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Optimum Selection of "Number of Seats/Cargo Volume" for Transports in Uncertain Business Environment

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Increasing competition in the transport commercial market has resulted in many changes in the aircraft design process. There is a great tendency to include economic factors such as "affordability" in the design process. On the other hand, the so-called market dynamics are also getting complicated and a design team has to deal with many uncertainties as far as the business environment is concerned. This leads to the need for new decision-making tools in the early stages of the design process. This paper introduces a decision-making algorithm based on fuzzy logic systems which provides a structured approach to deal with uncertainties in the aircraft preliminary design. The developed tool leads the design team to a series of alternatives and a more robust solution for important parameters such as number of seats and cargo capacity to meet different market demands. To demonstrate the effectiveness of the new proposed approach, methodology was applied to two wide-body transport aircraft with missions similar to B-747-400 and A-380. The results show that existing uncertainties in the future economic environment would have more impact on A-380 compared with that of B-747-400. That is, wide-body transport airplanes with less than 520 passenger seats have more chance to fly economically if relying only on the passenger market. It is further shown that aircraft with more than 520 seats need special provisions to carry cargo loads for their extra payload capacities.

Nomenclature

N_s = number of passenger seats
R = range
S = wing area
W_F = airplane fuel weight

I. Introduction

A REVIEW of current issues facing the airline industry in areas such as operation, economics, financial, and regulatory, as well as institutional, reveals many challenging issues for aircraft designers. Design of a new transport is therefore a complicated process that involves many conflicting requirements imposed by different stakeholders.

The main responsibility of the design team is then to bring all the requirements to an acceptable level of agreement. This approach works as long as requirements are fixed in time and known to the design team. It so happens that this is not the case and new technologies emerge that somehow bring new constraints to even an existing design. The global economy, however, is much too complex to be effectively controlled with existing models. Cultural differences and unwritten socioeconomic laws always result in cost escalation in designing a new aircraft and bring more risk when the aircraft enters into service. This is where the "conceptual design phase" proves its importance. The significance of the airplane's conceptual design phase is that decisions made during this period have considerable effects on the overall system capabilities. Although it is well known that the early design stages account for a small fraction of the overall project cost, the design decisions made at this stage are responsible for a large portion of the system life-cycle cost [1]. This paper introduces some tools suitable for uncertainties typical to this phase which help in the decision-making process with no extra computation cost.

Many researchers have discussed different fundamental concepts for the economic analysis of airline systems [2,3]; this includes basic models of the operation of air transport markets together with neoclassical and microeconomic models. The main goal is normally to define market systems for air transport service in uncertain situations. The ultimate goal is to develop a theory to correlate pricing, demand, costs, and supply for regulated and unregulated, domestic and international markets. However, all these efforts must converge to a point where they could help a design team to make sound decisions about the number of seats for an aircraft while considering enough space to carry cargo and other types of payloads. This issue is addressed in this paper. That is, we intend to introduce a systematic decision-making tool that helps select the suitable combination for number of passenger seats together with cargo volume for a given route. This tool would be very useful, as it allows thinking of different arrangements (or versions) for a single aircraft in the early stages of the design process. Moreover, knowing the fact that every decision made must be evaluated for its effect during the aircraft life cycle, the proposed approach helps to deal more efficiently with uncertain issues such as fleet operation cost and travel patterns for both existing and future markets.

To effectively deal with uncertainties in systems, such as the case of the airplane design cycle, some well-known methods are available in the literature that have the capability to model uncertainties with more or less efficiency, among which response surface methodology (RSM) and probabilistic methods based on Monte Carlo simulations [4–6], are some examples. However, in these methods, the behavior of response governed by certain laws which can be approximated by a deterministic relationship between the response and the set of design variables. Unfortunately, many times the relationship between actual responses and predictors are either too complex or they require considerable empirical adjustments to determine the behavior of the system in time. Moreover, due to some undesirable exponential behavior, they still would not give meaningful results in an acceptable period of time and quickly become impractical to use in time domain [4–9]. In contrast, decision making and/or predictions based on fuzzy logic systems are easier to implement and use and they do not exhibit any undesirable behavior in the mathematical formulation. This paper shows how this approach could generally be used in the aircraft conceptual design process. In fact, to show the

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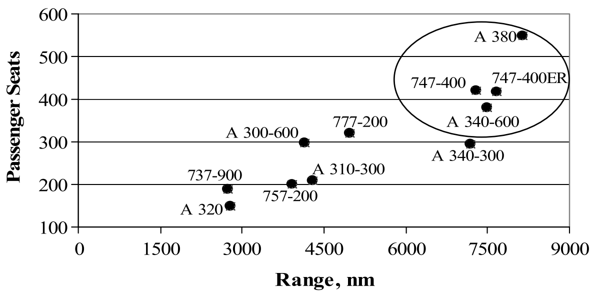


Fig. 1 Seat vs range for transport aircraft [10].

effectiveness of the method, we attempt to predict different suitable arrangements for "number of seats" and "cargo volume" while designing a wide-body, long-range transport.

II. Problem Definition

One of the main design issues for any commercial aircraft is the optimum payload capacity, as well as possible types and arrangement of payloads for a given range or market segment. This paper attempts to introduce a decision-making tool based on fuzzy logic systems which facilitates finding alternatives for those questions. In this process, we shall consider the dynamics of the existing markets and uncertainties in the future ones. Figure 1 shows a typical graph showing number of seats vs range for some existing transport aircraft [10].

This graph simply shows four different aircraft competing in a market segment demanding ranges above 7000 nm. Because these aircraft have different numbers of seats and cargo volumes, the question might be also to know which aircraft is going to be more successful considering the future uncertainties in the global world economy.

