MULTI-CRITERIA DECISION ANALYSIS TECHNIQUES IN AIRCRAFT CONCEPTUAL DESIGN PROCESS

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Abstract

In aerospace systems design, conflicting disciplines and technologies are always involved in the design process. Multi-Criteria Decision Analysis (MCDA) techniques can be helpful to effectively deal with such situations and make wise design decisions. In this paper, the feasibility and added values of applying the MCDA techniques in aircraft design are explored. A new optimization framework incorporating MCDA techniques in aircraft conceptual design process is established. An improved MCDA method is utilized to aggregate the multiple design criteria into one composite figure of merit, which serves as an objective function in the optimization process. It is demonstrated that the suitable MCDA method with improvement provides a better objective function for the optimization than the traditional weighted sum method.

Considering that the inherent uncertainties and subjectivities of the weighting factors have crucial impacts on the design solution, surrogate models for the multiple design criteria in terms of the weighting factors are constructed. The constructed surrogate model can provide efficient analysis tools for uncertainty assessment.

1 Introduction

Multi-Criteria Decision Analysis (MCDA) is a process that allows one to make decisions in the presence of multiple, potentially conflicting criteria [15], [7]. Although MCDA as a discipline has a relatively short history of about 40 years, over 70 MCDA techniques have been developed for facilitating the decision making process.

There are typically two strategies when implementing MCDA techniques in the engineering design process: a posteriori approach and a priori approach [15]. In the a posteriori approach, optimization techniques are applied firstly to search for a set of best trade-off solutions, usually in terms of a Pareto front. Then, MCDA techniques are used to select the most preferred design solution among several design alternatives from the Pareto front, taking multiple evaluation criteria into consideration simultaneously. In the a priori approach, MCDA techniques are utilized to aggregate the multiple design criteria into one figure of merit. Then, optimization techniques are applied to search for the best design solution, with the composite figure of merit as a single objective function.

Multi-objective optimization techniques play an important role in the a posteriori approach. For example, a three-objectives Genetic Algorithms (GA) were used to identify the trade-offs between environmental performances (noise and emission) and operating cost quantitatively [1]. A two-objectives GA were applied to the design of an aircraft that uses greener technologies [10]. However, multi-objective GA suffer from expensive computation. Furthermore, evolutionary optimization techniques are often not easily applicable for handling a large number of objectives [6].

The a priori approach can support designers to quickly assess the compromised design alternatives and be capable of dealing with large number of objectives. One of the classical a priori approaches, the weighted-sum approach (SAW), however, was criticized for over-simplified aggregation of the multiple design objectives [8].

In the a priori approach, the weighting factors create a compound figure of merit. The compound figure of merit serves as the objective function for optimization. Different weighting schemes result in different compound figure of merits. The selection of the figure of merit is critical to the determination of an optimal design, since if a design is optimized to the wrong figure of merit, it will not be the best design in terms of the real important measure. Especially, the inherent uncertainties and subjectivities of the weighting factors have significant impacts on the design solution.

In this paper, the a priori approach of implementing MCDA techniques in the design process is followed. A new multi-criteria optimization framework incorporating MCDA techniques in the aircraft conceptual design process is established, as illustrated in Fig.1. An improved MCDA method is utilized to aggregate the multiple design criteria into one composite figure of merit, which serves as an objective function in the optimization process. Furthermore, considering the crucial impacts of the weighting factors on the optimized design solution, surrogate models for the multiple design criteria in terms of the weighting factors are constructed.

The paper is organized as follows. Section 2 defines the aircraft design decision making problem. Section 3 presents the selection of the most appropriate MCDA method, through an developed intelligent multi-criteria decision support system. Section 4 presents the results of applying an improved MCDA method in the proposed multi-criteria optimization framework. In Section 5, surrogate model development for design criteria in terms of weighting factors is discussed. Finally, conclusions are drawn and presented in Section 6.

2 Definition of the Decision Making Problem

The focus of the proposed optimization framework is the assessment of the added values of incorporating MCDA techniques in the aircraft conceptual design process. Thus, in order to keep the design process transparent, the complexity of the design problem is limited. Five design variables for a conceptual aircraft design model are considered in this study: wing thickness-to-chord ratio, aspect ratio, reference area, cruise Mach number, and fuselage diameter.

