics discipline shows the lift and drag characteristics of aircraft based on an estimation method of Raymer [52] and Torenbeek [53]. Fig. 7 shows how the aerodynamics discipline was handled. 17 design variables and 11 parameters were used in this analysis module. The lift and drag results derive the thrust required and were compared with actual aircraft data. To maintain level flight, the net thrust must overcome the drag and it is given in Eq. (9) [52, 53].

$$T_R = \frac{W}{L/D} = \frac{W}{C_L/C_D} \tag{9}$$

The thrust value depends on velocity, altitude, aerodynamic shape and the weight of the aircraft. The previous research of the authors implemented this analysis module and normal distribution of its error has a mean value of 1.052, variance of 0.019, and standard deviation of 0.137 [41]. Fig. 8 shows a histogram and normal distribution of errors of thrust required. Left axis of the figure represents the frequency of error and right axis is frequency of normal distribution. The constraints in the aerodynamic discipline require the designs to generate a lift force greater than the gross weight. As described in the next section, the gross weight value was delivered from the weight estimation discipline.

### 3.2.2 Weight

The statistical group weight method was implemented




a) Span of main wing
b) Aspect ratio of main wing
c) Taper ratio of main wing
d) Length of fuselage
e) Span of horizontal tail
f) Span of vertical tail

Fig. 6. Feasible region of major design variables from the expert system

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for aircraft weight estimation. The statistical relationship of the weight and center of gravity for each major aircraft component allowed for an estimate of the overall empty weight of the aircraft. Many aircraft conceptual design publications described this method in detail [52, 53]. In general, the statistical equations are functions of the geometry and performance requirements of the aircraft while considering the payload capacity, cruise speed, and altitude. Moreover, the empty weight, the gross weight, the center of gravity, and the moments of inertia of the aircraft were also calculated. These equations cannot give the exact value of aircraft weight, but provided a reasonable estimation

Table 3. Normalized value and real value of design variables and requirements

| Design variable | B737-800 | | B737-900 | |
|---|---|---|---|---|
| | Normalized value | Real value | Normalized value | Real value |
| Wing Span (*ft*) | 0.206 | 111.52 | 0.206 | 111.52 |
| Wing Aspect Ratio | 0.566 | 8.73 | 0.566 | 8.73 |
| Wing Taper Ratio | 0.628 | 0.3 | 0.628 | 0.3 |
| Horizontal Tail Span (*ft*) | 0.336 | 47.07 | 0.336 | 47.07 |
| Vertical Tail Span (*ft*) | 0.524 | 25.96 | 0.524 | 25.96 |
| Length of Fuselage (*ft*) | 0.207 | 124.71 | 0.264 | 133.40 |
| Requirements | | | | |
| Number of Passengers | 0.228 | 184 | 0.238 | 189 |
| Range (*NM*) | 0.10 | 2,000 | 0.10 | 2,000 |

Table 4. Feasible range of design variables

| Design variable | Normalized value | | Real value | |
|---|---|---|---|---|
| | Lower boundary | Upper boundary | Lower boundary | Upper boundary |
| Wing Span (*ft*) | 0.02 | 0.52 | 87.83 | 151.66 |
| Wing Aspect Ratio | 0.5 | 1.0 | 8.52 | 10.10 |
| Wing Taper Ratio | 0.5 | 1.0 | 0.27 | 0.38 |
| Horizontal Tail Span (*ft*) | 0.02 | 0.5 | 33.65 | 54.05 |
| Vertical Tail Span (*ft*) | 0.02 | 0.76 | 14.44 | 30.66 |
| Length of Fuselage (*ft*) | 0.0 | 0.52 | 93.10 | 172.54 |

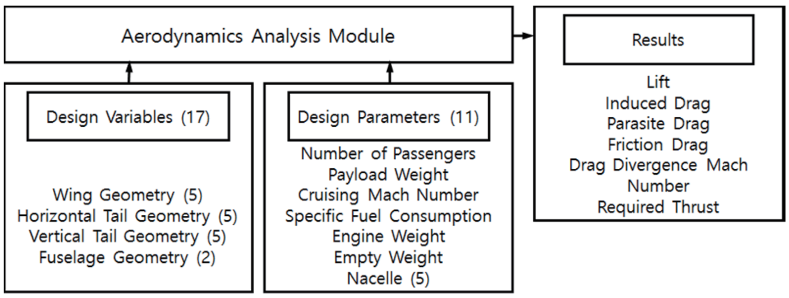


Fig. 7. The aerodynamics discipline analysis

of the group weight. The weight estimation module implemented 17 design variables and 7 parameters. Fig. 9 shows how analysis in the weight discipline was performed. The comparison between forty cases of predicted weight and database values has been done in the previous study [41]. The empty weight error term can be approximated by a normal distribution with a mean of 0.872, variance of 23.781 and a standard deviation of 4.877 [41]. It's shown in Fig. 10. The weight constraints coincide with those of the B737-900. The empty weight requirement values are shown in Table 1.