Current forecasts conducted by companies like Airbus[‡] and Boeing[§] suggest that the commercial transport market will continue to grow for the next 20 years until 2025 at an average rate of 5–6%. This means that air traffic will almost double in just 15 years. A portion of this traffic will be absorbed by creating new routes, decreasing separation minima between two adjacent aircraft, and finally an increase in flight frequency. However, in some congested markets where the infrastructure would not allow any expansion, the only solution would be to use aircraft with higher passenger capacities. Airbus expects that this type of large aircraft will account for 10% of the new aircraft demand in years to come, which corresponds to approximately 25% of the gross business forecasted. Therefore, it has been predicted that the demand for a 600–1000 passenger transport will be high in the transpacific and intrapacific markets [11–13]. This line of reasoning would not, however, provide the assurance needed to start a new design. In fact, the aforementioned studies would not even suggest the most appropriate number of seats as well as cargo volume for the transport of the next three decades. This paper intends to introduce a design tool for such vital questions while dealing with uncertainties in the future global economy. To show the effectiveness of such a tool, we apply the method to a B747-400, the heaviest commercial transport currently available, as well as a new design capable of carrying 600–800 passengers over both long and short routes with a 15–20% reduction in direct operating cost (DOC) with respect to the B-747-400.

It is worth mentioning that some concern, such as airport compatibility, is also a great concern for a new heavy transport airplane. Characteristics such as runway length, width, as well as strength are important factors for an airport and would not be easily enhanced, unless a good justification for new investment is forecast. For example, current gates at most airports cannot handle aircraft with wingspans greater than 80 m. In case such a constraint could not be observed in the aircraft wingspan, then designated airports must be enhanced accordingly. If not possible, this may significantly reduce the aircraft market as not many airport owners are willing to carry such burden. This obviously influences new heavy aircraft sales. In addition to the airport, other safety measures are also involved. Issues such as safe evacuation of passengers and prevention of fire propagation within the aircraft cabin are of great concern. These issues would not be addressed in this work, as yet there is no mathematical model available for such phenomenon. For aircraft manufacturers, any new design that answers future market demands presents a challenge. Besides being technically feasible, a considerable amount of investment would be needed during research and development phases. Uncertainties involved are due to the nature of the business environment and dynamics of stakeholders' demands [11–13].[‡§] All these constraints are summarized in Table 1. A good design tool must be somehow able to help making decisions based on

Table 1 Contributing factors in large transport aircraft seat range and cargo volume[d]

	Requirements	Parameter	Current limitation	Typical value A-380	Typical value 747-400
1	performance	TOFL, ft	less than 11,000	10,800[a]	10,450[a]
2		N_s	——	555[a]	420[a]
3		R, nm	——	8150[a]	7260[a]
4		wing span, m	less than 80	79.8[a]	64.4[a]
5		cruise speed, km/h	——	902[a]	912[a]
6	airline economy	DOC	less than 15–20% with respect to B-747-400	N/A	N/A
7		acquisition cost, M$	less than 200	285[a]	187[a]
8		passenger load factor	0.4–0.8	target: 0.66[‡§]	
9		ROIA	5–10%	target: 7%[‡§]	
10		$W_F/(N_s \cdot R)$	as low as possible	0.128[b]	0.127[b]
11		DOC/ASM	less than 2.45	target: 2.1[‡§]	
12		no. available airports	as much as possible	N/A	210[‡§]
13	manufacturing technology	RDTE cost	as low as possible	9.71 B$[c]	8.87 B$[c]
14		ROIM	10–20%	target: 15%[‡§]	

[a]Data From [10].
[b]Based on equation $W_F/(N_s \cdot R)$.
[c]Based on [18].
[d]RDTE: research, development, test, and evaluation; DOC: direct operating cost; ROIM: return of investment manufacturer; TOFL: takeoff field length; M$: million dollars; B$: billion dollars.

[‡]Airbus Industry, "Global Market Forecast 2004,"http://www.airbus.com/globalmarketforecast.htm.

[§]Boeing Industry, "Global Market Forecast: Demands for Commercial Airplanes 2005," http://www.Boeing.com/globalmarketforecast.htm.

a robust logic. Even in cases as complicated as shown in Table 1, where the dynamics of the market cannot be modeled mathematically, we still need to define the trend by some rules. A decision tool based on fuzzy logic systems, introduced in this work, has such desirable characteristics.

III. Fuzzy Logic Systems as Decision-Making Tools

One of the decision-making tools that could be used while dealing with irregular and uncertain conditions is fuzzy logic [14,15]. A brief history of how fuzzy concepts have evolved during the past 30 years will help to clarify the approach used in this work [16]. Fuzzy systems are among knowledge-based systems constructed from human knowledge which manifest themselves by IF-THEN statements. They provide a systematic procedure to transform human knowledge base, or even desires, into some mathematical form through a nonlinear mapping. Because of this transformation, one is able to use the same knowledge in different engineering applications, such as control, automation, communication, manufacturing [17]. Consequently, the analysis and design of the resulting combined systems can be performed in a mathematically rigorous fashion. Generally, a fuzzy system consists of four components: fuzzy rule base, fuzzy inference engine, fuzzifier, and defuzzifier as shown in Fig. 2.

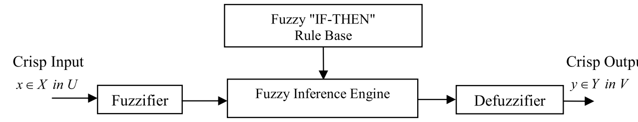


Fig. 2 Schematic of general fuzzy system [17].