The proposed optimization framework is applied to the design of a conventional 150-passenger, twin engine airliner with a design range 3200 *km* using the conceptual aircraft design tool VAMPzero(Virtual Aircraft Multidisciplinary Analysis and Design Processes). VAMPzero is developed at the German Aerospace Center (DLR e.V.) and licensed under the Apache 2.0 license [3].

2.1 Identification of Design Criteria

Selection of appropriate design criteria is critical to the determination of an optimal design. Some recommendations were provided in [14], which stated that the design criterion should represent a non-trivial and calculable indication of the worth of the concept, it should be significantly affected by the design variables and constraints, it should have clear meaning to designers and customers, and it needs clear rationale for methods and factors used for blending if it is blended.

In this study, in order to explore the interrelationships among the interest of manufacturers, the concern of fuel-based emissions, the concerns of airliners, and the consideration of passenger comfort explicitly, four design criteria are

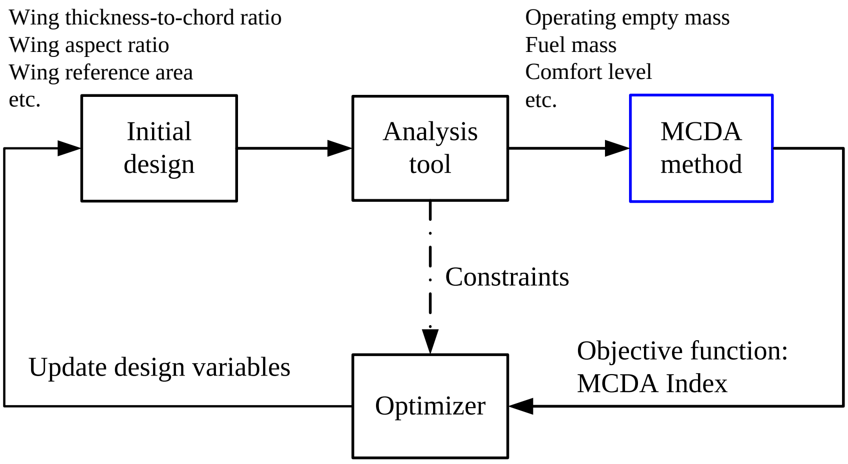

Fig. 1 The Framework of Incorporating MCDA Techniques in Aircraft Design

selected to feed into the MCDA method: Operating Empty Mass (OEM), fuel mass, utilization/(block time), and passenger density. The common practice of using Direct Operating Cost (DOC) as an objective function in the optimization appeared to be not appropriate in this study, considering that DOC has high correlation with all other design criteria. Nevertheless, DOC was traced as an aircraft performance measure, as well as aircraft price, fuel cost, and Take-off Mass (TOM).

The constraints imposed in the aircraft design process are wing span, fuel tank volume, take-off field length, landing field length, take-off wing loading, and cruise thrust. The design variables, constraints, and design criteria for this simplistic aircraft design model are summarized in Table 1.

Table 1 The Summary of Design Variables, Constraints, and Design Criteria in Aircraft Optimization Process

	Units	Values
Design Variables		
Thickness-to-chord ratio	–	$[0.1, 0.2]$
Aspect ratio	–	$[8, 12]$
Reference area	m^2	$[80, 140]$
Cruise Mach number	–	$[0.70, 0.84]$
Fuselage diameter	m	$[3.8, 4.2]$
Constraints		
Wing span	m	≤ 36
Fuel mass	kg	$\leq$ Fuel tank volume
Take-off field length	m	≤ 3000
Landing field length	m	≤ 2000
Take-off wing loading	kg/m^2	≤ 600
Cruise thrust	N	≤ 0.9 Take-off thrust
Design Criteria		
OEM	kg	–
Fuel mass	kg	–
Utilization/(block time)	–	–
Passenger density	Pax/m^2	–

3 Selection of an Appropriate MCDA Method

There are essentially two approaches to solve the decision making problems: non-compensatory and compensatory methods [9]. The non-compensatory methods do not permit trade-offs among criteria, that is to say, a disadvantage in one criterion cannot be offset by an advantage in other criterion. Compensatory methods permit trade-offs among criteria, in other words, small changes in one criterion can be offset by opposing changes in any other criterion. According to this classification, several widely used decision making methods are summarized in Table 2, where ELECTRE represents for Elimination and Choice Translation Reality [2], PROMETHEE stands for Preference Ranking Organization METHod for Enrichment Evaluations) method [4], and TOPSIS represents Technique for Order Preference by Similarity to Ideal Solution [9].