### 3.2.3 Performance

The net force acting on the aircraft was computed from drag, lift, and available thrust forces over a numerical simulation. The range is intimately connected with engine performance via the specific fuel consumption. In this research, the Breguet range equation was used for jet propelled aircraft and it is given in Eq. (10) [52].

$$R = \frac{2}{c_t}\sqrt{\frac{2}{\rho_\infty S_w}}\frac{C_L^{1/2}}{C_D}\left(W_0^{1/2} - W_1^{1/2}\right) \tag{10}$$

where $R$ is the range, $c_t$ is the thrust specific fuel consumption in a consistent unit, and $\rho_\infty$ is the air density. Moreover, $S_W$ is the wing area, $W_0$ is the gross weight, and $W_1$ is the weight with the fuel tanks empty. $C_L$ and $C_D$ are lift and drag coefficient respectively. The cruise range was selected as a performance constraint and defined by the performance characteristics of the B737-900. Fig. 11 shows the simple block diagram used in the performance analysis discipline.

The forty cases of cruise range prediction results were compared in the first author's previous work and normal distribution of its error has a mean value of 1.006 as well as a variance and standard deviation of 0.010 and 0.101 respectively [41]. Errors were represented in the histogram and normal distribution functions. It is shown in Fig. 12.

### 3.2.4 Stability and control

The static margin as well as lateral and directional stability were considered in the stability and control discipline. A static margin of 5% was used as a longitudinal stability constraint. Yaw static stability was enforced at a full thrust climb scenario with a failed engine. The stability and control

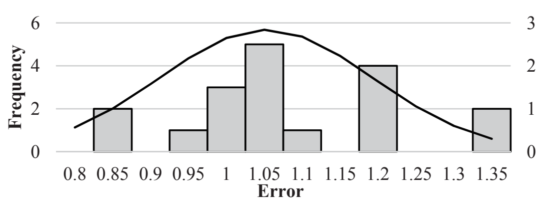


Fig. 8. Error distribution of thrust required

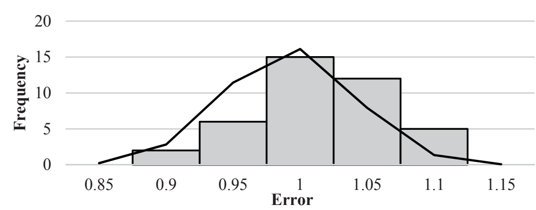


Fig. 10. Error distribution of empty weight of aircraft

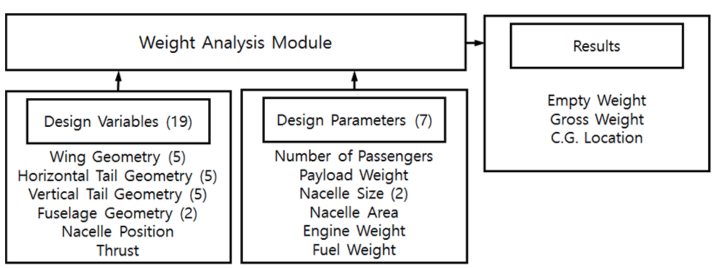


Fig. 9. The weight discipline analysis

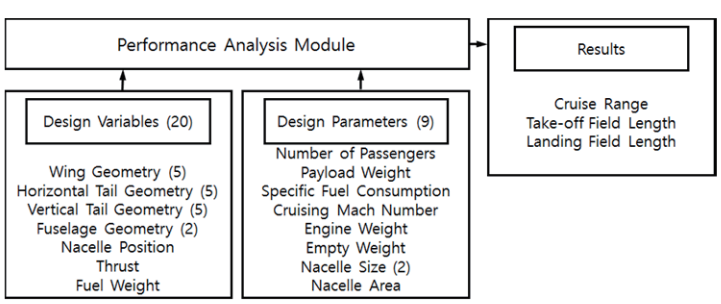


Fig. 11. The performance discipline analysis

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discipline defines the system constraints given in Table 5. However, uncertain parameters were not defined in this discipline. Fig. 13 shows how the stability and control discipline was handled.