The elements of fuzzy systems are shown in Fig. 2, in which we briefly describe what they do as far as airplane design is concerned. But first, one might note that in case of decision making in the airplane design process, all design variables (such as takeoff weight, number of seats., range, cargo volume, etc) are crisp variables, and so input and output of fuzzy systems should be a crisp value. However, a fuzzifier is devised which transforms a real valued variable into a fuzzy set and a defuzzifier that reverses the process. Besides this, we need a mechanism to manipulate fuzzy sets and help us to make decisions. This is done with the help of fuzzy rule bases together with a fuzzy inference engine. In general, a fuzzy rule base for an airplane design process should consist of a set of fuzzy IF-THEN rules which are appropriate for that class of airplane. The IF part shows the rule antecedent and the THEN part shows the rule consequent. Fuzzy IF-THEN rules are the heart of a fuzzy system in the sense that all decisions would be made based on these rules. In case a rule base is not as comprehensive and suitable, one should not expect appropriate decisions for outcome. In a fuzzy inference engine, fuzzy logic principles are used to combine the fuzzy IF-THEN rules. Because any practical fuzzy rule base constitutes more than one rule, the key question here is how to infer with a set of conflicting rules as is the case in airplane preliminary design.

There are two ways to infer with a set of rules: 1) composition based inference and 2) individual rule base inference. In composition base inference, all rules in the existing fuzzy rule base are combined into a single fuzzy relation which is viewed as a single fuzzy IF-THEN rule. In contrast, in an individual rule base, each rule in the fuzzy rule base determines an output fuzzy set and the output of the whole fuzzy inference engine is the combination of the M individual fuzzy outcome. The combination could be taken either by union (logical OR) or intersection (logical AND). For the airplane design process, however, each rule has its own effect on the outcome (Table 2), therefore, "logical AND" seems to be more appropriate. In fact, case studies by the author support such logic [16,17].

A class of commonly used fuzzy systems is as follows [17]:

$$y = f(x) = \frac{\sum_{l=1}^{M} \bar{y}^l \left[\min_{i=1}^{n} \mu_{A_i^l}(x_i) \right]}{\sum_{l=1}^{M} \min_{i=1}^{n} \mu_{A_i^l}(x_i)} \tag{1}$$

where M is the number of fuzzy IF-THEN rules l, $x \in X$ *in* U is the input variable and $y \in Y$ *in* V is the output of the fuzzy system, $\bar{y}^l$ is the center of membership function A in rule "L," i.e., $\mu_{A_i^l}(x)$.

To demonstrate how a fuzzy decision-making tool could be used to decide upon a parameter such as number of seats and cargo volume for a given range, proper IF-THEN rules must be first developed. These rules are normally demanded by both manufactures as well as airliners. It is worth noting that each airline might use its own rules (company rules) for different geographical location or routes. It is, in fact, the beauty of this approach that changing part of the rules would not invalidate the proposed decision-making process. Obviously, changing rules would change the outcoming decision. Therefore, we could think of a basic platform with different internal arrangements for seats and cargo volume, all resulting from a fuzzy decision-making tool, where each internal arrangement is the result of a specific set of rules.

Having limited access to industry data, a set of rules were developed based on methodologies explained in [18] and statistical data of [10]. Table 2 shows these rules (metric functions). It is well noted that most parameters associated with designing an aircraft could not be varied in a continuous manner. Moreover, domain of variation is also limited by laws of physics. For example, speed cannot be varied in a wide domain from subsonic to supersonic, as aerodynamic laws differ for subsonic and supersonic speed regimes. Therefore, designers must be careful about the domain of validity for each single rule. Fortunately, as described earlier, the methodology is not affected as soon as a rule is changed and one could easily repeat the process with different rules as soon as they are available.