Table 2 Typical Non-compensatory and Compensatory Decision Making Methods [9]

Non-compensatory	Compensatory
Conjunctive method	Analytic hierarchy process
Disjunctive method	Expected utility theory
Dominance method	Multi-attribute utility theory
ELECTRE	Multiplicative weighting
Elimination by aspects	PROMETHEE
Lexicographic method	Simple additive weighting
Maximin method	TOPSIS
Maximax method	

3.1 Development of an Intelligent Multi-Criteria Decision Support System

Among various developed MCDA techniques, the selection of the most appropriate method to solve the aircraft design problem is important since the use of inappropriate method often leads to misleading results. In this study, an intelligent knowledge-based decision support system is developed in MATLAB, which consists of a MCDA library storing the widely used MCDA methods and a knowledge base providing the information required for the method selection process. The selection of the most suitable MCDA method depends on how the characteristics of the method match the characteristics of the control problem, which is measured by Appropriateness Index (AI) [11],[16], as shown in Equation 1.

$$AI_j = \sum_{i=1}^{n} w_i b_{ji}$$
$$b_{ji} = \begin{cases} 1 \text{ if} c_{ji} = a_i \\ 0 \text{ if} c_{ji} \neq a_i \end{cases} \quad i = 1,2,...,n; j = 1,2,...,m \tag{1}$$

where n is the number of evaluation criteria used to examine the decision making methods with respect to the given problem, and m is the number of decision making methods stored in the method library, $\{w_1, w_2, ..., w_n\}$ are the weighting factors for the evaluation criteria, a_i is the value of the i-th characteristic of the decision problem, and c_{ji} is the value of i-th characteristic of the j-th method, b_{ji} is a Boolean number depending on the match of the i-th characteristic of the decision problem and the i-th characteristic of the j-th method. If the i-th characteristic of the decision problem matches the i-th characteristic of the j-th method, then $b_{ji} = 1$; otherwise, $b_{ji} = 0$.

3.2 Selection of the Most Appropriate Method using the Intelligent Multi-Criteria Decision Support System

In this example, the selection of the most appropriate MCDA method for the aircraft design problem is presented, through the developed intelligent multi-criteria decision support system. In order to identify the most appropriate method, 16 widely used MCDA methods are studied and their characteristics are stored in a method database. To compare the appropriateness of the methods with respect to the given problem, each method is evaluated based on the proposed 12 evaluation criteria. The 12 evaluation criteria can be captured by answering 12 questions relevant to the characteristics of the methods, as presented in Fig.2.

As shown in Fig.2, the infeasible MCDA methods are eliminated first by the three filter questions. Considering that in this aircraft design problem, the compound figure of merit for the four design criteria aggregated by MCDA method serves as objective function in the optimization, the scoring methods are more appropriate than the classification methods. Meanwhile, all non-compensatory methods are excluded since compensation is allowed in the aircraft optimization process. Moreover, the decision maker's preference information on the evaluation criteria can be defined using slide bars in the integrated user interface, with a subjective scale of 0 to 10, where 0 stands for extremely unimportant while 10 represents extremely important.

The AI of the MCDA methods are calculated and presented in Fig.3, where higher score represents more appropriateness of the method when solving the given problem. As indicated in Fig.3, TOPSIS gets the highest score among the MCDA methods for the problem under consideration, therefore, it is selected as the most appropriate method in this research.

