FLYING THROUGH DESIGN SPACES: EFFICIENT EVOLUTIONARY OPTIMISATION OF AIRCRAFT WINGS

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Abstract

Today's high-tech products, such as civil aircraft wings, are designed by multidisciplinary teams of experts. Dedicated modeling and simulation tools are used to assess the behavior of the design for each relevant discipline. The required consistency among the different single discipline models is achieved by using an integrated design model, which includes a (large) set of design parameters on which each of the discipline models is based. In order to find the best design, the application of optimization algorithms in combination with the modeling and simulation tools is common practice nowadays. However, for products that require complex models and extensive simulations to assess their behavior, like aircraft wings, such design optimizations may become infeasible due to complicated computational sequences or excessive computational cost. To alleviate such complications, the products' behavior should be assessed more efficiently. This paper presents a meta-modeling approach, applied to aircraft wing design where aircraft range and fuel consumption are optimized. This approach allows to quickly and conveniently evaluate the wing behavior, and to virtually fly through the considered wing design space. Extensive optimizations, exploiting thousands of meta-model evaluations, are performed using multi-objective genetic algorithms, yielding sets of Pareto optimal wing design points. These points represent those wing designs that have the best feasible fuel consumption for each value of range, and hence directly provide the designer with the most relevant design information.

Keywords: multidisciplinary analysis, integrated design model, meta-modeling, Pareto front, multi-objective optimization.

Presenting Author's biography

E. Kesseler received his Drs degree in physics in 1980 from the University of Amsterdam. He has worked at NLR Amsterdam, the Netherlands for over 20 years on a variety of IT and aerospace topics.

1 Introduction

Engineering and design analyses nowadays involve extensive numerical simulation techniques in order to predict the behaviour of the system under consideration for various conditions of use. For example in aeronautic design, advanced single discipline simulations such as structural mechanics and fluid dynamics analyses are commonly used in the aircraft design processes. Although these simulations provide a wealth of possibilities for assessments of design variations, the organization of integrated design analysis simulations often remains a challenge in terms of efficient computational execution and data exchange and storage. One approach to deal with this challenge is the use of simplified but adequate representations of the key aspects of interest of the considered design, which can be achieved by so-called meta-models or response surface methods [1].

This paper describes an investigation of multidisciplinary design and optimisation of transonic aircraft wings for civil air transport. The design objectives considered are the aircraft's performance in terms of range and fuel. The first objective is a common driver in aircraft design and the latter has environmental as well as economic relevance.

The design objectives in this investigation are evaluated with an integrated multidisciplinary analysis system for aircraft wings. In order to effectively deal with the two design objectives simultaneously, optimisations with multi-objective genetic algorithms are used to explore the considered design space. To limit, in this optimisation, the number of computationally expensive multidisciplinary wing design evaluations, simplified representations (or meta-models) of the considered design objectives are used instead. These simplified representations are created according to an advanced meta-modelling approach [1]. The result of the multi-objective design optimisation is a set of Pareto optimal [2] design points, from which the most promising design point is carefully selected. The range and fuel values in this most promising design point as predicted by the meta-models are validated by accurate evaluations with the multidisciplinary analysis system.

The subsequent sections give further details on the wing design study performed, the meta-models and optimisation approach used, the results found and the main conclusions and discussion.

2 Multidisciplinary aircraft wing design analyses

This multidisciplinary analysis system simulates the aircraft behaviour, i.e., it evaluates, among others, the aircraft range and fuel as a function of an extensive set of design parameters [3]. The design parameters are unambiguously defined and stored in a single central database (the integrated design model [4]) and include geometric wing parameters such as span (length of the wings), chord (wing width) and sweep (wing angle in horizontal plane), as well as "aircraft operational settings" such as maximum take-off weight (MTOW) and cruise altitude. With the design parameters (Fig. 1), the multidisciplinary analysis system consistently generates the aircraft and wing geometries (Fig. 2) that are used in the different wing analyses (aerodynamics, structural mechanics, etc., Fig. 3).

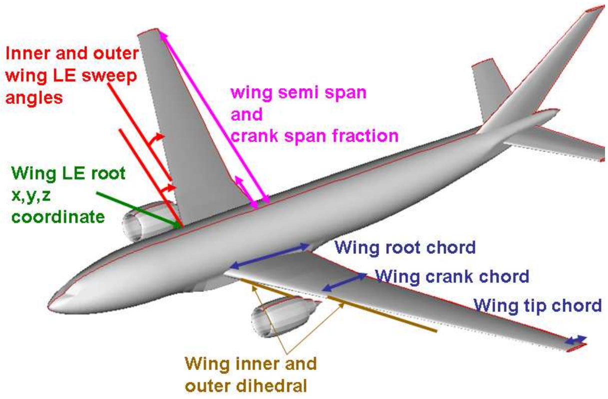

Fig. 1 Geometric design parameters of the wing planform as used in the multidisciplinary analysis system. Besides these parameters, also other parameters, like the positions of wing control surfaces, wing tanks and landing gears, can be varied in the multidisciplinary analysis system.