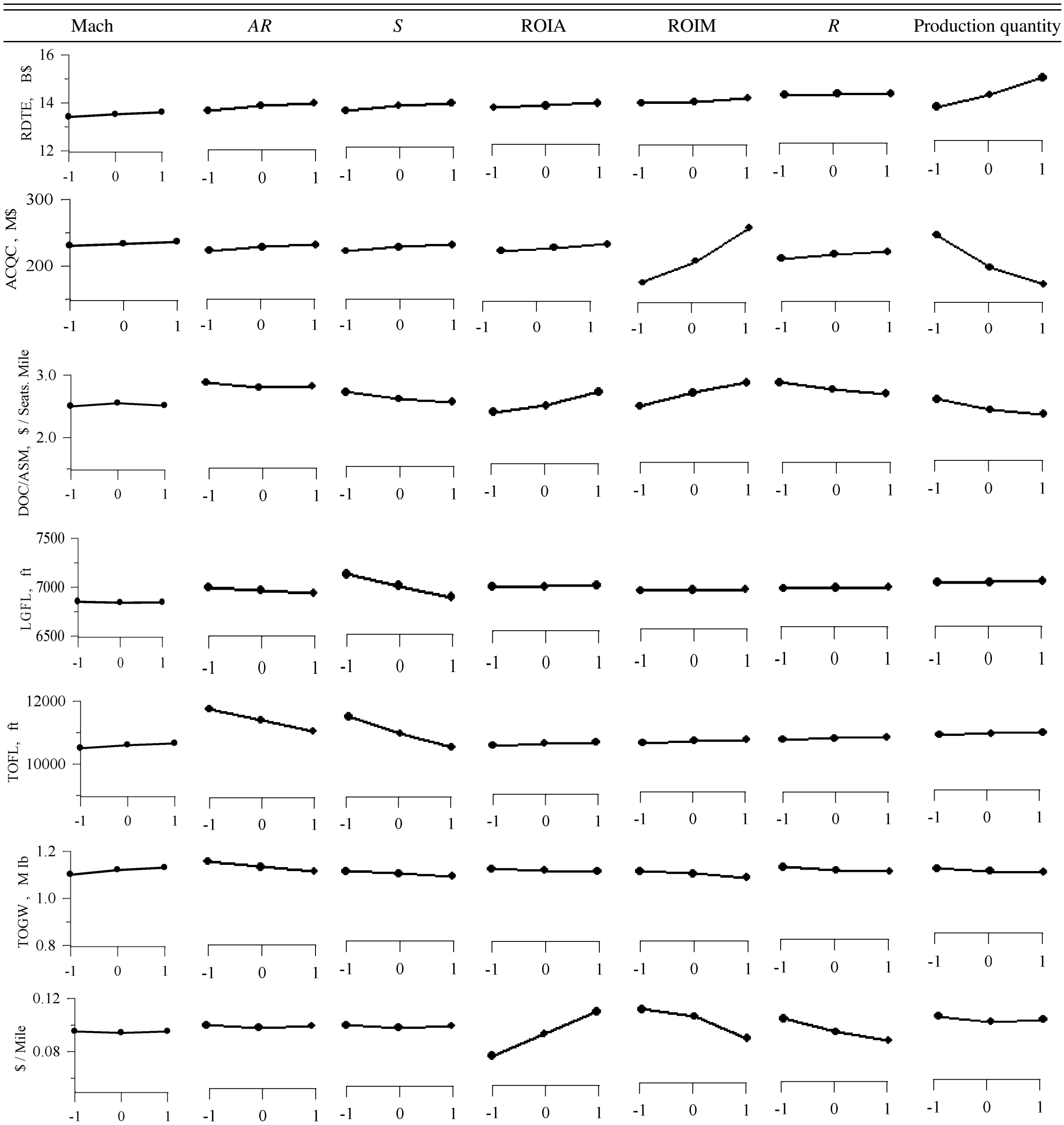
Consider another example of a large transport that is expected to carry a maximum of 500 passengers in a given range. Assuming a passenger load factor (PLF) of 60%, the aircraft is expected to be efficient for a passenger number between 300 and 500. This in turn means that the aircraft basic geometries should not show any appreciable change with the number of passengers changing from 300 to 500. This desire could be treated as a rule. However, if the aircraft had a maximum number of 1000 seats, even with a PLF of 60%, it would not be logical to use the same rule. That is, the aircraft would not stay efficient for 600 to 1000 passengers. Therefore, a rule expressed in (rule ith) would not apply to both aircraft.

To select the optimum number of seats for a wide-body transport, a suitable rule base is needed. This rule base should characterize the effect of each design parameter by means of linguistic rules such as given in Table 3. Table 2 shows the functions used to develop the rule base of Table 3. As it is seen from Table 2, the relationships between any two design and performance parameters could be either linear or nonlinear. Different case studies conducted by the authors show that in some cases even a slight nonlinearity would have a tangible effect on the outcome. Nevertheless, devising a nonlinear rule is much harder and more time consuming to develop.

In this work, the authors present the fuzzy membership functions with the effect of nonlinearity wherever needed (Figs. 3 and 4). For the case of computing an optimum number of seats and cargo volume, an acceptable level of complexity is needed. This leads us to a minimum of 98 IF-THEN rules for linear cases and 147 IF-THEN rules for nonlinear ones. Some linear and nonlinear rules are shown in Table 3.

Now, we need to describe the selected rules to some form of membership functions. Some varieties for membership functions are available such as trapezoidal, triangular, and Gaussian. There are two approaches to determine a membership function, as described in [17]. In the first approach, one could use available knowledge of human experts, that is, we ask available experts to specify the most desirable membership functions. In this approach, fuzzy sets are used to formulate human knowledge and the membership functions in fact represent parts of this accumulated knowledge. This approach normally leads to a rough formula for membership functions and needs fine-tuning. In the second approach, some statistical data might be used to determine the form of membership functions. This is normally done by specifying the general structure for the membership functions followed by a procedure for its fine-tuning.

Table 2 Metrics function for construction of fuzzy IF-THEN rule base[a]



[a]TOGW: takeoff gross weight; ASM: available seats per mile; LGFL: landing field length; ACQC: acquisition cost.

In this work, authors use a triangular form for the membership functions, as they agree with most trade studies in traditional approach to aircraft design and are therefore easier to interpret.

IV. Basis of Calculating Number of Seats

To show both the flexibility and sensitivity of a fuzzy system as a decision-making tool in calculating the proper number of seats for a wide-body transport airplane, different cases are presented as follows:

1) First, we present the results for the case in which variations of design variables (Table 2) for both linear and nonlinear functions are modeled by triangular membership functions.

2) Second, we investigate any change resulting from neglecting all nonlinear effects in variation of design parameters (Fig. 3).

3) Third, we investigate the results in which all nonlinearities, even small ones, are considered in variation of design parameters (Fig. 4).

4) Fourth, we also study the effect of type of fuzzy inference engine on the final result, that is, which type of inference engine suits the best for airplane design applications or at least the selection of number of seats and cargo volume.

The most popular inference engines used for this research are shown in Table 4, where $\mu_{B'}(y)$ is the output membership function in the respective inference engine, $\mu_{A'}(x)$ is the singleton fuzzifier, $\mu_{A_P}(X_P^*)$ is the minimum membership function value in rule Lth, $\mu_{B^l}(y)$ is the membership function of the output fuzzy membership function in the rule L, and M is the number of rules and n is the number of design variables in rule L.