### 3.3 Global Sensitivity Analysis (GSA) result

The design variables and their ranges were shown in Table 6. These values and ranges were defined using the results of the expert system. Span length and area of the wing can be derived from Eqs (11) and (12) respectively [52, 53]. Span length of the wing and empennage of the expert system result was implemented as constraints of optimization.

$$B = \sqrt{AR \times S} \tag{11}$$

$$S = \frac{AR}{4}\left(C_{Root}(1+TR)\right)^2 \tag{12}$$

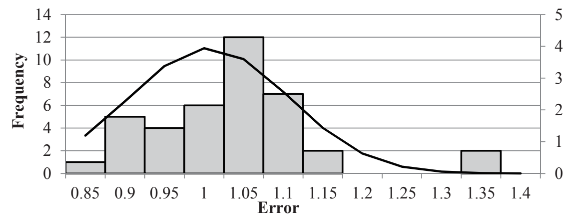


Fig. 12. Error distribution of cruise range

Table 5. Aerodynamics and Stability Local Constraints

| Constraint | Description | Value |
|---|---|---|
| $k_n$ | Static margin | $\geq 0.05$ |
| $C_{l\beta}$ | Dihedral effect | $< 0.0$ |
| $C_{n\beta}$ | Yaw stiffness | $> 0.0$ |

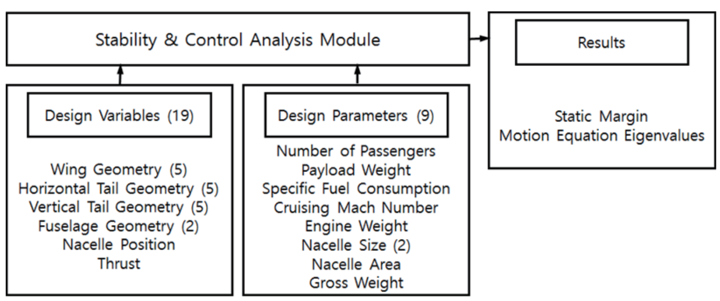


Fig. 13. The stability and control discipline analysis

Table 6. Range of design variables

| Design Variable | | Lower boundary | Upper boundary |
|---|---|---|---|
| Wing geometry | $AR_W$ | 8.52 | 10.10 |
| | $TR_W$ | 0.27 | 0.38 |
| | $C_{Root\_W}$ $(ft)$ | 15.0 | 26.0 |
| | $\Lambda_{LE\_W}$ $(deg)$ | 20.0 | 30.0 |
| | $S_{csW}$ $(ft^2)$ | 230.0 | 350.0 |
| Horizontal tail geometry | $AR_H$ | 3.8 | 6.0 |
| | $TR_H$ | 0.2 | 0.3 |
| | $C_{Root\_H}$ $(ft)$ | 10.5 | 28.5 |
| | $\Lambda_{LE\_H}$ $(deg)$ | 30.0 | 40.0 |
| | $S_{csH}$ $(ft^2)$ | 68.0 | 85.0 |
| Vertical tail geometry | $AR_V$ | 1.6 | 2.3 |
| | $TR_V$ | 0.2 | 0.35 |
| | $C_{Root\_V}$ $(ft)$ | 15.0 | 20.0 |
| | $\Lambda_{LE\_V}$ $(deg)$ | 35.0 | 45.0 |
| | $S_{csV}$ $(ft^2)$ | 53.0 | 70.0 |
| Fuselage geometry | $L_f$ $(ft)$ | 93.10 | 172.54 |
| | $L_T$ $(ft)$ | 38.0 | 64.0 |
| Engine | $T$ $(lbf)$ | 17,000.0 | 30,000.0 |
| | $W_f$ $(lb)$ | 18,000.0 | 45,100.0 |

$B$ is the span length, $C_{Root}$ is the root chord length, $TR$ is the taper ratio, $AR$ is the aspect ratio, and $S$ is the wing area.

Using the ranges of each design variable from Table 6, the e-FAST method was performed as a GSA for new requirements such as number of passengers, empty weight and cruise range. Table 7 shows the sensitivity indices and rankings for objective. Increasing number of passengers was new requirement for derivative design so fuselage length was increased. Moreover, design variables which related to fuselage length, weight, and cruise range had higher rank among the whole design variables as shown in Table 7. This result has similar trend of previous parametric studies [54, 55].

### 3.4 Optimum design result

The important design variables (based on their sensitivity rank) were selected for derivative design. To compare the results of the design variable selection, different numbers of design variables were used. Three cases with a different number of design variables were analyzed and compared with the B737-800 to select design variables for derivative design.

