Iranian Journal of Fuzzy Systems
Volume 18, Number 5, (2021), pp. 181-198
Original paper

A novel method for multi-objective design optimization based on fuzzy systems

M. R. Setayandeh[1] and A. R. Babaei[2]

[1,2] *Department of Mechanical Engineering, Malek Ashtar University of Technology, Shahin Shahr, Iran*

mohammad.setayandeh@gmail.com, arbabaei@aut.ac.ir

Abstract

A novel strategy to design optimization is expressed using the fuzzy preference function concept. This method efficiently uses the designer's experiences by preference functions and it is also able to transform a constrained multi-objective optimization problem into an unconstrained single-objective optimization problem. These two issues are the most important features of the proposed method which using them, you can achieve a more practical solution in less time. To implement the proposed method, two design optimizations of an unmanned aerial vehicle are considered which are: deterministic and non-deterministic optimizations. The optimization problem in this paper is a constrained multi-objective problem that with attention to the ability of genetic algorithm, this algorithm is selected as the optimizer. Uncertainties are considered and the Monte Carlo simulation (MCS) method is used for uncertainties modeling. The obtained results show a good performance of this technique in achieving optimal and robust solutions.

Keywords: Robust design, multidisciplinary design optimization, preference function, fuzzy logic, genetic algorithm.

1 Introduction

Although the aircraft classical design methods are respectable and valuable, generally these methods are costly and give a new optimal design [12, 14]. Multidisciplinary Design Optimization (MDO) is a design method that by eliminating the hierarchical relationship among design disciplines and with an optimal approach has been able to reduce the cost and find optimal designs [20]. In the real world, uncertainties in manufacturing and operations are certain and they should be considered in the design. Uncertainty, in addition to significant changes in system performance, adds cost to the system [6, 7]. Designers use the safety factor in the classical design methods to consider the uncertainty but this technique has some difficulties [18, 26]. In recent years, the Uncertainty-based Multidisciplinary Design Optimization (UMDO) technique has been expressed and used to consider uncertainty [17]. A lot of studies have been done that MDO and UMDO methods are used to solve design optimization problems [1, 3, 9, 10, 17, 19].

Design optimization problems are very complex in aerospace systems and in most cases, there is more than one objective function however there are various constraints in these problems too. These issues will increase the computational costs significantly. Converting a constrained multi-objective optimization problem to an unconstrained single-objective optimization problem can help reduce these costs. Therefore, it is recommended to use algorithms to do this issue. One of the most commonly used methods is Sum Weighted Method (SWM) that its efficiency is strongly dependent on the determination of weights. In this method, the determination of weights is based on try and error and this process is time-consuming and not smart. As well as if the optimization problem changes, it is necessary to determine weights again. Other multi-objective optimization algorithms (such as NSGA) also increase the computational cost by adding the necessary operators. It is worth noting that because evolutionary optimization algorithms must calculate objective functions and constraints at each iteration, so these algorithms have high computational costs and they don't suitable for high-fidelity analysis [11].

Corresponding Author: M. R. Setayandeh
Received: November 2020; Revised: February 2021; Accepted: May 2021.

Mirshams et al. [12] presented a technique for multi-objective optimization problems using Holistic Concurrent Design (HCD), concept. To validate the proposed method, design optimization of space launch system is considered. A fuzzy-multi-objective genetic algorithm is used to optimize the problem. Dexl et al. [4] studied multi-objective design optimization of a morphing wing by considering aerodynamic and structural objective functions and using the multidisciplinary design optimization approach. Wang et al. [25] presented a method for robust multidisciplinary design optimization. In this method, fuzzy logic has been used for the conceptual design of a hybrid rocket motor. Jafarian et al. [8] presented a novel method to solve multi-objective problems using fuzzy logic. This method is applicable for solving nonlinear problems. One advantage of this method is that the decision-maker continuously interacts with this method. Mohammad Zadeh et al. [13] presented a metamodel-based multi-objective multidisciplinary design optimization method for optimizing multi-objective problems. This technique has been used for the optimization of an unmanned aerial vehicle. Nguyen et al. [15] presented a robust multidisciplinary design optimization of a UAV. A new objective function is created that includes mean and variance values. A framework is developed for robust design optimization of UAV which MCS is used for uncertainty modeling. Nguyen et al. [16] submitted a non-deterministic design optimization of an unmanned aerial vehicle. The possibility-based design optimization method is used to implement. The considered objective function is flight endurance.

Despite the mentioned problems for the classical design methods, using the knowledge and expertise of the designer during the design process is the most important advantage of these methods. This advantage of the classical design methods is a flaw and inefficiency of design optimization methods because in these methods the experiment of the designer cannot be used effectively during the optimization process. The quality of solutions can be increased if the designer experiences used in the whole process of design optimization and therefore, this defect of optimization algorithms is resolved.

Fuzzy logic is a technique based on the experience of people and has been developed to deal with complex and non-deterministic systems. This concept converts the knowledge and experience of the expert people to nonlinear mathematical mapping and then this mapping performs such as a human. Some of the advantages that make this theory an efficient technique in engineering applications are proper simplicity and speed, no need for any complex calculations, finding acceptable answers in a short period of time, and using the experience of experts [22]. There are many studies about the application of fuzzy logic in the aerospace engineering field [5, 21, 23, 24].

It is tried in this paper to respond to the following challenges:

1. Converting a constrained multi-objective optimization problem to an unconstrained single-objective optimization problem and therefore reducing the computer run-time, cost, and solving the mentioned problems about the SWM and the NSGA approaches.

2. Creating a smart structure to use designer experiences in design optimization and utilize this important source.

Both of these challenges have been responded using a function entitled "fuzzy preference function". This function provides a structure to apply designer experiences and finally converts a multi-objective optimization problem to a single-objective optimization problem. So it can be expected that the more quality solution will achieve in less time. Therefore, the quality of optimal solutions will be increased systematically due to the use of this experience. The main advantages of this method compared with other methods are:

1. Using the knowledge and experience of expert people during design optimization by defining fuzzy preference functions.

2. Converting a constrained multi-objective optimization problem to an unconstrained single-objective optimization problem without the need to determine the weights for combining objective functions and constraints.

3. Decreasing complexity and computing time.

4. No need for widespread changes in fuzzy rules by changing the optimization problem.

It is worth noting that, this method can be used for deterministic and non-deterministic design optimization problems. The proposed method is applied to deterministic and non-deterministic multidisciplinary design optimization of an Unmanned Aerial Vehicle (UAV).

The organization of this paper is as follows. The proposed methodology has been introduced in Section 2. The application of this method for deterministic and non-deterministic multidisciplinary design optimization of an aircraft is presented in Section 3. In Section 4, design optimization results are expressed and finally, conclusions are presented in Section 5.

2 Theory of the presented multi-objective design optimization method

In this paper, a method is presented that has been able to reduce optimization time and apply the designer experiences in the design optimization process intelligently. The main logic of the proposed method is based on fuzzy logic and preference function concepts. The steps of this procedure are shown in Figure 1. At first, objective functions, constraints, and design variables must be determined. In the multidisciplinary analysis module, various disciplines are modeled based on design variables, mission requirements, and uncertain parameters. The mean and standard deviation of objective functions and constraints are as outputs of this module. In the next, fuzzy preference function for any objective functions and constraints created in next module. Finally, preference functions of objective functions and constraints combine together in several steps and a representative function is created for the whole problem. It is worth noting that to use this method for deterministic optimization, the uncertainty modeling module is deleted. In Figure 1, n is the number of constraints, m is the number of objectives, p is the number of steps to combine constraints, q is the number of steps to combine objectives, $\mathrm{F_{ji}}$ is the preference function of $\mathrm{i^{th}}$ objective function, $\mathrm{F_{ci}}$ is the preference function of $\mathrm{i^{th}}$ constraint, $\mathrm{F}_{\mathrm{j}_{i,k}}$ is the preference function of $\mathrm{i^{th}}$ objective function in $\mathrm{k^{th}}$ step, $\mathrm{F}_{\mathrm{c}_{i,k}}$ is the preference function of $\mathrm{i^{th}}$ constraint in $\mathrm{k^{th}}$ step, $\mathrm{F_J}$ and $\mathrm{F_C}$ are the representative functions of objective functions and constraints respectively.