It is noted that all design parameters (such as shown in Table 5) are brought to the [0–1] interval by means of Euclidean's norm Eq. (2) for the sake of simplicity in evaluating the result.

Table 3 Selected fuzzy IF-THEN rules for optimum seat calculation[a]

IF antecedent	THEN antecedent
1) IF range is high	THEN TOGW is high
2) IF range is high	THEN DOC/ASM is low
3) IF ROIA is low	THEN dollar per mile is low
4) IF ROIM is high	THEN ACQC is high
5) IF ROIM is high	THEN DOC/ASM is high
6) IF airplane acquisition cost is high	THEN ROIA is high
7) IF passenger seat no. is high	THEN TOGW is high
8) IF TOGW is high	THEN DOC/ASM is high
9) IF TOGW is high	THEN ACQC is high
10) IF TOGW is high	THEN RDTE cost is high
11) IF wing area is high	THEN TOFL is low
12) IF wing aspect ratio is high	THEN TOFL is low
13) IF range *or* passenger seat no. is high	THEN dollar per mile is low
14) IF TOGW is high *and* LGFL is high *and* TOFL is high *and* RDTE cost is high *and* ACQC is high *and* S is high	THEN number of seats is high
15) IF dollar per mile is low *and* ROIA is high *and* ROIM is low *and* DOC per ASM is low	THEN range is high
16) ——	——

[a]Category for "low/medium/high" in design or market variables are as follows: $R < 4500$ nm is low, $4500 \text{ nm} < R < 8000$ nm is medium, $R > 8000$ nm is high. Seats < 250 is low, 250 < seats < 450 is medium, seats > 450 is high. TOFL < 6500 ft is low, 6500 < TOFL < 9000 ft is medium, TOFL > 9000 ft is high. ROIM < 10% is low, 10 < ROIM < 15% is medium, ROIM > 15% is high. ROIA < 5% is low, 5 < ROIA < 7% is medium, ROIA > 7% is high.

$$\bar{X} = \frac{X_i}{\sqrt{\sum_{i=1}^{n} X_i^2}} \quad \text{for } x \in X \tag{2}$$

In Eq. (2), X_i is any design parameter, and $\bar{X}$ is s nondimensional parameter of X_i.

V. Case Studies

In this section, we show the fuzzy design tool could predict important parameters such as number of seats N_s, floor area, and cargo volume of a wide-body transport for a given range. It is worth mentioning that number of seats and floor area are not mutually independent parameters, as one could lead to the other with a little mathematical manipulation together with some data on seat types, as well as seat pitch such as those provided in [18]. In large transports, a typical combination of 10% first class seats, 20% business class seats, and 70% economy seats is used. The same combination is used to find N_s in this work. Moreover, to have a basis for comparison as well as evaluation of the results, we consider future market predictions based on [11–13] for airliners as well as manufacturers.[‡§] Needless to say, such figures have some degree of uncertainty, however, a fuzzy preliminary design (PD) tool works fine with such figures.

To make the study more attractive, we turn the clock back to the time when a B-747-400 was to be designed. That is, we would like to investigate whether a fuzzy PD tool could in fact help B-747-400 designers to properly decide on number of seats of that aircraft at the time it was being designed. To make a distinction, we call this aircraft F-747-400 (where F stands for fuzzy outcome). Obviously, if the developed tool could successfully propose an appropriate value for the seat range/cargo volume, then we would have more confidence to apply it to a new wide-body transport with a mission similar to A-380.

Table 5 shows the number of passenger seats, range/cargo volume, and total delivery of each type of B-747 family and A-380. As it is shown, B-747-400 could capture a large portion of this market, that is, any new large wide-body transport must be able to compete with this airplane. As a measure of being competitive, it is important for commercial transports to be able to carry as many different types of containers as possible. Of course, the volume of cargo strongly depends on the operators and their route systems. In passenger transports, the cargo is usually carried below the cabin floor. Besides, there could be a so-called quick-change or combi-configuration to carry a mixture of cargo and passengers. For the current work, the following assumptions are made [18]:

1) Baggage weight per passenger for long haul flights is 45 lb.
2) Average baggage density is 12.5 lb/ft^3.
3) Baggage loading efficiency is 85%.

Using the developed fuzzy tool, we first compute the optimum numbers of seats and cargo volume for F-747-400. These results are given in Table 6 for different inference engines and linear membership function, and in Table 7 for the same inference engines but nonlinear membership functions. Figures 5 and 6 compare the results found for F-747-400 with that of the existing capabilities of the B-747-400. These figures reveal that the developed fuzzy PD tool is in fact capable of proposing a proper figure for number of seats, cargo volume, as well as cabin floor area. In fact, the fuzzy tool suggests different combinations for number of seats/cargo volume for different ranges which all satisfy our cost function (Tables 6 and 7). It is interesting to note that N_s for an existing B-747-400 is not too far from that of F-747-400 and because B-747-400 has in fact served successfully in its routes, we might conclude that our developed PD