Table 8 shows a comparison between B737-800 data and four cases. Case 2 shows similar performance characteristics while using a reduced number of design variables. In addition, Table 8 shows the computational CPU time for each case. CPU time was computed from the intrinsic subroutine of the Fortran compiler as Eq. (13) [56]. In this paper, a laptop with an AMD Phenom™ II P820 Triple-Core Processor with 4 GB RAM memory was used to perform the optimization problems. Fig. 14 shows the aircraft configuration of each case. Each case had different number of design variables and had different main wing and empennage geometries.

$$CPU\ time = t_e - t_s \tag{13}$$

From these results, 16 design variables from Case

Table 7. Global sensitivity analysis result

| Design Variable | | 1st order | Total | Rank |
|---|---|---|---|---|
| Wing geometry | $AR_W$ | 0.07310 | 0.13804 | 3 |
| | $TR_W$ | 0.07371 | 0.14196 | 2 |
| | $C_{Root\_W}$ | 0.06451 | 0.12477 | 5 |
| | $\Lambda_{LE\_W}$ | 0.04946 | 0.09555 | 13 |
| | $S_{csW}$ | 0.03859 | 0.07568 | 15 |
| Horizontal tail geometry | $AR_H$ | 0.04920 | 0.09591 | 12 |
| | $TR_H$ | 0.01574 | 0.03121 | 19 |
| | $C_{Root\_H}$ | 0.05017 | 0.09764 | 11 |
| | $\Lambda_{LE\_H}$ | 0.02170 | 0.04286 | 18 |
| | $S_{csH}$ | 0.04428 | 0.08635 | 14 |
| Vertical tail geometry | $AR_V$ | 0.06173 | 0.11698 | 9 |
| | $TR_V$ | 0.06972 | 0.13113 | 4 |
| | $C_{Root\_V}$ | 0.05493 | 0.10654 | 10 |
| | $\Lambda_{LE\_V}$ | 0.03808 | 0.07414 | 16 |
| | $S_{csV}$ | 0.02213 | 0.04376 | 17 |
| Fuselage geometry | $L_f$ | 0.06417 | 0.12417 | 6 |
| | $L_T$ | 0.08313 | 0.15846 | 1 |
| Engine | $T$ | 0.06314 | 0.12210 | 7 |
| | $W_f$ | 0.06252 | 0.11698 | 8 |

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2 were used for aircraft derivative designs that were comparable with B737-900 performance. The system objective function was defined to maximize cruise range. In this problem, the number of passengers was fixed as the target aircraft. The error distributions from low fidelity analysis results of each discipline were simulated while incorporating the uncertainty. This uncertainty in each discipline was considered in the CO with RBDO and PBDO algorithms. Four disciplines, described in the previous section, were considered in the CO method. For RBDO and PBDO formulation, the constraints satisfied a normal distribution and used a fuzzy membership function that was defined using error estimation. RBDO and PBDO methods had a target reliability level of 99.87% probability. In Table 9, the performance of B737-900 was compared with the results of deterministic optimization, RBDO, and PBDO with the selected design variables. These results showed small errors. Resultant configurations were shown in Fig. 15.

RBDO and PBDO results indicated smaller cruise range than the deterministic optimization result. These results fall in the feasible region when constraints were adjusted to consider uncertainty while satisfying the target reliability index level. The amount of information for uncertainty from each discipline was not the same as described in the previous section. Therefore, RBDO result cannot guarantee accuracy in the optimization result since its accuracy depends on the accuracy of the uncertainty distribution even though it showed the better cruise range than PBDO result.

Table 8. Comparison of design results (B737-800)