2.1 Fuzzy preference function

The fuzzy preference function is a function that describes the satisfaction degree of objective functions and constraints. These functions allow good use of the designer experiences during system optimization by using writing fuzzy rules. In other words, the designer experiences apply in fuzzy rules and after this, fuzzy rules (such as a designer or decision-maker) assign a satisfaction degree to the objective functions and the constraints.

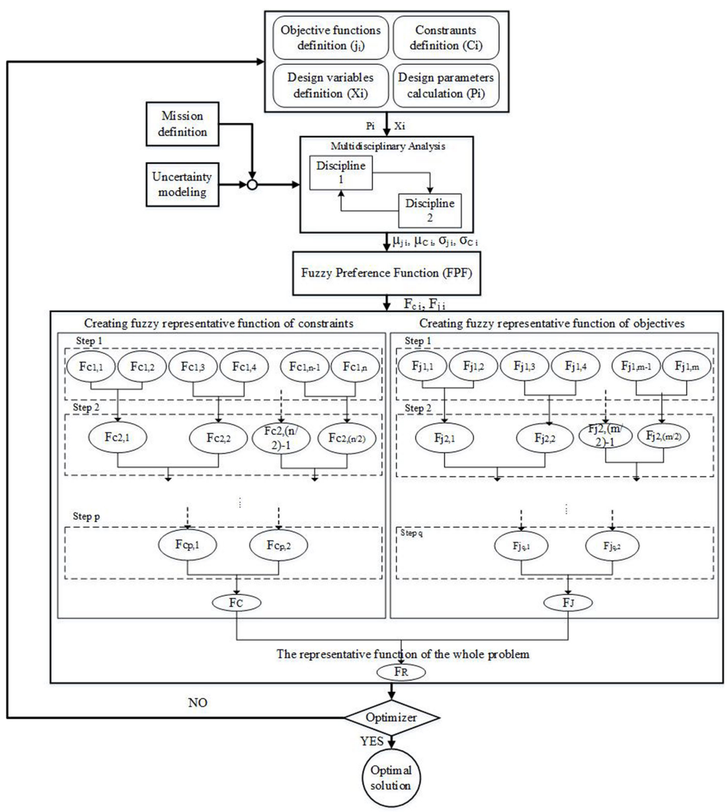

Figure 1: Flowchart of the proposed methodology.

In deterministic design, to create these functions, some satisfaction degrees are defined for the objective functions and constraints by the designer (in the horizontal axis). In other words, the designer classifies the horizontal axis to different regions in terms of satisfaction of the objective function (and constraint). Then the vertical axis, which indicates the preference function is divided into several regions same as the horizontal axis. The basis of the division of both axes (horizontal and vertical) is designer (decision maker) experiences. It is worth noting that the preference function value is between zero and one and maximization of the preference function (the greatest satisfaction degree) is the purpose of optimization. Figure 2 shows an example of the preference function. The relationship between the objective function (constraint) and the preference function is created using fuzzy logic (Figure 3) and it can be said that the fuzzy preference functions change the shape of the objective functions and the constraints of the optimization problem and it is necessary to apply the opinions and experiences of the experts for this change. In other words, the designer experiences are used in two shapes in this method: 1) Axis division from the point of view of the degree of satisfaction and 2) making fuzzy rules to create preference functions. Since the aim of the robust design is to minimize the variance due to noise parameters, the logic of this method is as follows.

In robust design, the variance and the mean value of the objective function and the constraint should initially be calculated. Then different satisfaction degrees are determined for these values (as mentioned above) and preference functions corresponding to the objective functions and constraints variance and mean values are produced with fuzzy logic. This process is shown in Figure 4. Now, maximizing these preference functions is the aim of optimization algorithms (the highest satisfaction degree). In other words, objective functions and constraints of the optimization problem are the set of preference functions that all of them must be maximized.

2.2 Fuzzy representative function

The purpose of this section is to create a representative function for the whole problem. In other words, a constrained multi-objective problem converts to an unconstrained single-objective problem in this section. As shown in Figure 1, the preference functions of objective functions and constraints must be combined with each other separately until two representative functions to be created for objective functions and constraints and then these two representative functions are combined together and the total representative function is obtained. To combine preference functions, similar to the method of preference function creation, the x-axis (which expresses preference functions) must first be divided into several regions (in terms of satisfaction degree of preference function). Then the vertical axis, which indicates the new preference function, is divided into several regions too. Finally, using fuzzy logic, the two preference functions are combined and a new preference function is created.

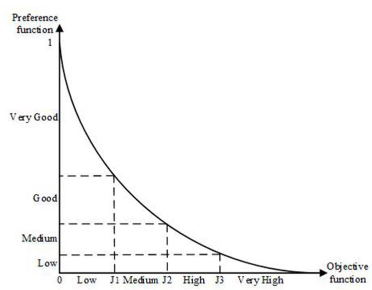

Figure 2: An example of relationship between objective function and preference function for a minimization problem.

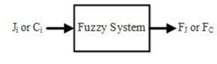

Figure 3: Creating fuzzy preference function for deterministic design optimization.

Figure 4: Creating fuzzy preference function for robust design optimization.

A representative function of objective functions (F_J) (describes the satisfaction degree of objective functions behavior) and a representative function of the constraints (F_C) (describes the satisfaction degree of constraints behavior) are created by repeating these steps. The number of steps in this process depends on the number of objective functions and the constraints of the optimization problem. These two representative functions are also combined in a similar process and finally, one representative function (F_R) is obtained for the whole problem which indicates the satisfaction degree of the objective functions and the constraints. Now the optimizer uses this function to find the optimal solution.

3 Application of the proposed method for multidisciplinary design optimization of an aircraft

3.1 Optimization problem definition

In this study, deterministic design optimization and non-deterministic design optimization of a tactical UAV are done. Both of them are multidisciplinary design optimization problems and MultiDisciplinary Feasible (MDF) approach is used to implement. Minimization of take-off weight (W_{TO}) and the drag of the cruise phase (Dr_{cr}) are considered as objective functions for both problems. The mathematical formulation of deterministic and non-deterministic design optimizations are as follows:

$$\begin{aligned} &\text{Minimize} \qquad W_{TO} \;\&\; Dr_{cr} \\ &s.t. \quad G_i\left(x\right) \qquad i=1,2,\ldots,\ 23 \end{aligned} \tag{1}$$

$$\begin{aligned} &\text{Minimize} \qquad (\mu,\sigma)_{W_{TO}\ \&\ Dr_{cr}} \\ &s.t. \quad (\mu,\sigma)_{G_i(x)} \qquad i=1,2,\ldots,\ 23 \end{aligned} \tag{2}$$

It is worth noting that G, μ, and σ are constraints, mean value, and standard deviation respectively. Since the proposed method converts a constrained multi-objective design optimization problem to an unconstrained single-objective design optimization problem and because the goal in the proposed method is to maximize the preference functions so the mathematical expression of both optimization problems is as in equation (3). F_R is the representative function of the whole problem. As previously stated, one of the advantages of the proposed method is to reduce the complexity of the problem in addition to reducing the computational cost. This issue is easily understood by comparing equations (1), (2) and (3).

$$\text{Maximize} \qquad F_R \tag{3}$$

As previously stated, in the deterministic design optimization the value of objective functions and constraints are as inputs to the fuzzy system but in the robust design optimization, the values of the mean and standard deviation of objective functions and constraints are as inputs. For both design optimizations, 22 design variables, and 23 constraints are considered. Design variables, design constraints and their numerical ranges have been shown in Table 1 and Table 2 respectively. The presented ranges have been determined based on special limitations, requirements, similar UAVs database, and designer experiences.