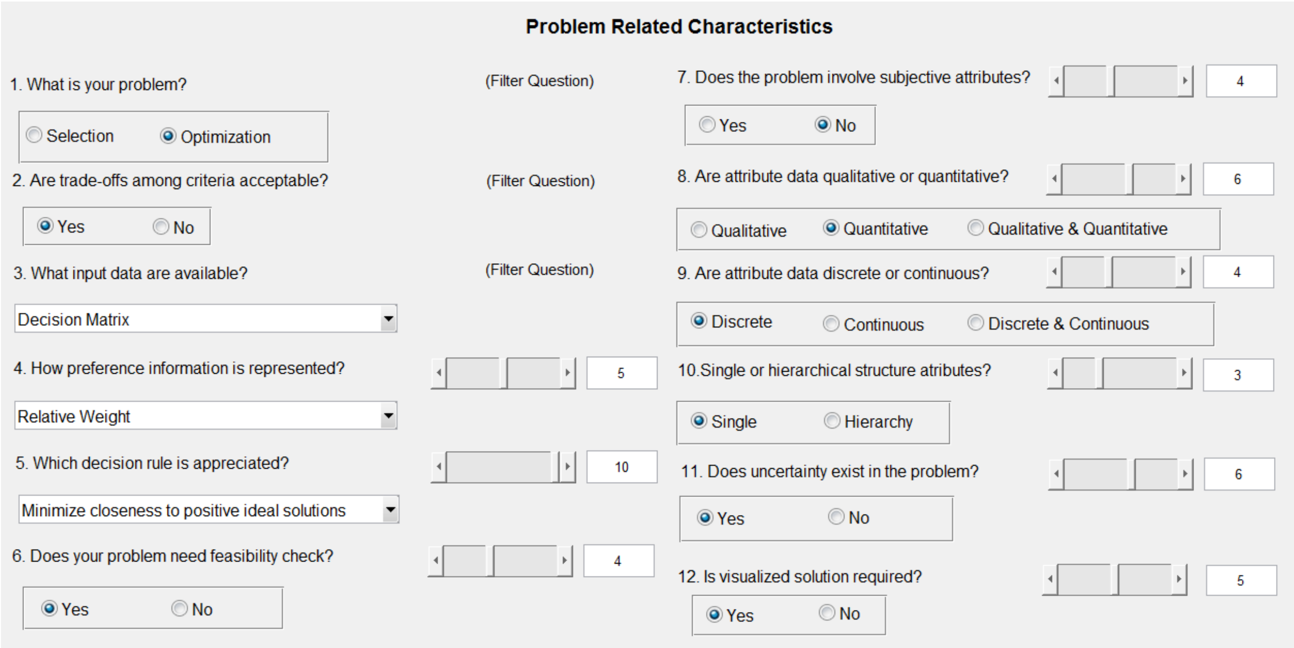

Fig. 2 Questions Related to Evaluation Criteria for Method Selection in Aircraft Design Process

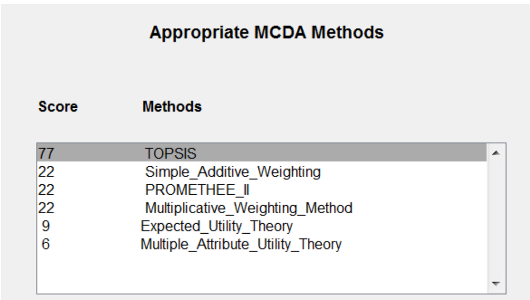

Fig. 3 MCDA Methods Ranking List with Scores in Aircraft Design Process

3.3 An Improved TOPSIS (ITOPSIS)

TOPSIS is one of the most widely used MCDA methods [9]. TOPSIS is based on the concept that the most preferred alternative should have the shortest Euclidean distance to the positive ideal solution and the furthest Euclidean distance from the negative ideal solution.

In the original TOPSIS method, when an alternative is removed from or added to the candidate alternatives, the two hypothetical solutions will probably change and the Euclidean distances to the two hypothetical ideal solutions will also change. Thus, the top-ranked alternative would probably be inconsistent when the candidate alternatives are changed. It has been pointed out that the cause of rank inconsistency with TOPSIS lies in the determination of the positive ideal solution and negative ideal solution, and a pair of absolute ideal solutions instead of the relative ideal solutions was introduced to eliminate the rank inconsistency of TOPSIS method [5].

In this research, an Improved TOPSIS (ITOPSIS) will be utilized to aggregate the four design criteria into one compound figure of merit for optimization. The positive ideal solution and negative ideal solution are set beforehand in order to avoid the ranking inconsistency. In our case, two kinds of optimizations are conducted for each of the four design criteria: minimization and maximization. The positive ideal solutions and negative ideal solutions for the four design criteria are searched within the results of eight optimizations, as summarized in Table 3. It should be noted that the utilization/(block time) ratio is a benefit criterion, and the other three are cost criteria.

4 Optimization with Equal Weighting Factors

In this example, based on parametric studies, all design variables under investigation are continu-

Table 3 The Positive Ideal Solution and Negative Ideal Solution in ITOPSIS

Ideal solutions	OEM	Fuel mass	Utilization/ (block time)	Pax density
Positive	36943	11767	796.86	1.2875
Negative	50521	20864	715.08	1.4063

ous, and the objective functions with respect to the design variables in the conceptual aircraft design tool (VAMPzero) are rather smooth. Therefore, gradient-based methods are used in the optimization framework.