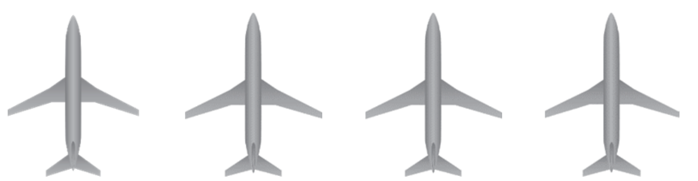
| Design Variable | | B737-800 | Case 1 (19) | Case 2 (16) | Case 3 (13) | Case 4 (9) |
|---|---|---|---|---|---|---|
| Wing geometry | $AR_W$ | 8.73 | 8.73 | 8.73 | 8.74 | 8.82 |
| | $TR_W$ | 0.3 | 0.3 | 0.3 | 0.3 | 0.3 |
| | $C_{Root\_W}$ (ft) | 17.29 | 20.0 | 20.0 | 20.0 | 21.8 |
| | $\Lambda_{LE\_W}$ (deg) | 25.02 | 25.02 | 25.0 | 25.01 | - |
| | $S_{csW}$ ($ft^2$) | 259.95 | 280.0 | 280.0 | - | - |
| Horizontal tail geometry | $AR_H$ | 5.88 | 5.6 | 5.0 | 5.0 | - |
| | $TR_H$ | 0.226 | 0.228 | - | - | - |
| | $C_{Root\_H}$ (ft) | 15.85 | 15.85 | 15.80 | 15.85 | - |
| | $\Lambda_{LE\_H}$ (deg) | 34 | 34 | - | - | - |
| | $S_{csH}$ ($ft^2$) | 80.95 | 80.94 | 80.95 | - | - |
| Vertical tail geometry | $AR_V$ | 2.08 | 2.08 | 2.08 | 2.09 | 2.09 |
| | $TR_V$ | 0.23 | 0.23 | 0.24 | 0.234 | 0.23 |
| | $C_{Root\_V}$ (ft) | 18.99 | 19.0 | 18.91 | 18.97 | - |
| | $\Lambda_{LE\_V}$ (deg) | 40 | 40 | 40 | - | - |
| | $S_{csV}$ ($ft^2$) | 67.08 | 67.09 | - | - | - |
| Fuselage geometry | $L_f$ (ft) | 124.71 | 123.97 | 123.97 | 123.97 | 123.97 |
| | $L_T$ (ft) | 55.348 | 55.35 | 55.35 | 55.35 | 55.35 |
| Engine | $T$ (lbf) | 27,300 | 27,300 | 27,300 | 27,300 | 27,300 |
| | $W_f$ (lb) | 19,500 | 19,500 | 19,500 | 19,500 | 19,500 |
| Cruise range | $R$ (NM) | 1,990 | 1,960 | 1,950 | 1,885 | 1,860 |
| Error | (%) | - | 1.51% | 2.01% | 5.28% | 6.53% |
| CPU time | (sec) | - | 16.23 | 15.50 | 15.32 | 14.86 |

a) B737-800 b) Case 1 c) Case 2 d) Case 3 e) Case 4

Fig. 14. Comparison of aircraft design result with B737-800

Table 9. Comparison of design results (B737-900)

| Design Variable | | B737-900 | CO | RBDO | PBDO |
|---|---|---|---|---|---|
| Wing geometry | $AR_W$ | 8.73 | 8.92 | 8.86 | 8.78 |
| | $TR_W$ | 0.3 | 0.3 | 0.3 | 0.3 |
| | $C_{Root\_W}$ $(ft)$ | 17.29 | 20.0 | 20.0 | 20.0 |
| | $\Lambda_{LE\_W}$ $(deg)$ | 25.02 | 25.02 | 25.0 | 25.0 |
| | $S_{csW}$ $(ft^2)$ | 259.95 | 264.80 | 262.65 | 261.33 |
| Horizontal tail geometry | $AR_H$ | 5.88 | 5.6 | 5.7 | 5.7 |
| | $TR_H$ | 0.226 | - | - | - |
| | $C_{Root\_H}$ $(ft)$ | 15.85 | 15.86 | 15.86 | 15.85 |
| | $\Lambda_{LE\_H}$ $(deg)$ | 34 | - | - | - |
| | $S_{csH}$ $(ft^2)$ | 80.95 | 80.94 | 80.95 | 80.95 |
| Vertical tail geometry | $AR_V$ | 2.08 | 2.12 | 2.10 | 2.10 |
| | $TR_V$ | 0.23 | 0.25 | 0.24 | 0.23 |
| | $C_{Root\_V}$ $(ft)$ | 18.99 | 18.93 | 18.96 | 18.98 |
| | $\Lambda_{LE\_V}$ $(deg)$ | 40 | 40 | 40 | 40 |
| | $S_{csV}$ $(ft^2)$ | 67.08 | - | - | - |
| Fuselage geometry | $L_f$ $(ft)$ | 133.40 | 134.01 | 134.01 | 134.01 |
| | $L_T$ $(ft)$ | 60.99 | 58.53 | 58.53 | 58.53 |
| Engine | $T$ $(lbf)$ | 27,300 | 27,300 | 27,300 | 27,300 |
| | $W_f$ $(lb)$ | 25,700 | 25,700 | 25,700 | 25,700 |
| Cruise range | $R$ $(NM)$ | 2,060 | 2,170 | 2,127 | 2,097 |
| Improvement | (%) | - | 5.34% | 3.25% | 1.80% |
| CPU time | (sec) | - | 15.37 | 16.02 | 15.69 |



a) B737-900 b) CO result c) RBDO result d) PBDO result

Fig. 15. Comparison of aircraft design result with B737-900

## 4. Conclusion

In this research, an enhanced derivative design optimization process was proposed. The expert system as well as a global sensitivity analysis method were applied to select the design variables for the derivative design. A reduced number of design variables was helpful for decreasing the redesign cost for the developing derivatives of a baseline product. Furthermore, the RBDO and PBDO methods were proposed to obtain reliable results while considering the associated uncertainty.