Table 1: Design variables

No.	Design variables	Description	Lower limit	Upper limit	Unit
1	$\mathrm{S_w}$	Wing area	0.8	1.8	$\mathrm{m^2}$
2	Λ_{LE}	Sweep angle	15	35	degree
3	AR	Aspect ratio	3.5	5.5	-
4	λ	Taper ratio	0.4	0.8	-
5	$\overline{\mathrm{C}}_\mathrm{A}/\overline{\mathrm{C}}$	Aileron mean chord to mean chord ratio	0.2	0.4	-
6	$\mathrm{a_{b_A}}$	A constant for calculation of aileron span	0.15	0.25	-
7	$\mathrm{a_{y_{outA}}}$	A constant for calculation of aileron outboard distance	0.25	0.35	-
8	$\mathrm{X_{A_w}}$	Longitudinal position of the wing from the aircraft nose	1.9	2.3	m
9	ε	Twist angle	-3	0	degree
10	$\mathrm{S_{ht}}$	Horizontal tail area	0.2	0.4	$\mathrm{m^2}$
11	Λ_{LEht}	Horizontal tail leading edge sweep angle	15	30	degree
12	$\mathrm{AR_{ht}}$	Horizontal tail aspect ratio	3.5	5.5	-
13	λ_{ht}	Horizontal tail taper ratio	0.2	0.6	-
14	$\overline{\mathrm{C}}_\mathrm{E}/\overline{\mathrm{C}}_\mathrm{ht}$	Elevator mean chord to horizontal tail mean chord ratio	0.2	0.5	-
15	$\mathrm{i_H}$	Horizontal tail incidence angle	-3	0	degree
16	$\mathrm{S_{vt}}$	Vertical tail area	0.1	0.3	$\mathrm{m^2}$
17	Λ_{LEvt}	Vertical tail leading edge sweep angle	25	45	degree
18	λ_{vt}	Vertical tail taper ratio	0.2	0.6	-
19	$\mathrm{AR_{vt}}$	Vertical tail aspect ratio	0.5	2	-
20	$\overline{\mathrm{C}}_\mathrm{R}/\overline{\mathrm{C}}_\mathrm{vt}$	Rudder mean chord to vertical tail mean chord ratio	0.15	0.45	-
21	δ_1	First angle of boat tail	5	15	degree
22	δ_2	Second angle of boat tail	5	15	degree

Table 2: Design constraints

No.	Constraints	Description	Unit
1	Cruise angle of attack	$-3\leq\alpha_{\rm cr}\leq 3$	degree
2	Cruise elevator deflection angle	$-3\leq\delta_{\rm Ecr}\leq 3$	degree
3	Cruise side slip angle	$-2\leq\beta_{\rm cr}\leq 2$	degree
4	Cruise aileron deflection angle	$-2\leq\delta_{\rm Acr}\leq 2$	degree
5	Cruise rudder deflection angle	$-2\leq\delta_{\rm Rcr}\leq 2$	degree
6	Turn angle of attack	$0\leq\alpha_{\rm tu}\leq 8$	degree
7	Pull up angle of attack	$0\leq\alpha_{\rm pu}\leq 8$	degree
8	Pull down angle of attack	$0\leq\alpha_{\rm pd}\leq 8$	degree
9	Turn side slip angle	$-4\leq\beta_{\rm tu}\leq 4$	degree
10	Turn elevator deflection angle	$-15\leq\delta_{\rm Etu}\leq 15$	degree
11	Pull up elevator deflection angle	$-15\leq\delta_{\rm Epu}\leq 15$	degree
12	Pull down elevator deflection angle	$-15\leq\delta_{\rm Epd}\leq 15$	degree
13	Turn aileron deflection angle	$-8\leq\delta_{\rm Atu}\leq 8$	degree
14	Turn rudder deflection angle	$-8\leq\delta_{\rm Rtu}\leq 8$	degree
15	Static margin	$0.03\leq{\rm SM}\leq 0.06$	-
16	Short period frequency	$\min(\omega_{\rm sp})\geq 0.5$	rad/sec
17	Short period damping coefficient	$0.2\leq\min(\xi_{\rm sp})\leq 0.6$	-
18	Phugoid frequency	$0.05\leq\min(\omega_{\rm ph})\leq 1$	rad/sec
19	Phugoid damping coefficient	$0.05\leq\min(\xi_{\rm ph})\leq 0.4$	-
20	Dutch roll frequency	$\min(\omega_{\rm DR})\geq 1$	rad/sec
21	Dutch roll damping coefficient	$0.05\leq\min(\xi_{\rm DR})\leq 0.6$	-
22	Spiral time constant	$\max({\rm T_{spiral}})\geq 1$	s
23	Rolling time constant	$0\leq\max({\rm T_{roll}})\leq 1$	s

3.2 Aircraft mission definition

The flight profile is shown in Fig. 5 for both design optimizations. The considered mission is listed in Table 3.

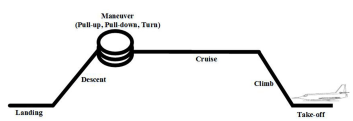

Figure 5: Intended flight profile.

Table 3: The considered mission

$h_{cr}(m)$	$W_{pay}(kg)$	$E(hr)$	$S_{TO}(m)$	$V_{cr}(m/s)$
12000	60	1.5	480	238

3.3 Flight uncertainty modeling

In this study, two uncertainties are considered: 1) environmental uncertainties (Aleatory uncertainties), and 2) uncertainties due to modeling and lack of knowledge (Epistemic uncertainties). The altitude of the cruise phase is considered as the aleatory uncertainty that a uniform distribution ($h{=}h_m{*}\ lhsdesign(1{,}N)$) is used to create sample points. All parameters that are considered constant (such as propeller efficiency, constructive material density, fuel conception and etc.) and all parameters that are calculated in the multidisciplinary analysis process (such as landing distance, the weight of components, aerodynamic coefficients) are considered as epistemic uncertainties. A normal distribution ($X{=}X{+}(X{*}\Delta X{*}\ lhsnorm\,(1{,}N)\,)$) is used to create sample points for these uncertainties. Since one of the Monte Carlo Simulation (MCS) method defects is its calculation time, so Latin Hypercube Sampling (LHS) method is used. LHS method reduces the computational time by reducing the number of sample points and maintaining proper dispersion. In this study, the value of $\rm h_m$ is 12000 m and the considered percentage of errors (ΔX) for epistemic uncertainties are listed in Table 4. With attention to the accuracy of the aerodynamic relationships, the error is considered 15% and 30%. MCS method is used for uncertainty modeling in this study.

Table 4: The considered percentage of errors

	Constant parameters	Weight specifications	Aerodynamic specifications
ΔX	10%	10%	15% & 30%

3.4 Multidisciplinary design analysis

Calculation of the objective functions and the considered constraints (in deterministic optimization) and mean values and standard deviations of them (in non-deterministic design optimization) is the aim of this section. In this study, the multidisciplinary analysis section consists of the following modules: Input, Geometry, Performance, Weight, Aerodynamic, Center of Gravity, Trim, and Dynamic stability. Fig. 6 shows the relationship between these disciplines.

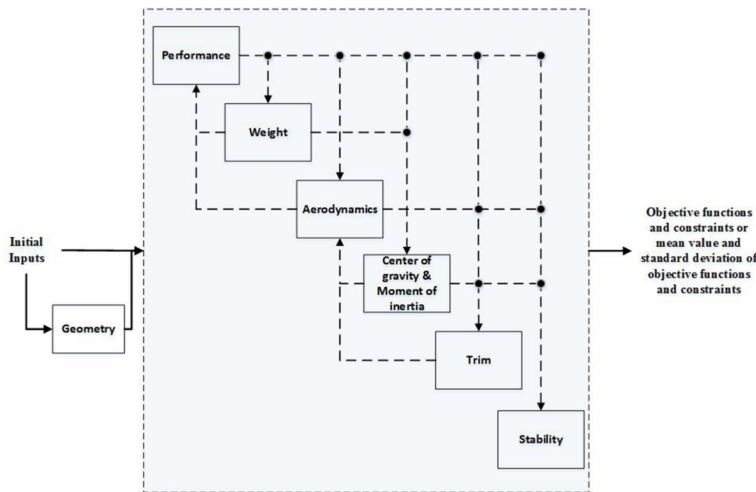

Figure 6: The flowchart of aircraft multidisciplinary analysis.

3.5 Fuzzy preference function

In this study, preference functions are generated by using the product inference engine, singleton fuzzifier, and center average defuzzifier as follows:

$$f(x) = \frac{\sum_{l=1}^{m} \overline{y}^l (\Pi_{i=1}^{n} \mu_{A_i^l}(x_i))}{\sum_{l=1}^{m} (\Pi_{i=1}^{n} \mu_{A_i^l}(x_i))} \tag{4}$$

The details about the creation of fuzzy preference functions for deterministic and non-deterministic design optimization problems are discussed in the following. As mentioned ago, the experiences of expert are applied in the design optimization by using fuzzy rules.