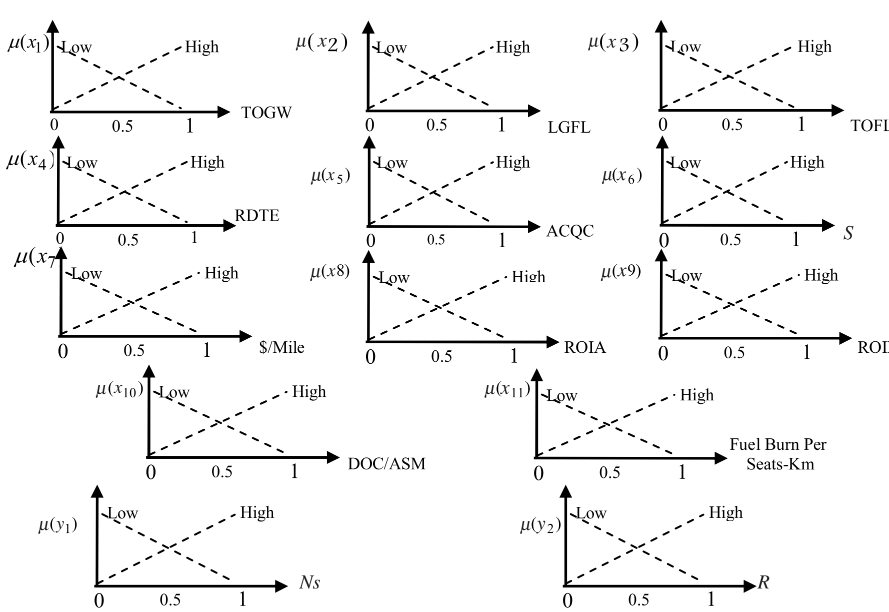


Fig. 3 Membership functions of design parameters: linear variation.

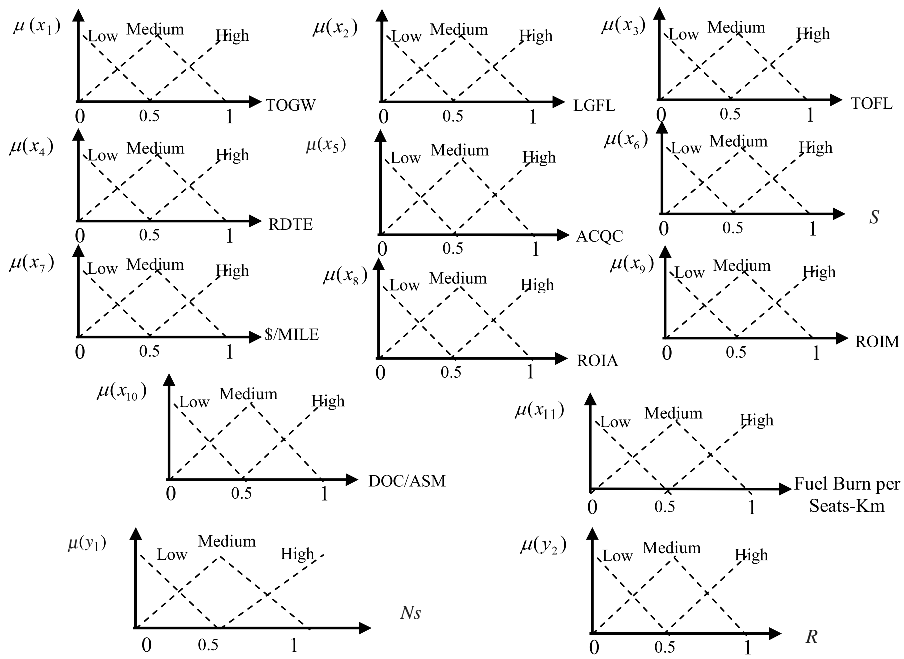


Fig. 4 Membership functions of design parameters: nonlinear variation.

tool provides appropriate figures, at least as far as predicting number of seats/cargo volume is concerned. Tables 6 and 7 present the sensitivity of the results to different parameters. These parameters are as follows: 1) market uncertainty defined by return of investment airliner (ROIA), cost/mile, passenger load factor, and finally DOC; 2) type of fuzzy inference engine (Table 4); 3) fuzzy IF-THEN rules (Fig. 3 for linear cases and Fig. 4 for nonlinear ones).

It is noted that different inference engines result in different figures, however, results for the Mamdani inference engine are closer to the existing B-747-400. This does not mean that a fuzzy PD tool based on the Mamdani inference engine is a better one because no manufacturer has ever tried other possible configurations proposed by other tools. In fact, there is a good possibility that other proposed configurations fly more efficiently. Like for any software, we need to have some experiments for the final judgment. Moreover, considering the degree of approximation involved in PD work, results for linear membership functions are not too much different from cases with nonlinear behavior. As it is shown in Tables 6 and 7 (or Figs. 5–8) for B-747-400, the results of fuzzy PD are very close to the actual figures. Effects of market uncertainties (cases 1–4), provide different results for N_s as well as seat range/cargo volume. Results in case 4, though being optimistic, are very close to the actual figures of the existing B-747-400 Combi.

As for the second set of case studies, we apply the fuzzy PD tool to an aircraft with a similar mission to that of an A-380. We call this aircraft F-380 for convenience. That is, we would like to use our fuzzy PD tool to investigate the proper number of seats and cargo volume for F-380 while considering the future market uncertainties. The results for these cases are given in Tables 6 and 7 (and Figs. 7 and 8). As it is seen, the fuzzy tool suggests a maximum number of seats of 506 with a cargo volume of slightly over 9300 ft^3 for the cases with linear membership functions. For the nonlinear ones, these figures change to 518 seats together with 8600 ft^3 for cargo volume. For both cases, the F-380 has a shorter range compared with that of A-380. This is true for all inference engines, which means that the fuzzy PD tool suggests that F-380 carry more cargo, less passengers, and shorter range compared with that of A-380 based on given market uncertainties. It is interesting to note that results for the cabin length (or floor area) suggest that the F-380 could not be a single deck fuselage (Table 7, case 4).