The proposed derivative design process was implemented in the civil jet aircraft derivative design problem. It performed to compare the actual B737-800 characteristics with the derivative design result that implemented the baseline of B737-300. The number of design variables was selected from this comparing result which shows small error. Then B737-900 was defined as the comparable target of the derivative of B737-300. The number of design variables was fixed as previous case study with B737-800. Additionally, uncertainty considered in the analysis methods depended on the statistical or the simplified analytical equations. The error terms were defined as the ratio of predicted performance to that of the observed performance taken from the aircraft database. The deterministic optimization result had an improvement compared to B737-900, but the design result laid on near the constraint boundaries. Enforcing target reliability indices moved the optimum result into the

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feasible region of the design space by implementing the RBDO and PBDO. The accuracy of the RBDO result was not guaranteed from this result since the aerodynamic analysis module had the relatively small amount of data on the uncertain parameter. On the other hand, the PBDO result can guarantee target probability even though the analysis module had an insufficient amount of data for uncertain parameter. If the aerodynamic analysis module increases the data of its uncertain parameter, the accuracy of the RBDO result will be increased too. According to the results of this paper, when a designer has sufficient information of uncertain parameters, the RBDO gives reliable results. However, when limited information is used, the PBDO is superior. In addition, the proposed derivative design process reduced the computation time by implementing of logically reduced number of design variables.

The proposed process is applicable to other types of engineering products and may save considerable amount of time and effort for the derivative design. The sensitivity analysis result can be used for not only approximation model and the low fidelity analysis tools, but also the high fidelity analysis tools such as FEM and CFD. The proposed method as RBDO with CO and PBDO with CO are useful to consider the error of the approximation models or the low fidelity analysis tools.

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## References

[1] Hibma, R. and Wegner, D., "The Evolution of a Strategic Bomber", *AlAA 1981 Annual Meeting and Technical Display*, Long Beach, California, 1981.

[2] Brown, R. B. and Swihart, J. M., "A New Family of Passenger Friendly Commercial Air Transports", *39th AIAA Aerospace Sciences, Meeting & Exhibit*, Reno, 2001.

[3] Kumar, D., Chen, W. and Simpson, T. W., "A Market-Driven Approach to the Design of Platform-Based Product Families", *11th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference*, Portsmouth, 2006.

[4] Yearsley, J. D. and Mattson, C. A., "Interactive Design of Combined Scale-based and Module-based Product Family Platforms", *12th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference*, Victoria, 2008.

[5] Simpson, T. W. and D'Souza, B., "Assessing Variable Levels of Platform Commonality Within A Product Family Using A Multiobjective Genetic Algorithm", *Concurrent Engineering*, Vol. 12, No. 2, 2004, pp. 119-129.

[6] Simpson, T. W., Bobuk, A., Slingerland, L. A., Brenna, S., Logan, D. and Reichard, K., "From User Requirements to Commonality Specifications: an Integrated Approach to Product Family Design", *Research in Engineering Design*, Vol. 23, No. 2, 2012, pp. 141-153.

[7] Kudikala, R., Mills, A. R., Fleming, P. J., Tanner, G. F. and Holt, J. E., "Real World System Architecture Design Using Multi-criteria Optimization: A Case Study", *EVOLVE - A Bridge between Probability, Set Oriented Numerics, 245 and Evolutionary Computation IV, Advances in Intelligent Systems and Computing*, Vol. 227, 2013, pp. 245-260.

[8] Moon, S. K., Park, K. J. and Simpson, T. W., "Platform Design Variable Identification for a Product Family Using Multi-Objective Particle Swarm Optimization", *Research in Engineering Design*, Vol. 25, Issue 2, 2014, pp. 95-108.

[9] Lim, D. and Mavris, D. N., "A Design Methodology for Lifelong Aircraft Evolution", *48th AIAA Aerospace Sciences Meeting Including the New Horizons Forum and Aerospace Exposition*, Orlando, 2010.

[10] Allison, J., Roth, B., Kokkolaras, M., Kroo, I. and Papalambros, P. Y., "Aircraft Family Design Using Decomposition-based Methods", *11th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference*, Portsmouth, 2006.

[11] Youn, B. D., Choi, K. K. and Du, L., "Enriched Performance Measure Approach for Reliability-Based Design Optimization", *AIAA Journal*, Vol. 43, No. 4, 2005, pp. 874-884.

[12] Du, L., Choi, K. K., Youn, B. D. and Gorsich, D., "Possibility-Based Design Optimization Method for Design Problems with Both Statistical and Fuzzy Input Data", *Journal of Mechanical Design*, Vol. 128, No. 4, 2006, pp. 928-936.