3.5.1 Fuzzy preference function for the deterministic optimization problem

To create preference functions of objective functions and constraints, their normalized values are entered into the fuzzy system and the preference functions of each one are produced. The membership functions of objective functions, constraints and preference function (as the output of fuzzy logic) are shown in Fig. 7, Fig. 8, and Fig. 9.

In the case of the membership function of the constraints, we must say that if the constraints fall within the intended ranges, the constraints are respected so between 0 and 1 numbers are acceptable from the constraints point of view. So the whole area between 0 and 1 is defined by one membership function. By approaching the 0 and 1 boundaries, a strict condition is taken into account. For this reason, although between 0 to 0.2 and 0.8 to 1 are acceptable from the constraints point of view, in these areas, other membership functions are also defined. The fuzzy rules set to create preference functions of objectives and constraints are listed in Table 5 and Table 6.

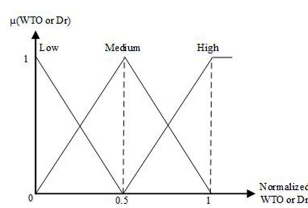

Figure 7: The membership function of normalized objective functions for deterministic optimization.

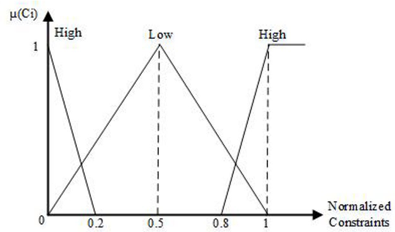

Figure 8: The membership function of normalized constraints for deterministic optimization.

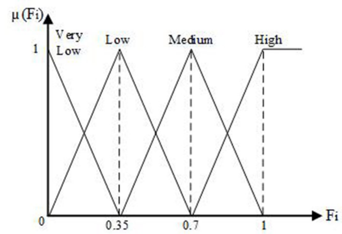

Figure 9: The membership function of preference functions.

Table 5: Fuzzy rule set to create preference function of objective functions

1. If ($\mathrm{j_i}$ is high) then ($\mathrm{F}_{\mathrm{j}_i}$ is very low).
2. If ($\mathrm{j_i}$ is medium) then ($\mathrm{F}_{\mathrm{j}_i}$ is medium).
3. If ($\mathrm{j_i}$ is low) then ($\mathrm{F}_{\mathrm{j}_i}$ is high).

Table 6: Fuzzy rule set to create preference function of constraints

1. If ($\mathrm{C_i}$ is high) then ($\mathrm{F}_{\mathrm{C}_i}$ is very low).
2. If ($\mathrm{C_i}$ is low) then ($\mathrm{F}_{\mathrm{C}_i}$ is high).

3.5.2 Fuzzy preference function for the robust optimization problem

In the robust optimization problem, the values of the mean and standard deviation of normalized objective functions and constraints are entered into the fuzzy system and their preference functions are produced. The membership functions of the mean and standard deviation of normalized objective function and constraints are shown in Fig. 10 and Fig. 11. The membership function of the preference function is similar to Fig. 9. The used fuzzy rules to create preference functions of objective functions and constraints are also listed in Table 7 and Table 8.

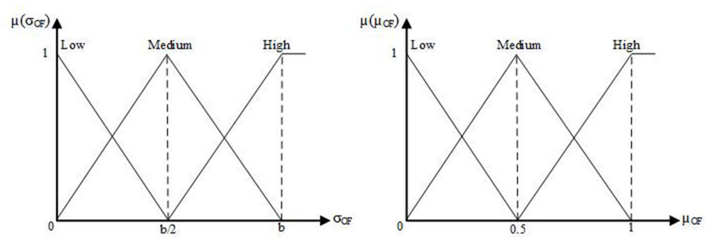

Figure 10: The membership function of mean and standard deviation values of objective functions for robust optimization.

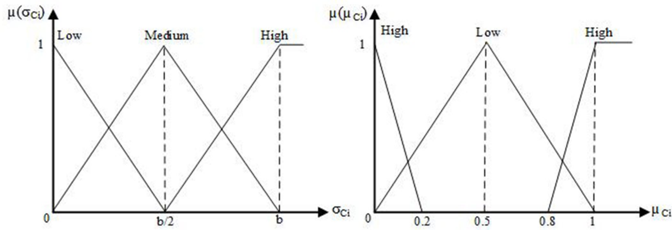

Figure 11: The membership function of mean and standard deviation values of constraints for robust optimization.

Table 7: Fuzzy rule set to create preference function of objective functions

1. If ($\mu_{\rm OF}$ is high) and ($\sigma_{\rm OF}$ is high) then ($\rm F_{OF}$ is very low).
2. If ($\mu_{\rm OF}$ is high) and ($\sigma_{\rm OF}$ is medium) then ($\rm F_{OF}$ is very low).
3. If ($\mu_{\rm OF}$ is high) and ($\sigma_{\rm OF}$ is low) then ($\rm F_{OF}$ is low).
4. If ($\mu_{\rm OF}$ is medium) and ($\sigma_{\rm OF}$ is high) then ($\rm F_{OF}$ is very low).
5. If ($\mu_{\rm OF}$ is medium) and ($\sigma_{\rm OF}$ is medium) then ($\rm F_{OF}$ is medium).
6. If ($\mu_{\rm OF}$ is medium) and ($\sigma_{\rm OF}$ is low) then ($\rm F_{OF}$ is medium).
7. If ($\mu_{\rm OF}$ is low) and ($\sigma_{\rm OF}$ is high) then ($\rm F_{OF}$ is low).
8. If ($\mu_{\rm OF}$ is low) and ($\sigma_{\rm OF}$ is medium) then ($\rm F_{OF}$ is medium).
9. If ($\mu_{\rm OF}$ is low) and ($\sigma_{\rm OF}$ is low) then ($\rm F_{OF}$ is high).

Table 8: Fuzzy rule set to create preference function of constraints

1. If ($\mu_{{\rm C}_i}$ is high) and ($\sigma_{{\rm C}_i}$ is high) then (${\rm F}_{{\rm C}_i}$ is very low).
2. If ($\mu_{{\rm C}_i}$ is high) and ($\sigma_{{\rm C}_i}$ is medium) then (${\rm F}_{{\rm C}_i}$ is very low).
3. If ($\mu_{{\rm C}_i}$ is high) and ($\sigma_{{\rm C}_i}$ is low) then (${\rm F}_{{\rm C}_i}$ is low).
4. If ($\mu_{{\rm C}_i}$ is low) and ($\sigma_{{\rm C}_i}$ is high) then (${\rm F}_{{\rm C}_i}$ is low).
5. If ($\mu_{{\rm C}_i}$ is low) and ($\sigma_{{\rm C}_i}$ is medium) then (${\rm F}_{{\rm C}_i}$ is medium).
6. If ($\mu_{{\rm C}_i}$ is low) and ($\sigma_{{\rm C}_i}$ is low) then (${\rm F}_{{\rm C}_i}$ is high).

3.6 Fuzzy representative function

The considered membership functions to combine preference functions of objective functions (in several steps) are shown in Fig. 12. The membership functions to combine preference functions of constraints are similar to membership functions of Fig. 12.

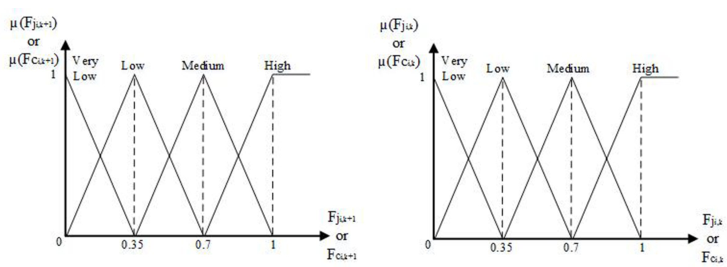

Figure 12: Membership functions of preference functions.

Since there are two inputs for the fuzzy system at each stage and each of the inputs has four modes, therefore, 16 fuzzy rules must be written. The satisfaction degree of preference function is the logic of writing fuzzy rules. If the inputs to the fuzzy system have inappropriate conditions (very low or low) so the output of the fuzzy system should show undesirable conditions (very low or low) and vice versa. There are also different situations between desirable and undesirable conditions that the fuzzy rules are written for them based on designer experiences and the purpose of design.

For example, the fuzzy rules to combine preference functions of objective functions, preference functions of the first two constraints ($\alpha_{\ cr}$ & $\delta_{E\ cr}$), and the combination of the representative functions of the objective functions and the constraints (to create the whole representative function) are expressed in Table 9, Table 10, and Table 11.