4.1 Comparison Using Different MCDA Indices as Objective Functions

The optimization results with equal weighting factors among the four design criteria when using ITOPSIS index as an objective function are summarized in the second column in Table 4. For the purpose of comparison, the proposed optimization framework is also performed when using weighted sum (SAW) index as an objective function, the optimization results are summarized in the third column in Table 4.

It is observed from Table 4 that with equally assigned weighting factors, the optimized design using ITOPSIS index as an objective function is heavier but more fuel efficient than the design which was optimized using SAW index as an objective function.

Furthermore, in the same running environment (Windows 7, 2.66 GHz Intel Core 2 Quad CPU, 4 GB RAM, and Matlab 2010a version), the convergence rates when using ITOPSIS index and using SAW index as objective functions are summarized in Table 5. It is seen that the optimization using ITOPSIS index as an objective function need less iterations and less computation time (in seconds) than using SAW index as an objective function.

However, only with the conduction of one set of weighting factors, it cannot be concluded which MCDA method is more appropriate for the optimization, considering the crucial impact of the weighting factors on the optimized design. The roles of the weighting factors in the framework of incorporating MCDA techniques in aircraft design will be further investigated in the following section.

Table 5 Comparison of Convergence Rates, Using ITOPSIS Index and SAW Index as Objective Functions

Objective function	Iterations	Optimization time
ITOPSIS index	5	304
SAW index	39	3005

5 Surrogate Model Construction for Design Criteria in terms of Weighting Factors

The weighting factors have crucial impacts on the design solution, since the objective function in the optimization process is aggregated through the weighting factors. An uncertainty assessment that demonstrates this impact must consider different combinations of the weighting factors. However, in the proposed multi-criteria optimization framework, the computation time for one set of weighting factors is at least 5 minutes. A Monte Carlo based uncertainty analysis with 10,000 samples would take at least 35 days. The long computation time makes the uncertainty assessment an intractable computational task.

In this study, in order to facilitate the uncertainty assessment of the weighting factors, surrogate models for the four design criteria in terms of the weighting factors are constructed. Each point of this surrogate model represents an optimized aircraft design for a given set of the weighting factors. The whole framework of incorporating MCDA techniques in aircraft design process is treated as a black box. An overview of surrogate modeling process for design criteria in terms of weighting factors is shown in Fig.4.

There are typically four steps in surrogate model building process: sample the design space using experimental design, choose a model to represent the input and output data, select a method to fit the model, and validate the constructed model [8]. The construction of surrogate models for design criteria in terms of weighting factors will follow this process.

Table 4 Optimization Results Using ITOPSIS Index and SAW Index as Objective Functions, When Weighting Factors are Evenly Distributed

	Baseline Design	Optimized Design (ITOPSIS)	Optimized Design (SAW)
Design Variables			
Thickness-to-chord ratio	0.13	0.135	0.1304
Aspect ratio	9.396	9.414	9.118
Reference area (m^2)	122.4	117.01	116.9
Cruise Mach number	0.78	0.76	0.77
Fuselage diameter (m)	4	3.8	3.8
Design Criteria			
OEM (kg)	40980	38705	38552
Fuel mass (kg)	12903	12242	12344
Utilization/(block time)	763	752	756.5
Passenger density (pax/m^2)	1.35	1.4211	1.4211
Traced Performance Measures			
DOC (Euro/h)	4818	4588	4612
Aircraft price (Euro)	36077718	34397326	34284714
Fuel cost (Euro/h)	1686	1571	1596
TOM (kg)	73133	70197	70147

5.1 Experimental Design

In order to explore the design space thoroughly, experimental design with spatially uniform distribution is one effective approach. There are several space filling strategies [12], among which Latin Hypercube Sampling (LHS) is one reliable method to generate random candidate samples, with guarantee that these samples are relatively uniformly distributed in the design space [13].

In this study, the weighting factors $\{w_1, w_2, ..., w_n\}$ generated by experimental design have to satisfy two conditions:

1. $0 \leq w_i \leq 1$
2. $\sum_{i=1}^{n} w_i = 1$

The standard LHS meets the condition 1 that all the factor settings range from 0 to 1. However, for each experimental run, the sum of the factor settings in each run do not equal to 1. In this case, in order to generate experimental designs fulfilling the conditions 1 and 2, standard LHS is conducted first, then the samples generated by LHS are rectified by Dirichlet distribution.