[13] Sumita, J., "An Application of Fuzzy Expert Concept for Unmanned Air Vehicles", *2nd AIAA Unmanned Unlimited Systems, Technologies, and Operations — Aerospace, Land, and Sea Conference*, San Diego, 2003.

[14] Athanasopoulos, G., Riba, C. R. and Athanasopoulou, C., "A Decision Support System for Coating Selection Based on Fuzzy Logic and Multi-criteria Decision Making", *Expert Systems with Applications*, Vol. 36, Issue 8, 2009, pp. 10848–10853.

[15] Sobol', I. Y. M., "On Sensitivity Estimates for Nonlinear Mathematical Models", Matem Modelirovanie, Vol. 2, No. 1, 1990, pp. 112–118, [in Russian]. English translation : *Math Model Comput Exp*, Vol. 1, No. 4, 1993, pp. 407–414.

[16] Frey, H. C. and Patil, S. R., "Identification and Review of Sensitivity Analysis Methods", *Risk Analysis*, Vol. 22, No. 3, 2002, pp. 553-578.

[17] Saltelli, A. and Annoni, P., "How to Avoid a Perfunctory Sensitivity Analysis", *Environmental Modeling & Software*, Vol. 25, No. 12, 2010, pp. 1508-1517.

[18] Yang, J., "Convergence and Uncertainty Analyses in Monte-Carlo Based Sensitivity Analysis", *Environmental Modeling & Software*, Vol. 26, No. 4, 2011, pp. 444-457.

[19] Saltelli, A. and Sobol', I., "About the Use of Rank Transformation in Sensitivity Analysis of Model Output", *Reliability Engineering & System Safety*, Vol. 50, No. 3, 1995, pp. 225-239.

[20] Du, L., Choi, K. K., Youn, B. D. and Gorsich, D., "Possibility-based Design Optimization Method for Design Problems with Both Statistical and Fuzzy Input Data", *Journal of Mechanical Design*, Vol. 128, No. 928, 2006, pp. 928-936.

[21] Youn, B. D., Choi, K. K., Gu, L. and Yang, R. J., "Reliability-based Design Optimization for Crashworthiness of Side Impact", *Journal of Structural Multidisciplinary Optimization*, Vol. 26, No. 3, 2004, pp. 272–283.

[22] Lee, I., Choi, K. K., Noh, Y. and Lamb, D., "Comparison Study Between Probabilistic and Possibilistic Methods for Problems Under a Lack of Correlated Input Statistical Information", *Structural Multidisciplinary Optimization*, Vol. 47, 2013, pp. 175–189.

[23] Cremona, C. and Gao, Y., "The Possibilistic Reliability Theory: Theoretical Aspects and Applications", *Structural Safety*, Vol. 19, No. 2, 1997, pp. 173-201.

[24] Zhao, D. and Xue, D., "Parametric Design with Neural Network Relationships and Fuzzy Relationships Considering Uncertainties", *Computers in Industry*, Vol. 61, 2010, pp. 287-296.

[25] He, L. P. and Qu, F. Z., "Possibility and Evidence Theory-based Design Optimization: an Overview", *Kybernetes*, Vol. 37, Issue 9/10, 2008, pp. 1322-1330.

[26] Venter, G. and Scotti, S. J., "Accounting for Proof Test Data in a Reliability-Based Design Optimization Framework", *AIAA Journal*, Vol. 50, No. 10, 2012, pp. 2159-2167.

[27] Weck, O., Eckert, C. and Clarkson, J., "A Classification of Uncertainty for Early Product and System Design", *International Conference on Engineering Design*, ICED'07, 2007.

[28] Sahinidis, N. V., "Optimization Under Uncertainty: State-of-the-art and Opportunities", *Computers and Chemical Engineering*, Vol. 28, 2004, pp. 971-983.

[29] Thunnissen, D. P., "Uncertainty Classification for the Design and Development of Complex Systems", *3rd Annual Predictive Methods Conference*, Newport Beach, 2003.

[30] Uebelhart, S. A., Mille, D. W. and Blaurock, C., "Uncertainty Characterization in Integrated Modeling", *46th AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics & Materials Conference*, Austin, 2005.

[31] Zadeh, L. A., "Fuzzy Sets", *Information and Control*, Vol. 8, No. 3, 1965, pp. 338-353.

[32] Savoia, M., "Structural Reliability Analysis Through Fuzzy Number Approach, with Application to Stability", *Computers & Structures*, Vol. 80, No. 12, 2002, pp. 1087-1102.

[33] Braun, R. D. and Kroo, I. M., *Development and application of the collaborative optimization architecture I n a multidisciplinary design environment, Technical Report*, NASA Langley Technical Report Server, 1995.