Table 9: Fuzzy rule set for combination of objective functions

1. If (F_{D} is very low) and (F_{WTO} is very low) then (F_{J} is very low).
2. If (F_{D} is very low) and (F_{WTO} is low) then (F_{J} is very low).
3. If (F_{D} is very low) and (F_{WTO} is medium) then (F_{J} is very low).
4. If (F_{D} is very low) and (F_{WTO} is high) then (F_{J} is low).
5. If (F_{D} is low) and (F_{WTO} is very low) then (F_{J} is very low).
6. If (F_{D} is low) and (F_{WTO} is low) then (F_{J} is very low).
7. If (F_{D} is low) and (F_{WTO} is medium) then (F_{J} is low).
8. If (F_{D} is low) and (F_{WTO} is high) then (F_{J} is low).
9. If (F_{D} is medium) and (F_{WTO} is very low) then (F_{J} is very low).
10. If (F_{D} is medium) and (F_{WTO} is low) then (F_{J} is low).
11. If (F_{D} is medium) and (F_{WTO} is medium) then (F_{J} is medium).
12. If (F_{D} is medium) and (F_{WTO} is high) then (F_{J} is medium).
13. If (F_{D} is high) and (F_{WTO} is very low) then (F_{J} is low).
14. If (F_{D} is high) and (F_{WTO} is low) then (F_{J} is low).
15. If (F_{D} is high) and (F_{WTO} is medium) then (F_{J} is medium).
16. If (F_{D} is high) and (F_{WTO} is high) then (F_{J} is high).

Table 10: Fuzzy rule set for combination of two constraints

1. If ($F_{\alpha\ cr}$ is very low) and ($F_{\delta_{E\ cr}}$ is very low) then (F_{11} is very low).
2. If ($F_{\alpha\ cr}$ is very low) and ($F_{\delta_{E\ cr}}$ is low) then (F_{11} is very low).
3. If ($F_{\alpha\ cr}$ is very low) and ($F_{\delta_{E\ cr}}$ is medium) then (F_{11} is low).
4. If ($F_{\alpha\ cr}$ is very low) and ($F_{\delta_{E\ cr}}$ is high) then (F_{11} is low).
5. If ($F_{\alpha\ cr}$ is low) and ($F_{\delta_{E\ cr}}$ is very low) then (F_{11} is very low).
6. If ($F_{\alpha\ cr}$ is low) and ($F_{\delta_{E\ cr}}$ is low) then (F_{11} is very low).
7. If ($F_{\alpha\ cr}$ is low) and ($F_{\delta_{E\ cr}}$ is medium) then (F_{11} is low).
8. If ($F_{\alpha\ cr}$ is low) and ($F_{\delta_{E\ cr}}$ is high) then (F_{11} is medium).
9. If ($F_{\alpha\ cr}$ is medium) and ($F_{\delta_{E\ cr}}$ is very low) then (F_{11} is very low).
10. If ($F_{\alpha\ cr}$ is medium) and ($F_{\delta_{E\ cr}}$ is low) then (F_{11} is very low).
11. If ($F_{\alpha\ cr}$ is medium) and ($F_{\delta_{E\ cr}}$ is medium) then (F_{11} is medium).
12. If ($F_{\alpha\ cr}$ is medium) and ($F_{\delta_{E\ cr}}$ is high) then (F_{11} is high).
13. If ($F_{\alpha\ cr}$ is high) and ($F_{\delta_{E\ cr}}$ is very low) then (F_{11} is low).
14. If ($F_{\alpha\ cr}$ is high) and ($F_{\delta_{E\ cr}}$ is low) then (F_{11} is low).
15. If ($F_{\alpha\ cr}$ is high) and ($F_{\delta_{E\ cr}}$ is medium) then (F_{11} is medium).
16. If ($F_{\alpha\ cr}$ is high) and ($F_{\delta_{E\ cr}}$ is high) then ($F_{11}$is high).

Table 11: Fuzzy rule set for combination of representative functions

1. If (F_C is very low) and (F_J is very low) then (F_{R} is very low).
2. If (F_C is very low) and (F_J is low) then (F_{R} is very low).
3. If (F_C is very low) and (F_J is medium) then (F_{R} is low).
4. If (F_C is very low) and (F_J is high) then (F_{R} is low).
5. If (F_C is low) and (F_J is very low) then (F_{R} is very low).
6. If (F_C is low) and (F_J is low) then (F_{R} is very low).
7. If (F_C is low) and (F_J is medium) then (F_{R} is low).
8. If (F_C is low) and (F_J is high) then (F_{R} is low).
9. If (F_C is medium) and (F_J is very low) then (F_{R} is low).
10. If (F_C is medium) and (F_J is low) then (F_{R} is low).
11. If (F_C is medium) and (F_J is medium) then (F_{R} is medium).
12. If (F_C is medium) and (F_J is high) then (F_{R} is medium).
13. If (F_C is high) and (F_J is very low) then (F_{R} is low).
14. If (F_C is high) and (F_J is low) then (F_{R} is low).
15. If (F_C is high) and (F_J is medium) then (F_{R} is medium).
16. If (F_{C} is high) and (F_{J} is high) then (F_{R} is high).

To create the representative function of the objective functions, the preference functions of take-off weight and drag are combined with each other using fuzzy logic and F_J is created. The steps of combining preference functions of constraints are shown in Fig. 13. As it is clear, the constraints are classified from the point of view of the flight phase and the modes of motion in the first step ($F_{\alpha_{cr}}$ with $F_{\delta E_{cr}}$, $F_{\delta A_{tu}}$ with $F_{\beta_{tu}}$, *and* $F_{\omega_{ph}}$ with $F_{\xi_{ph}}$). The outputs of this stage represent the behavior of the constraints in the desired flight phase and the modes of motion. Then in the second stage, constraints are classified from the point of view of longitudinal motion and lateral-directional motion (F_{15} with F_{16} *and* F_{18} with F_{19}). The outputs of this stage represent the behavior of the constraints in the longitudinal and lateral-directional motions. This process continues until the representative function of constraints (FC) is created. Finally, using the same method, the two representation functions are combined and the whole representative function of the problem (F_R) is obtained.

3.7 Optimizer

Since the considered optimization problem in this study is a complex problem and with regard to the capabilities of evolutionary algorithms, Genetic Algorithm (GA) is selected as the optimizer. The specifications of GA for optimization are expressed in Table 4. In this study, the crossover type is uniform crossover. It is worth noting that in the NSGA method, the population size must be large enough to provide a good Pareto front. So to solve the optimization problem with this approach the population size is considered 200.

Table 12: Specifications of GA

Parameter	Value
Generation	50
Population size	50
Mutation rate	0.1
Selection rate	0.5

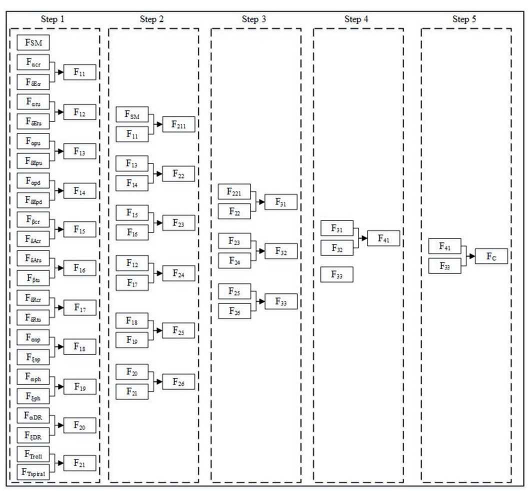

Figure 13: The creation process of representative function of constraints.

4 Design optimization results

Using the proposed method, deterministic design optimization was done. The histories of objective functions during the different generations are shown in Fig. 14 and Fig. 15 for deterministic design optimization. As these figures show, the proposed method has been able to minimize both objective functions in the optimization. To validate the proposed method, this problem is redesigned using two other famous methods and the results of them are compared to each other. In addition, information of an aircraft with a similar mission (Mirach 150), which was designed using the classical design method, is also used. These two methods are: 1) Design optimization using Sum Weighted Method (SWM), and 2) Multi-objective design optimization using the Non-dominated Sorting Genetic Algorithm (NSGA). It is worth noting that, the modules for creating preference functions and representative function have been deleted in design optimization using WSM and NSGA approaches and numerical values of objective functions and constraints have been used. Also, the constraints in these two methods have been applied using the penalty function method. The

NSGA method has been created a set of optimal solutions known as Pareto front that best of these optimal solutions has been selected for comparison based on utopian distance concept. For more information about this concept refer to [2]. The full specifications of the obtained designs are presented in Table 13, Table 14, Table 15, and Table 16. Non-deterministic design optimization is done using the proposed method after confirming it. It is worth noting that the PC characteristics for design optimization in this study are: Core i5, CPU 2.5 GHz, RAM 4 GB.