One Modified LHS with Dirichlet Distribution

Dirichlet distribution is a family of continuous multivariate probability distributions parameterized by a vector $\alpha = (\alpha_1, \alpha_2, ..., \alpha_k,)$ of positive reals. Dirichlet distribution is one multivariate generalization of the beta distribution and is defined as Equation 2

$$Dir(X,\alpha) = \frac{\Gamma(\alpha_1+\alpha_2+...+\alpha_k)}{\Gamma(\alpha_1)\Gamma(\alpha_2)...\Gamma(\alpha_k)} \prod (x_1{}^{\alpha_1-1} x_2{}^{\alpha_2-1} ... x_k{}^{\alpha_k-1}) \quad (2)$$

where $X = (x_1, x_2, ..., x_{k-1})$, satisfying $x_i > 0$ and $\sum_{i=1}^{k-1} x_i < 1$. Besides, $x_k = 1 - x_1 - x_2 - ... - x_{k-1}$. In a symmetric Dirichlet distribution, the components of vector α are equal. If each component of α is 1, the symmetric Dirichlet distribution is equivalent to a uniform distribution; if each component of α is bigger than 1, it prefers dense, evenly distributed distribution, and if each component of α is smaller than 1, it prefers sparse distribution.

When using the modified LHS with Dirichlet distribution, although the modified sample values

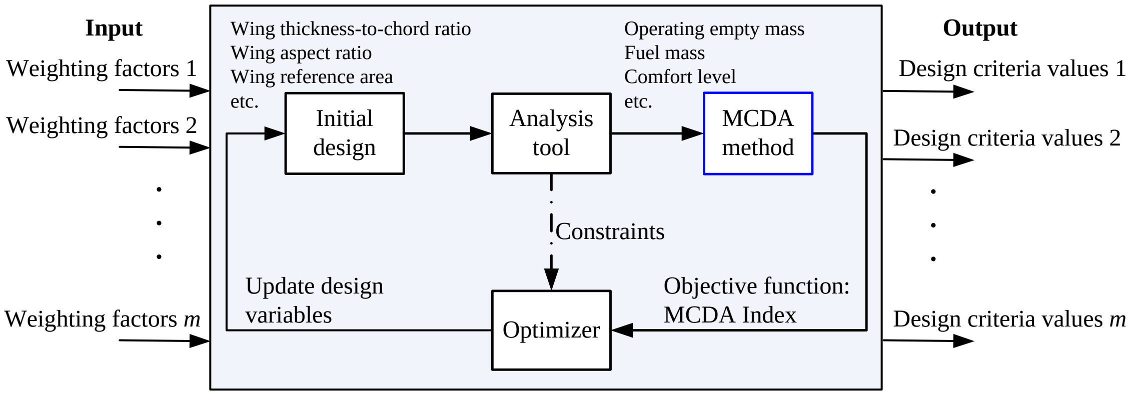

Fig. 4 The Overview of Surrogate Modeling Process for Design Criteria in Terms of Weighting Factors

are not strictly uniform any more, Dirichlet distribution can keep the ranges of the sample values larger once they are normalized, while maintaining the appealing Latin properties. In this example, one hundred sets of weighting factors are generated by the LHS with Dirichlet distribution.

5.2 Model Choice and Model Fitting

Response surface models have been widely used in the surrogate model construction in engineering design [8]. There are several advantages using response surface models, such as ease of implementation, minimal efforts required to train models, and ideality for uncertainty analysis. In this research, response surface is utilized to construct the surrogate models. A widely used statistics software package JMP@ is employed to fit response surface models.

5.3 Model Validation

The actual values versus the predicted values for the four design criteria when using ITOPSIS index as an objective function are shown in Fig. 5. For the purpose of comparison, the actual values versus the predicted values for the four design criteria using SAW index as an objective function are also conducted and are shown in Figure 6. In the actual by predicted plot, the horizontal dotted blue line represents the mean of the actual values, the red line shows the 45 degree diagonal line, and the two red dotted lines show the 95% confidence intervals.