Table 4 Different fuzzy inference engine [17]

	Fuzzy inference engine	Output membership function
1	min. Mamdani	$\mu_{B'}(y) = \max_{L=1}^{M}\{\sup_{x\in U} \min[\mu_{A'}(x), \mu_{A_p}(x_p^*), \mu_{B^l}(y)]\}$
2	Lukasiewicz	$\mu_{B'}(y) = \min_{L=1}^{M}\{\sup_{x\in U} \min[\mu_{A'}(x), 1-\mu_{A_p}(x_p^*)+\mu_{B^l}(y)]\}$
3	Dienes–Rescher	$\mu_{B'}(y) = \min_{L=1}^{M}(\sup_{x\in U} \min\{\mu_{A'}(x), \max[1-\mu_{A_p}(x_p^*)], \mu_{B^l}(y)\})$

Table 5 Wide-body transport airplane [10][‡§]

	N_s	R, nm	TOGW, lb	TOFL, ft	$W_F/(N_s \cdot R)$, lb/(seats · mile)	Cargo volume, ft^3	Total delivery
A300-600	298	4150	378,500	7800	0.112	5205	580
777-200	320	4990	506,000	9800	0.13	8468	430
747-100	366–452	6100	735,000	9900	0.097	5497	250
747-200	366–452	7900	833,000	9900	0.233	5497	393
747-300	412	7700	833,000	9900	0.262	5497	81
747-400	420	7300	875,000	10,450	0.115	combi 10,422 747-400ER 5599	614
A-380	555	8150	1,234,588	10,850	0.127	6226	159 order

Table 6 Results of case study for different fuzzy inference engines, linearized membership functions

		Mamdani inference engine				Lukasiewicz inference engine				Dienes–Rescher inference engine			
	Case	1[a]	2[b]	3[c]	4[d]	1[a]	2[b]	3[c]	4[d]	1[a]	2[b]	3[c]	4[d]
F-747-400	N_s	443	417	——	408	483	463	——	442	394	381	——	374
	R, nm	7602	7624	——	7415	7923	7634	——	7453	6953	7423	——	7625
	cargo volume, ft^3	9583	10,245	——	10,480	8566	9075	——	9608	10,927	11,160	——	11,337
	cabin length, ft	193.6	181.3	——	176.6	212.8	203.2	——	193.1	170.5	164.1	——	160.9
	cabin floor area, ft^2	3482.5	3262.3	——	3177.6	3830.1	3656	——	3474.5	3067.1	2951.3	——	2896.4
F-380	N_s	435	460	456	506	428	445	442	498	419	426	421	465
	R, nm	7417	7697	7772	2974	6852	7126	7342	7685	6234	6368	6453	7164
	cargo volume, ft^3	13,967	12,354	12,615	9387	14,419	13,322	13,516	9903	15,000	14,548	14,870	12,032
	cabin length, ft	190.1	201.8	200.1	223.9	186.2	194.5	193.1	220.4	182.2	185.3	183.1	204.1
	cabin floor area, ft^2	3418.8	3632	3600	4029.2	3349.6	3498.5	3474.5	3964.7	3278.1	3333.7	3294	3671.9

[a]Case 1: market parameters as in Table 1.
[b]Case 2: ROIA, 1% better than case 1; $/mile, 10% better than case 1; passenger load factor, 10% better than case 1.
[c]Case 3: $/mile, 20% better than case 1; DOC, 20% lower than with respect to B-747.
[d]Case 4: current target for airliner and manufacturer; ROIA = 10%, passenger loading factor = 80%, and cargo loading efficiency = 85%.

Table 7 Results of case study for different fuzzy inference engines, nonlinear membership functions

		Mamdani inference engine				Lukasiewicz inference engine				Dienes–Rescher inference engine			
	Case	1[a]	2[b]	3[c]	4[d]	1[a]	2[b]	3[c]	4[d]	1[a]	2[b]	3[c]	4[d]
F-747-400	N_s	447	421	——	412	491	472	——	456	399	392	——	383
	R, nm	7618	7768	——	7384	7823	7424	——	7435	7653	7432	——	7615
	cargo volume, ft^3	9482	10,142	——	10,570	8363	10,083	——	9253	10,700	10,879	——	11,108
	cabin length, ft	195.4	183.1	——	178.4	217.2	207.2	——	200.1	172.7	169.6	——	164.9
	cabin floor area, ft^2	3514.4	3294	——	32,092	3908.3	3728.1	——	3599.9	3106.5	3051.3	——	2967.1
F-380	N_s	453	471	465	518	438	453	456	502	429	436	458	467
	R, nm	7237	7369	7572	7838	7368	7137	7574	7728	6392	6485	6748	7278
	cargo volume, ft^3	12,806	11,645	12,032	8613	13,774	12,824	12,612	9645	13,543	13,903	12,483	11,903
	cabin length, ft	198.7	206.8	204.1	230.1	191.4	198.8	200.1	222.2	186.6	190.5	201	205
	cabin floor area, ft^2	3576	3720.1	3672	4140.1	3442.7	3576	3600	3996.9	3357.5	3426.7	3616	3688

[a]Case 1: market parameters as in Table 1.
[b]Case 2: ROIA, 1% better than case 1; $/mile, 10% better than case 1; passenger load factor, 10% better than case 1.
[c]Case 3: $/mile, 20% better than case 1; DOC, 20% lower than with respect to B-747.
[d]Case 4: current target for airliner and manufacturer; ROIA = 10%, passenger loading factor = 80%, and cargo loading efficiency = 85%.