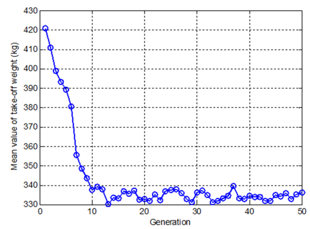

Figure 14: The mean value of take-off weight for each generation in deterministic design optimization.

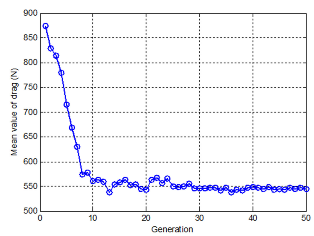

Figure 15: The mean value of drag for each generation in deterministic design optimization.

Table 13: Objective functions values for different designs

	WTO(Kg)	Drag(N)
Mirach 150	350	568.4
SWM	344.93	512.47
NSGA	334.1	494.02
Proposed method (Optimal design (OD))	333.6	469

Table 14: Design variables of base, optimal and robust designs

Design variables	Mirach 150	Proposed method	SWM	NSGA	Unit
S_w	1.1	0.92	1.01	0.89	m^2
Λ_{LE}	27	21.8	17.2	21.8	degree
AR	4.81	4.96	4.7	4.59	-
λ	0.4	0.42	0.57	0.44	-
$\overline{C}_A/\overline{C}$	0.29	0.31	0.29	0.26	-
a_{b_A}	0.25	0.16	0.21	0.23	-
$a_{y_{outA}}$	0.25	0.27	0.27	0.32	-
X_{A_w}	1.99	2.04	2.11	2.04	m
ε	-	-0.27	-0.74	-1.03	degree
S_{ht}	0.29	0.22	0.26	0.34	m^2
Λ_{LEht}	27	16.6	19.5	22.9	degree
AR_{ht}	4.02	4.28	3.93	4.43	-
λ_{ht}	0.36	0.2	0.37	0.4	-
$\overline{C}_E/\overline{C}_{ht}$	-	0.42	0.41	0.35	-
i_H	-	-1.8	-0.26	-0.13	degree
S_{vt}	0.2	0.26	0.29	0.16	m^2
Λ_{LEvt}	34	38.4	43.5	36.1	degree
λ_{vt}	0.48	0.25	0.39	0.35	-
AR_{vt}	1.94	0.57	1.94	1.73	-
$\overline{C}_R/\overline{C}_{vt}$	-	0.27	0.26	0.27	-
δ_1	5	9.2	9.2	7.4	degree
δ_2	10	8.6	9.2	8	degree

Table 15: Optimal and robust design constraints

No.	Constraints	Proposed method	SWM	NSGA	Unit
1	Cruise angle of attack	1.3	1.78	1.7	degree
2	Cruise elevator deflection angle	0.29	-2.7	-1.78	degree
3	Turn angle of attack	4	4.4	4.4	degree
4	Pull up angle of attack	6.9	6.3	6.9	degree
5	Pull down angle of attack	6.9	6.3	6.9	degree
6	Turn side slip angle	0.1	0.11	0.1	degree
7	Turn elevator deflection angle	0.13	-2.6	-1.9	degree
8	Pull up elevator deflection angle	-0.4	-3.2	-2.2	degree
9	Pull down elevator deflection angle	-0.4	-3.2	-2.2	degree
10	Turn aileron deflection angle	-2.5	-3.6	-2.5	degree
11	Turn rudder deflection angle	0.63	0.42	0.63	degree
12	Static margin (min)	0.048	0.032	0.038	-
13	Short period frequency (min)	0.64	0.58	0.63	Rad/sec
14	Short period damping coefficient (min)	0.24	0.3	0.3	-
15	Phugoid frequency (min)	0.073	0.073	0.071	Rad/sec
16	Phugoid damping coefficient (min)	0.05	0.07	0.137	-
17	Dutch roll frequency (min)	1.23	2.08	1.04	Rad/sec
18	Dutch roll damping coefficient (min)	0.035	0.045	0.04	-
19	Spiral time constant (max)	17.7	6	13.5	s
20	Rolling time constant (max)	0.7	0.6	0.76	s

Table 13 states that the obtained optimal design from the proposed method has lower take-off weight and drag and this issue represents the good ability of this method compared to other famous methods. Table 16 states that the proposed method has been able to dramatically reduce computational time compared to the other method, and this is another advantage of this method.

The third advantage of the proposed method is the simplicity of implementation because this method converts a constrained multi-objective optimization problem to an unconstrained single-objective optimization problem and it is much easier to accomplish unconstrained single-objective optimization than constrained multi-objective optimization (because of the constraints implementation using the penalty function method and assigning their weights and adding more operators to multi-objective optimization). So three main advantages of the proposed method relative to other methods are:

1. Provide optimal solutions from the point of view of objective functions.
2. Reduce optimization time.
3. Easier implementation of design optimization.

The last two advantages are due to the conversion of a constrained multi-objective optimization problem to an unconstrained single-objective optimization problem.

Table 16: Optimization time for different methods

	Proposed method	SWM method	NSGA method
Optimization time (min)	25	25.5	120

After validating the proposed method, this method is used for the non-deterministic design optimization of UAV in the next step. Table 17 to Table 19 show the specifications of robust and optimal designs.

Table 17: Objective functions values for optimal and robust designs of UAV

	WTO(Kg)	Drag(N)
Optimal design (OD)	333.6	469
Robust design (RD)	366.2	804

Table 18: Design variables of base optimal and robust designs

Design variables	OD	RD	Unit
S_w	0.92	0.82	m^2
Λ_{LE}	21.8	16	degree
AR	4.96	3.85	-
λ	0.42	0.41	-
$\overline{C}_A/\overline{C}$	0.31	0.39	-
a_{b_A}	0.16	0.23	-
$a_{y_{outA}}$	0.27	0.31	-
X_{A_w}	2.04	2.13	m
ε	-0.27	-0.8	degree
S_{ht}	0.22	0.25	m^2
Λ_{LEht}	16.6	20.1	degree
AR_{ht}	4.28	4.17	-
λ_{ht}	0.2	0.28	-
$\overline{C}_E/\overline{C}_{ht}$	0.42	0.32	-
i_H	-1.8	-2.3	degree
S_{vt}	0.26	0.22	m^2
Λ_{LEvt}	38.4	37.8	degree
λ_{vt}	0.25	0.25	-
AR_{vt}	0.57	0.54	-
$\overline{C}_R/\overline{C}_{vt}$	0.27	0.42	-
δ_1	9.2	9.7	degree
δ_2	8.6	9.7	degree

Table 19: Optimal and robust design constraints

No.	Constraints	OD	RD	Unit
1	Cruise angle of attack	1.3	0.092	degree
2	Cruise elevator deflection angle	0.29	2.12	degree
3	Turn angle of attack	4	6.3	degree
4	Pull up angle of attack	6.9	3	degree
5	Pull down angle of attack	6.9	3	degree
6	Turn side slip angle	0.1	0.13	degree
7	Turn elevator deflection angle	0.13	1.7	degree
8	Pull up elevator deflection angle	-0.4	1.9	degree
9	Pull down elevator deflection angle	-0.4	1.9	degree
10	Turn aileron deflection angle	-2.5	-4.9	degree
11	Turn rudder deflection angle	0.63	0.8	degree
12	Static margin (min)	0.048	0.041	-
13	Short period frequency (min)	0.64	0.81	Rad/sec
14	Short period damping coefficient (min)	0.24	0.33	-
15	Phugoid frequency (min)	0.073	0.075	Rad/sec
16	Phugoid damping coefficient (min)	0.05	0.089	-
17	Dutch roll frequency (min)	1.23	0.97	Rad/sec
18	Dutch roll damping coefficient (min)	0.035	0.047	-
19	Spiral time constant (max)	17.7	27	s
20	Rolling time constant (max)	0.7	0.98	s

The results showed that the drag and take-off weight of robust design has been increased relative to optimal design. The reason for this is that the cruise altitude of robust design is considered between sea level and 12000 meters and this increases the density. Increasing the density also increases the drag and as a result, fuel weight and take-off weight will increase. In other words, increasing the objective functions is a penalty for achieving a design that can function optimally in a range of cruise altitudes and also has a robust performance against the uncertainties.