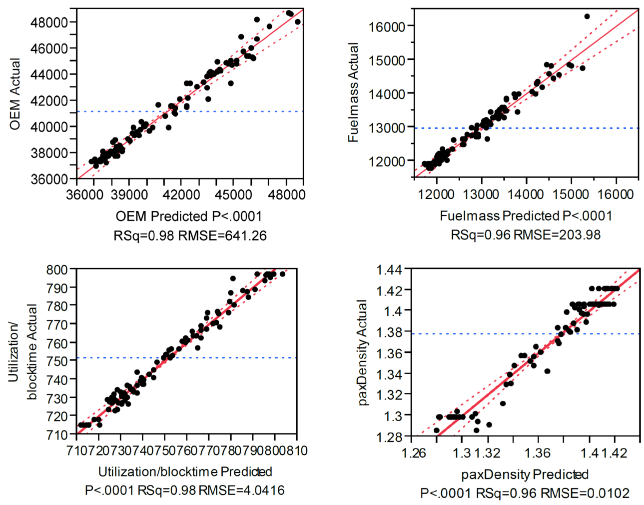

Fig. 5 The Actual by Predicted Plots of OEM, Fuel Mass, Utilization/(Block time), and Passenger Density, when using ITOPSIS Index as an Objective Function

The actual by predicted plots illustrate how well the predicted responses match the actual data. A quick assessment of the model is to eyeball a 45 degree pattern in these plots. In our case, the scatter plots when using ITOPSIS index as an objective function and using SAW index as an objective function all follow a 45 degree pattern. Specifically, the scatter plots when using ITOPSIS index as an objective function are less divergent along the diagonal line than the scatter plots when using SAW index as an objective function. This is one indicator of better goodness of fit when ITOPSIS is used for the multiple criteria aggregation than SAW.

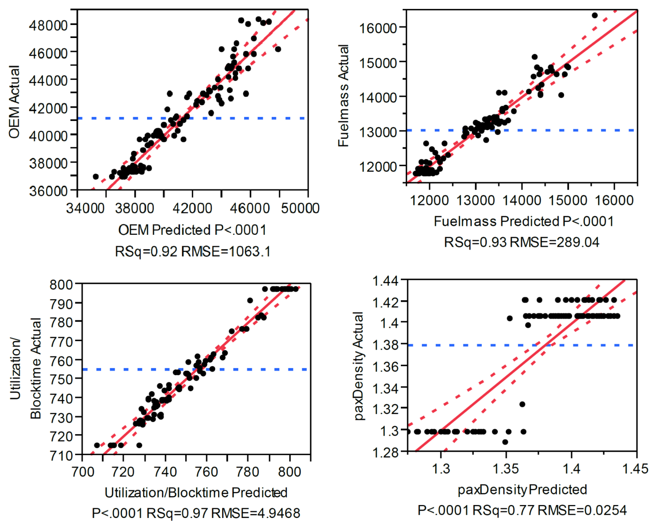

Fig. 6 The Actual by Predicted Plots of OEM, Fuel Mass, Utilization/(Block time), and Passenger Density, when using SAW Index as an Objective Function

The diagnostics of each response surface model, including R^2, R^2_{Adj}, and Root Mean Square Error (RMSE) in percentage, are listed in Table 6. R^2 measures the proportion of the variation explained by the regressed polynomial model, R^2_{Adj} adjusts the R^2 value to make it more comparable over models with different numbers of parameters, and RSME estimates the standard deviation of the random error. The percent RMSE shown in Table 6 is normalized by its mean of response.

Table 6 The Diagnostics of Response Surface Models for Design Criteria, Using ITOPSIS Index and SAW Index as Objective Functions

Diagnostics	OEM	Fuel mass	Utilization/ (block time)	Pax density
ITOPSIS				
R^2	0.975	0.964	0.983	0.957
R^2_{Adj}	0.963	0.951	0.976	0.945
RMSE	1.56%	1.57%	0.54%	0.74%
SAW				
R^2	0.916	0.934	0.973	0.774
R^2_{Adj}	0.9	0.92	0.965	0.743
RMSE	2.58%	2.22%	0.66%	1.84%

It is observed from Table 6 that the values of R^2 and R^2_{Adj}, when ITOPSIS is used for the aggregation of the four design criteria, are all higher than when SAW is used. The percent RSME, when ITOPSIS is used for the aggregation of the four design criteria, are all lower than when SAW is used. Especially, R^2 of passenger density when ITOPSIS is used is 0.957, while it is only 0.774 when SAW is used. The higher values of R^2 and R^2_{Adj} and lower values of percent RSME are strong evidences of goodness of fit. Therefore, it is obtained that the constructed response surface models using ITOPSIS for multiple criteria aggregation are better fitted than using SAW for multiple criteria aggregation.