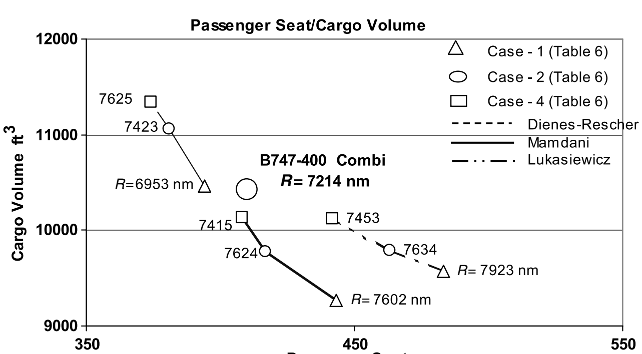


Fig. 5 Comparison of F-747-400 and B-747-400 for linear membership functions.

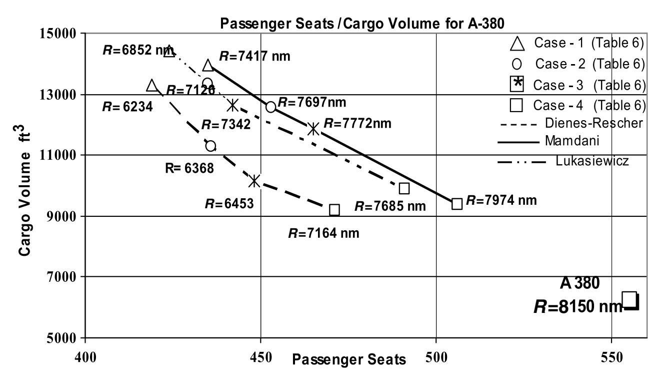


Fig. 7 Comparison of F-380 and A-380 for linear membership functions.

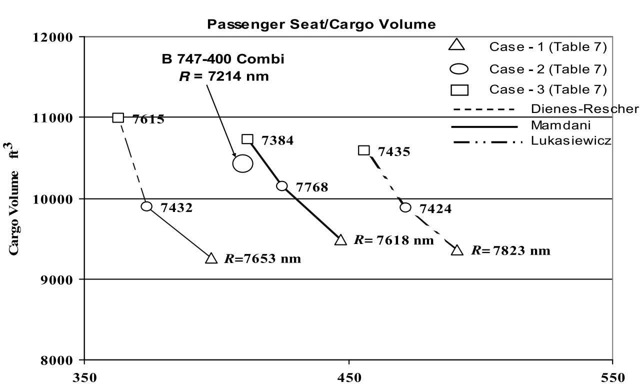


Fig. 6 Comparison of F-747-400 and B-747-400 for nonlinear membership functions.

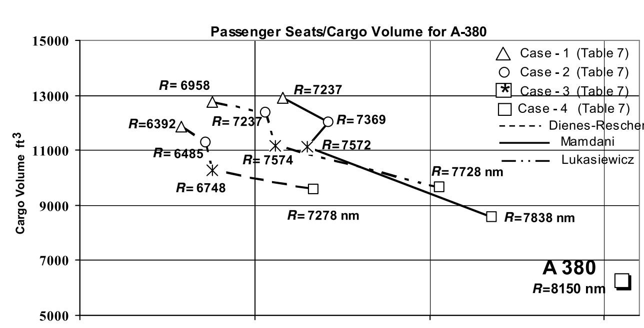


Fig. 8 Comparison of F-380 and A-380 for nonlinear membership functions.

VI. Discussion and Conclusions

This paper shows how a decision-making tool could be developed and used based on "fuzzy logic." It is further shown that a fuzzy PD tool could effectively be used to decide important parameters such as number of seats, cabin floor area, as well as cargo volume in wide-body transports. To somehow verify the results of the developed fuzzy tool, we select B-747-400 mission. It is shown that the results of the PD tool agree with the existing B-747-400 configuration with an acceptable level of accuracy. However, it would not support the idea to build a wide body with more than 520 seats and a cargo volume less than 9000 ft^3, at least for the next 15 years. With this statement, we would not suggest that a design similar to that of A-380 would be unsuccessful. In fact, A-380 has a versatile configuration and could easily adjust its internal arrangement to carry more cargo volume and fewer passengers. The primary intention of this work is, however, to show the flexibility and the power of fuzzy logic systems as a tool in aircraft preliminary design. This is an important feature of the developed PD tool that could easily suggests different arrangements and provide a better understanding of what aircraft should be able to do in an uncertain economic environment. Although the existing tool uses fuzzy logic to decide only the number of passenger seats range, cabin floor area, and cargo volume, other important parameters such as internal layout of the cabin as well as the cargo compartment might also be brought into the design scenario. For example, we might be willing to use a certain type of container such as LD-2 or LD-3; a simple IF-THEN rule could easily be used to support that desire as follows:

IF cargo volume < 5000 ft^3, THEN cargo volume -(cargo volume / volume of LD-2) * volume of LD-2 equal 0.

IF cargo volume > 5000 ft^3 THEN cargo volume -(cargo volume / volume of LD-3) * volume of LD-3 equal 0.

These rules serve to show that a fuzzy PD tool could also be used to design a new aircraft with new features with less effort compared with that of other techniques, such as brainstorming. We might simply do this by describing our desire or wishes in terms of new IF-THEN rules and adding them to the existing rules base or by replacing some rules with new ones. Nevertheless, authors suggest using all inference engines until enough experience is gained in dealing with a specific class of aircraft. Different case studies conducted by the authors suggest that the results based on the Mamdani inference engine to be a bit closer to some existing design in the class of long-range transports.

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