To evaluate the robustness of the designs, the probabilistic analysis was carried out on both designs. Table 20 indicates the proper robustness of the robust design against the uncertainties. About the take-off weight, the standard deviations of the robust design and the optimal design are closed to each other. The reason is that the altitude has no significant effect on the take-off weight. But in the case of drag, the situation is completely different because the altitude strongly affects the drag. On the other hand, a higher percentage of error is considered for the aerodynamic specifications. To better assess the robustness of designs, two performance indexes (endurance and range) are reviewed. Robust design is a design that performance indexes have the least changes to the uncertainties. It is worth noting, that, the ideal values of endurance and range are 90 min and 1284 km respectively. By performing the analysis of robustness, it was observed that the objective functions and performance indexes of robust design have good robustness to the uncertainties. But the robustness of the constraints must also be investigated. To verify the robustness of the constraints, two criteria are considered. Maintaining the mean values of the constraints derived from probabilistic analysis on the values obtained from the design optimization (the values of Table 19) is the first criterion. If this criterion is violated, the standard deviation is the second criterion. Using the histogram diagrams (Fig. 16 to Fig. 22) and the mean value and standard deviation (Table 21), the robustness analysis is performed.

Table 20: Standard deviations and performance indexes of optimal and robust designs

Items	$\sigma_{W_{TO}}(kg)$	$\sigma_{Dr_{cr}}(N)$	μ_E(min)	$\mu_R(km)$
OD	8.6	241	63.1	900
RD	7.3	182	86.9	1220

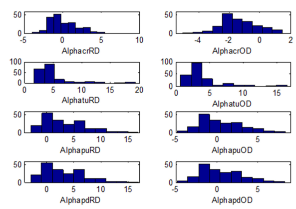

Figure 16: Scattering of angle of attack in the presence of uncertainties for robust design and optimal design.

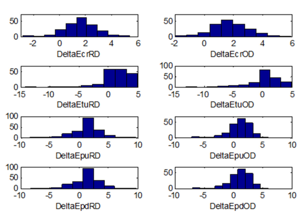

Figure 17: Scattering of elevator deflection angle in the presence of uncertainties for robust design and optimal design.

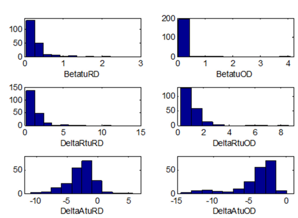

Figure 18: Scattering of aileron and rudder deflection angles of turn in the presence of uncertainties for robust design and optimal design.

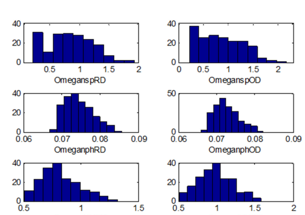

Figure 19: Scattering of frequency of motion modes in the presence of uncertainties for robust design and optimal design.

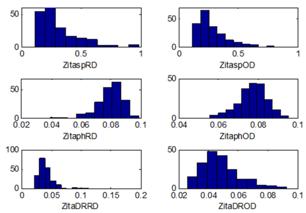

Figure 20: Scattering of damping coefficient of motion modes in the presence of uncertainties for robust design and optimal design.

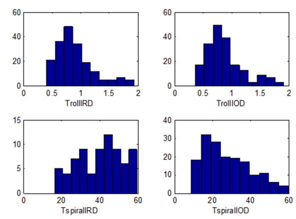

Figure 21: Scattering of spiral and turn time constants in the presence of uncertainties for robust design and optimal design.

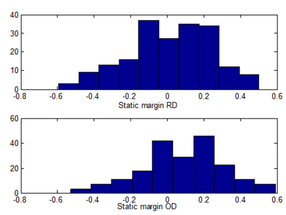

Figure 22: Scattering of static margin in the presence of uncertainties for robust design and optimal design.

Table 21: Mean values and standard deviations of considered constraints for optimal design and robust design

	$\sigma_{\alpha_{cr}}$	$\mu_{\alpha_{cr}}$	$\sigma_{\alpha_{tu}}$	$\mu_{\alpha_{tu}}$	$\sigma_{\alpha_{pu}}$	$\mu_{\alpha_{pu}}$	$\sigma_{\delta_{E\,cr}}$	$\mu_{\delta_{E\,cr}}$	$\sigma_{\delta_{E\,tu}}$	$\mu_{\delta_{E\,tu}}$	$\sigma_{\delta_{E\,pu}}$	$\mu_{\delta_{E\,pu}}$
OD	1.3	-1.7	2.9	3.96	2.6	0.33	1.4	-0.6	1.8	-1.1	2.4	-1.8
RD	1.7	0.03	2.7	4.9	3.5	3	1.2	1.7	2.5	0.92	2.3	1.25
Unit	deg	deg	deg	deg	deg	deg	deg	deg	deg	deg	deg	deg

Table 22: Mean values and standard deviations of considered constraints for optimal design and robust design

	$\sigma_{\beta_{tu}}$	$\mu_{\beta_{tu}}$	$\sigma_{\delta_{R\,tu}}$	$\mu_{\delta_{R\,tu}}$	$\sigma_{\delta_{A\,tu}}$	$\mu_{\delta_{A\,tu}}$	$\sigma_{\omega_{sp}}$	$\mu_{\omega_{sp}}$	$\sigma_{\xi_{sp}}$	$\mu_{\xi_{sp}}$	$\sigma_{\omega_{ph}}$	$\mu_{\omega_{ph}}$
OD	0.24	0.2	2.4	3	2.8	-4	0.42	0.86	0.11	0.27	0.003	0.072
RD	0.29	0.27	0.97	1.2	2.1	-2.9	0.36	0.84	0.13	0.29	0.0035	0.074
Unit	deg	deg	deg	deg	deg	deg	$\frac{rad}{s}$	$\frac{rad}{s}$	–	–	$\frac{rad}{s}$	$\frac{rad}{s}$

Table 23: Mean values and standard deviations of considered constraints for optimal design and robust design

	$\sigma_{\xi_{ph}}$	$\mu_{\xi_{ph}}$	$\sigma_{\omega_{DR}}$	$\mu_{\omega_{DR}}$	$\sigma_{\xi_{DR}}$	$\mu_{\xi_{DR}}$	$\sigma_{T_{roll}}$	$\mu_{T_{roll}}$	$\sigma_{T_{spiral}}$	$\mu_{T_{spiral}}$	σ_{SM}	μ_{SM}
OD	0.0066	0.078	0.092	0.64	0.014	0.05	0.33	0.86	8.7	45	0.23	0.09
RD	0.0075	0.08	0.15	0.82	0.013	0.04	0.29	0.86	10.7	39.5	0.24	0.045
Unit	–	-	$\frac{rad}{s}$	$\frac{rad}{s}$	–	-	s	s	s	s	–	-

According to Figure 17 to Figure 27 and also the values of Table 21 it can be found that in total the robust design has more robustness relative to the optimal design from the considered constraints point of view. Table 22 shows a simpler form of the results of constraints robustness analysis which confirms the more robustness of the robust design. Choosing both designs for some constraints indicates that there is no difference between the two designs. For example, the cruise angle of attack is analyzed. According to the results of Table 19, optimal and robust designs have the angle of attack 1.3 and 0.093 respectively. But optimal and robust designs have the angle of attack -1.7 and 0.03 respectively according to Table 21. So it is clear that the robust design has been able to better fit the angle of attack on its average value in the presence of uncertainties. The robustness analysis of the rest of the constraints is also done in a similar fashion.