In conclusion, ITOPSIS index is a better objective function for the optimization framework of incorporating MCDA techniques in aircraft design process than the traditional SAW index.

6 Conclusions

In this paper, the feasibility and the added values of applying MCDA techniques in aircraft design problems are explored. A new optimization framework incorporating MCDA techniques for aircraft conceptual design process is established. An intelligent multi-criteria decision support system is developed to select the most appropriate MCDA method. It is demonstrated that the chosen MCDA method with improvement provides a better objective function for the optimization than the traditional weighted sum method.

Furthermore, the weighting factors of the design criteria have significant impacts on the design solution. Surrogate models for the multiple design criteria in terms of the weighting factors are constructed. The constructed surrogate models can enable efficient uncertainty assessment for the weighting factors.

In future work, hybrid optimizers combining genetic algorithms and gradient-based methods could be investigated for aircraft design problems to provide a more global optimization and include discrete design variables. The application of the MCDA techniques could be extended to assess air transportation systems, for balancing social, economic, ecological, and technical etc. constraints.

References

[1] N. Antoine, I. Kroo, K. Willcox, and G. Barter. A framework for aircraft conceptual design and environmental performance studies. In *10th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Albany, New York*, 30 August - 1 September 2004.

[2] R. Benayoun, B. Roy, and N. Sussman. Manual de reference du programme electre. *Psychoemtrika*, 38:337–369, 1973.

[3] D. Boehnke, B. Nagel, and V. Gollnick. An approach to multi-fidelity in distributed design environments. In *IEEE Aerospace Conference,Big Sky, USA*, 2011.

[4] J. Brans and P. Vincke. A preference ranking organization method: The promethee method for mcdm. *Management Science*, 31:647–656, 1985.

[5] W. Chen. On the problem and elimination of rank reversal in the application of topsis method. *Operations Research and Management Science*, 14:50–55, 2005.

[6] K. Deb, A. Sinha, P. Korhonen, and J.Wallenius. An interactive evolutionary multi-objective optimization method based on progressively approximated value functions. *IEEE Transactions on Evolutionary Computation*, 14:723–739, 2010.

[7] M. Ehrgott, J. Figueira, and S. Greco. *Trends in Multiple Criteria Decision Analysis*. Springer, 2010.

[8] A. Forrester, A. Sobester, and A. Keane. *Engineering Design via Surrogate Modelling*. Wiley, 2008.

[9] C. L. Hwang and K. Yoon. *Multiple Attribute Decision Making Methods and Applications: A State of the Art Survey*. Springer, 1981.

[10] S. Lehner and W. Crossley. Combinational optimization to include greener technologies in a short-to-medium range commercial aircraft. In *The 26th Congress of International Council of Aeronautical Sciences (ICAS), Anchorage, Alaska*, 14-19 September 2008.

[11] Y. Li. *An Intelligent Knowledge-based Multiple Criteria Decision Making Advisor for Systems Design*. PhD thesis, Aerospace Systems Design Laboratory, School of Aerospace Engineering, Georgia Institute of Technology, 2007.

[12] A. Lovison and E. Rigoni. Adapative sampling with a lipschitz criterion for a accurate metamodeling. *Communications in Applied and Industrial Mathematics*, 1:110–126, 2010.

[13] M. D. Mckay, R. J. Beckman, and W. Conover. Comparison of 3 methods for selecting values of input variables in the analysis of output from a computer code. *Technometrics*, 21:239–245, 1979.

[14] D. Raymer. *Enhancing Aircraft Conceptual Design using Multidisciplinary Optimization*. PhD thesis, Royal Institute of Technology, 2002.

[15] P. Sen and J. B. Yang. *Multiple Criteria Decision Support in Engineering Design*. Springer, 1998.

[16] X. Sun and Y. Li. An intelligent multi-criteria decision support system for systems design. In *13th Multidisciplinary Analysis and Optimization (MAO) and 10th Aviation Technology Integration and Operations (ATIO) Conference, Texas, USA*, 13-15 September 2010.

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