[34] Koch, P. N., Wujek, B. and Golovidov, O., "A Multi-stage, Parallel Implementation of Probabilistic Design Optimization in an MDO Framework", *Proceeding of the 8th AIAA/USAF/NASA/ISSMO Symposium on Multidisciplinary Analysis and Optimization*, Long Beach, 2000.

[35] Du, X. and Chen, W., "An Efficient Approach to Probabilistic Uncertainty Analysis in Simulation-based Multidisciplinary Design", *Proceedings of the 38th AIAA Aerospace Sciences Meeting and Exhibit*, Reno, 2000.

[36] Jeon, Y. H., Jun, S., Kang, S. and Lee, D. H., "Systematic Design Space Exploration and Rearrangement of the MDO Problem by Using Probabilistic Methodology", *Journal of Mechanical Science and Technology*, Vol. 26, No. 9, 2012, pp. 2825-2836.

[37] Ahn, J. and Kwon, J. H., "An Efficient Strategy for Reliability-based Multidisciplinary Design Optimization Using BLISS", *Structural and Multidisciplinary Optimization*, Vol. 31, 2006, pp. 363-372.

[38] McDonald, M. and Mahadevan, S., "All-at-once Multidisciplinary Optimization with System and Component-Level Reliability Constraints", *Proceedings of the 12th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference*, Victoria, 2008.

[39] Du, X., Guo, J. and Beeram, H., "Sequential Optimization and Reliability Assessment for Multidisciplinary Systems Design", *Structural and Multidisciplinary Optimization*, Vol. 35, 2008, pp. 117-130.

[40] Neufeld, D., Behdinan, K. and Chung, J., "Aircraft Wing Box Optimization Considering Uncertainty in Surrogate Models", *Structural and Multidisciplinary Optimization*, Vol. 42, No. 2, 2010, pp. 745-753.

[41] Park, H. U., Chung, J., Lee, J. W. and Behdinan, K., "Uncertainty Based MDO for Aircraft Conceptual Design", *Aircraft Engineering and Aerospace Technology*, Vol. 87, Issue 4, 2015, pp. 345-356.

[42] Park, H. U., Chung, J., Behdinan, K. and Lee, J. W., "Multidisciplinary Wing Design Optimization Considering Global Sensitivity and Uncertainty of Approximation

Models", *Journal of Mechanical Science and Technology*, Vol. 28, Issue 6, June 2014, pp. 2231-2242.

[43] Neufeld, D., Chung, J. and Behdinan, K., "Aircraft Conceptual Design Optimization Considering Fidelity Uncertainties", *Journal of Aircraft*, Vol. 48, No. 5, 2011, pp. 1602-1612.

[44] Neufeld, D., Nhu-Van, N., Lee, J. W. and Kim, S. A., "Multidisciplinary Possibility Approach to Light Aircraft Conceptual Design", *53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference*, Honolulu, 2012.

[45] Jaeger, L., Gogu, C., Segonds, S. and Bes, C., "Aircraft Multidisciplinary Design Optimization Under Both Model and Design Variables Uncertainty", *Journal of Aircraft*, Vol. 50, No. 2, 2013, pp. 528-538.

[46] Park, H. U., Chung, J., Lee, J. W., Behdinan, K. and Neufeld, D., "Reliability and Possibility Based Multidisciplinary Design Optimization for Aircraft Conceptual Design", *11th AIAA Aviation Technology, Integration, and Operations (ATIO) conference*, Virginia Beach, 2011.

[47] Jackson, P., *Jane's All The World's Aircraft, Jane's Information Group Inc.*, 2005.

[48] Airbus, http://www.airbus.com.

[49] The Boeing Company, http://www.boeing.com.

[50] Bombardier Aerospace, http://www.bombardier.com/en/aerospace.html.

[51] Embraer, http://www.embraer.com.

[52] Raymer, D., *Aircraft design: a Conceptual Approach. Reston VA: American Institute of Aeronautics and Astronautics, 3rd ed.*, Inc., Reston, VA, 1999.

[53] Torenbeek, E., *Synthesis of Subsonic Airplane Design*. Delft Univ. Pr., 1976.

[54] Altman, A., "A Parametric Study on Design Variables Effecting HALE UAV Aircraft Design for a Conventional Configuration", *Proceedings of the 1st AIAA Technical Conference and Workshop on Unmanned Aerospace Vehicles*, Virginia, 2002.

[55] Malone, B. and Mason, W. H., "Aircraft Concept Development Using Global Sensitivity Approach and Algebraic Technology Models", *VPI-Aero-184*, 1991.

[56] Compaq Visual Fortran Professional Edition, 2000.