Table 24: Summary of robustness analysis of considered constraints for robust design and optimal design

	α_{cr}	α_{pu}	α_{tu}	δ_{Ecr}	δ_{Epu}	δ_{Etu}	β_{tu}	δ_{Atu}	δ_{Rtu}	ω_{sp}	ξ_{sp}	ω_{ph}	ξ_{ph}	ω_{DR}	ξ_{DR}	T_{rol}	T_{spi}	SM
OD			√			√	√				√	√				√	√	
RD	√	√		√	√		√	√	√	√	√	√	√	√	√	√		√

5 Conclusion

In this paper, an attempt has been made to solve the challenges of multi-objective optimization problems by presenting a new method, and the designer's experiences are applied during the design optimization process. These two issues are achieved by the definition of fuzzy representative function and fuzzy preference function. In this method, first, fuzzy preference functions are created for objective functions and constraints. Then these preference functions are combined in several steps using fuzzy logic and finally, a representative function is obtained for the whole problem. Some benefits of this strategy are: using the designer's experiences, reducing the computation time, performing various design optimizations with variable degrees of robustness, and simplicity. To show the performance of the proposed method, two multidisciplinary design optimization problems was carried out. The first is the deterministic optimization and the second is the non-deterministic optimization. The results show acceptable solutions for both optimizations (both in terms of optimality and robustness) and indicate the efficiency of this method.

References

[1] M. I. Alam, R. S. Pant, *Multi-objective multidisciplinary design analysis and optimization of high altitude airships*, Aerospace Science and Technology, **78** (2018), 248-259.

[2] A. R. Babaei, M. R. Setayandeh, *Constrained optimization of a commercial aircraft wing using non-dominated sorting genetic algorithm*, International Journal of Advanced Design and Manufacturing Technology, **8**(4) (2015), 51-61.

[3] M. Bidoki, M. Mortazavi, M. Sabzehparvar, *A new multidisciplinary robust design optimization framework for an autonomous underwater vehicle in system and tactic design*, Journal of Engineering for the Maritime Environment, **233**(3) (2019), 918-936.

[4] F. Dexl, A. Hauffe, K. Wolf, *Multidisciplinary multi-objective design optimization of an active morphing wing section*, Structural and Multidisciplinary Optimization, **62** (2020), 2423-2440.

[5] S. Du, L. Wang, *Aircraft design optimization with uncertainty based on fuzzy clustering analysis*, Journal of Aerospace Engineering, **29**(1) (2016), 1-9.

[6] T. Erfani, S. V. Utyuzhnikov, *Control of robust design in multi-objective optimization under uncertainties*, Structural and Multidisciplinary Optimization, **45** (2012), 247-256.

[7] J. Fang, Y. Gao, G. Sun, C. Xu, Q. Li, *Multi-objective robust design optimization of fatigue life for a truck cab*, Reliability and Engineering System Safety, **135** (2015), 1-8.

[8] E. Jafarian, J. Razmi, M. F. Baki, *An flexible programming approach based on intuitionistic fuzzy optimization and geometric programming for solving multi-objective nonlinear programming problems*, Expert Systems with Applications, **93** (2018), 245-256.

[9] W. Li, L. Gao, A. Garg, M. Xiao, *Multidisciplinary robust design optimization considering parameter and metamodeling uncertainties*, Engineering with Computers, **4** (2020), 23-30.

[10] W. Li, L. Gao, M. Xiao, *Multidisciplinary robust design optimization under parameter and model uncertainties*, Engineering Optimization, **52**(3) (2020), 426-445.

[11] F. Mastroddi, S. Gemma, *Analysis of pareto frontiers for multidisciplinary design optimization of aircraft*, Aerospace Science and Technology, **28** (2013), 40-55.

[12] M. Mirshams, H. Naseh, H. R. Fazeley, *Multi-objective multidisciplinary design of space launch system using holistic concurrent design*, Aerospace Science and Technology, **33** (2014), 40-54.

[13] P. Mohammad Zadeh, M. Sayadi, A. Kosari, *An efficient metamodel-based multi-objective multidisciplinary design optimization framework*, Applied Soft Computing, **74** (2019), 760-782

[14] N. V. Nguyen, S. M. Choi, W. S. Kim, J. W. Lee, S. Kim, D. Neufeld, *Multidisciplinary unmanned combat air vehicle system design using multi-fidelity model*, Aerospace Science and Technology, **26** (2013), 200-210.

[15] N. V. Nguyen, J. W. Lee, Y. D. Lee, H. U. Park, *A multidisciplinary robust optimization framework for UAV conceptual design*, Aeronautical Journal, **118**(1200) (2014), 123-142.

[16] N .V. Nguyen, J. W. Lee, M. Tyan, D. Lee, *Possibility-based multidisciplinary optimization for electric-powered unmanned aerial vehicle design*, Aeronautical Journal, **119**(1221) (2015), 1397-1414.

[17] J. Roshanian, A. A. Bataleblu, M. Ebrahimi, *A novel evolution control strategy for surrogate-assisted design optimization*, Structural and Multidisciplinary Optimization, **58** (2018), 1255-1273.

[18] J. Roshanian, M. Ebrahimi, *Latin hypercube sampling applied to reliability-based multidisciplinary design optimization of a launch vehicle*, Aerospace Science and Technology, **28** (2013), 297-304.

[19] Y. Sun, H. Smith, *Low-boom low-drag optimization in a multidisciplinary design analysis optimization environment*, Aerospace Science and Technology, **94** (2019), 1-29.

[20] H. Tianyuan, Y. Xiongqing, *Aerodynamic/ Stealthy/ Structural multidisciplinary design optimization of unmanned combat air vehicle*, Chinese Journal of Aeronautics, **22**(4) (2009), 380-386.

[21] M. Tyan, N. V. Nguyen, S. Kim, J. W. Lee, *Database adaptive fuzzy membership function generation for possibility-based aircraft design optimization*, Journal of Aircraft, **54**(1) (2017), 1-11.

[22] L. X. Wang, *A course in fuzzy systems and control*, Prentice Hall International Inc, Upper Saddle River, 1997.

[23] J. Wang, Z. Lu, Y. Shi, *Aircraft icing safety analysis method in presence of fuzzy inputs and fuzzy state*, Aerospace Science and Technology, **82** (2018), 172-184.

[24] C. Wang, H. G. Matthies, M. Xu, Y. Li, *Hybrid reliability analysis and optimization for spacecraft structural system with random and fuzzy parameters*, Aerospace Science and Technology, **77** (2018), 353-361.

[25] P. Wang, H. Tian, H. Zhu, G. Cai, *Multi-disciplinary design optimization with fuzzy uncertainties and its application in hybrid rocket motor powered launch vehicle*, Chinese Journal of Aeronautics, **33**(3) (2020), 1454-1467.

[26] W. Yao, X. Chen, W. Luo, M. V. Tooren, J. Guo, *Review of uncertainty-based multidisciplinary design optimization methods for aerospace vehicles*, Progress in Aerospace Sciences, **47**(6) (2011), 450-479.

Iranian Journal of Fuzzy Systems
Volume 18, Number 5 (2021), pp. 212
University of Sistan and Baluchestan

A novel method for multi-objective design optimization based on fuzzy systems

M. R. Setayandeh and A. R. Babaei

یک روش جدید برای بهینه‌سازی طراحی چندهدفه بر مبنای سیستم‌های فازی

چکیده. یک استراتژی جدید برای بهینه‌سازی طراحی با استفاده از مفهوم تابع برتری فازی بیان شده است. این روش به شکل مؤثری از تجربیات طراح با استفاده از توابع برتری استفاده می‌کند و همچنین قادر است یک مسأله بهینه‌سازی چندهدفه مقید را به یک مسأله بهینه‌سازی تک‌هدفه نامقید تبدیل کند. این دو موضوع مهمترین خصوصیات روش ارائه شده است که با استفاده از آن‌ها می‌توان به حل کاربردی‌تر در زمان کمتر رسید. برای پیاده‌سازی روش ارائه شده، دو بهینه‌سازی طراحی یک هواپیمای بی‌سرنشین در نظر گرفته شده است که عبارتند از: بهینه‌سازی معین و بهینه‌سازی نامعین. مسأله بهینه‌سازی در این مقاله یک مسأله چندهدفه مقید است که با توجه به توانایی الگوریتم ژنتیک، این الگوریتم به عنوان بهینه‌ساز انتخاب شده است. عدم‌قطعیت‌هایی نیز در نظر گرفته شده که از روش شبیه‌سازی مونت-کارلو برای مدل‌سازی آن‌ها استفاده شده است. نتایج به دست آمده عملکرد خوب این روش را در دستیابی به حل‌های بهینه و مقاوم نشان می‌دهد.