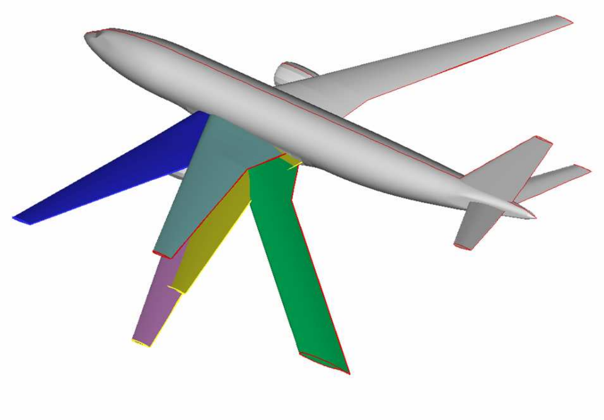

Fig. 2: Illustration of several different wing geometries (coloured left wing), as generated by the multidisciplinary analysis system with various values for wing span, sweep angle and chords. Also illustrated are the fixed geometries for fuselage and empennages.

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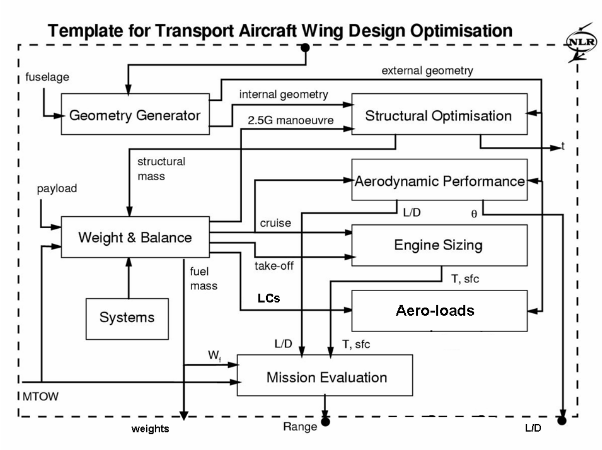

Fig. 3: Schematic overview of the multidisciplinary analysis system. The data communication among the different analyses, as indicated by the arrows, takes place through a single central database (the integrated design model).

From the outcomes of the multidisciplinary analyses the corresponding aircraft behaviour is predicted in terms of specific results (e.g., weight breakdown information) and more global results (e.g., maximum range and fuel consumption). Just like the design parameters, these analysis results are also stored in the integrated design model.

For each of the disciplinary analyses in this MDO simulation system, a different operational condition of the aircraft is considered as most relevant load case, because a valid aircraft design must withstand several critical loading conditions while progressing through the various flight phases. For example, the engines are sized for power during take-off with maximum take-off weight. The wing structural components, on the other hand, are sized by structural optimisation using finite element analyses for the loads occurring during a +2.5 *g* pull-up manoeuvre, as required by the certifying authorities. The wing aerodynamic lift over drag performance is evaluated by Computational Fluid Dynamics (CFD) simulations for the cruise condition.

3 Optimisation of aircraft range and fuel by wing design

The aircraft design parameters considered in the present optimisation study are the wing semi-span (i.e., single wing length), wing chords, outer wing sweep angle, and aircraft MTOW. The objectives in this optimisation study are to find those design points that yield the best possible range and minimum fuel consumption.

The multi-objective optimisation algorithm that is used to solve this design optimisation problem is based on a Pareto optimum search procedure [5] that typically requires thousands of objective evaluations. The meta-models that are made for the objective functions for range and fuel are further described in the following section.

4 Meta models

In order to create the meta-models, first a suitable sample of the aircraft behaviour in the considered design domain is pursued. This is achieved by a limited number of evaluations with the MDO simulation system in certain selected design points. These design points are defined according to a sequence of fractional factorial (i.e., fractions of full-factorial) sets of samples [6] of the four dimensional design space (i.e., parameter space of the design parameters: wing semi-span, outer wing sweep angle, wing chord, and aircraft MTOW). The semi-span is varied between 29 m and 32 m. The outer wing sweep angle is varied between 21 deg and 39 deg. The wing chords at 3 stations (wing root, crank and tip) are equally varied by one single chord scale factor, which is varied between 1.000 and 1.075. MTOW is varied between 150000 and 280000 kg.

In total, 99 design points are created in this parameter space and are evaluated with the full MDO simulation system, yielding (among many other data available in the integrated design model) the values of range and fuel consumption in these design points. As a quick preliminary design assessment, these range and fuel values are ordered according to a basic Pareto ranking procedure [7] in order to obtain a first indication of the interesting design regions. In this ranking procedure, the best (or non-dominated) design points, i.e. those points having the best values for range and fuel consumption, are assigned Pareto rank 1, the set of second best points are assigned Pareto rank 2, and so forth until all design points have been assigned a rank value.

The resulting rank values for these 99 design points, and their distribution in the objective space and their parameter values are given in Fig. 4 below. It should be noted that fuel consumption in this study is expressed as fuel-efficiency, i.e. the number of kilometres flown per litre of fuel burnt per passenger, which allows for easy comparison of the environmental impact of air transport with other transport modes.

The resulting data set with the values of the design parameters and of the range and fuel objectives in these 99 design points, is then used to create the meta models. The meta-models shall approximate as good as possible the objectives in each point of the parameter space.

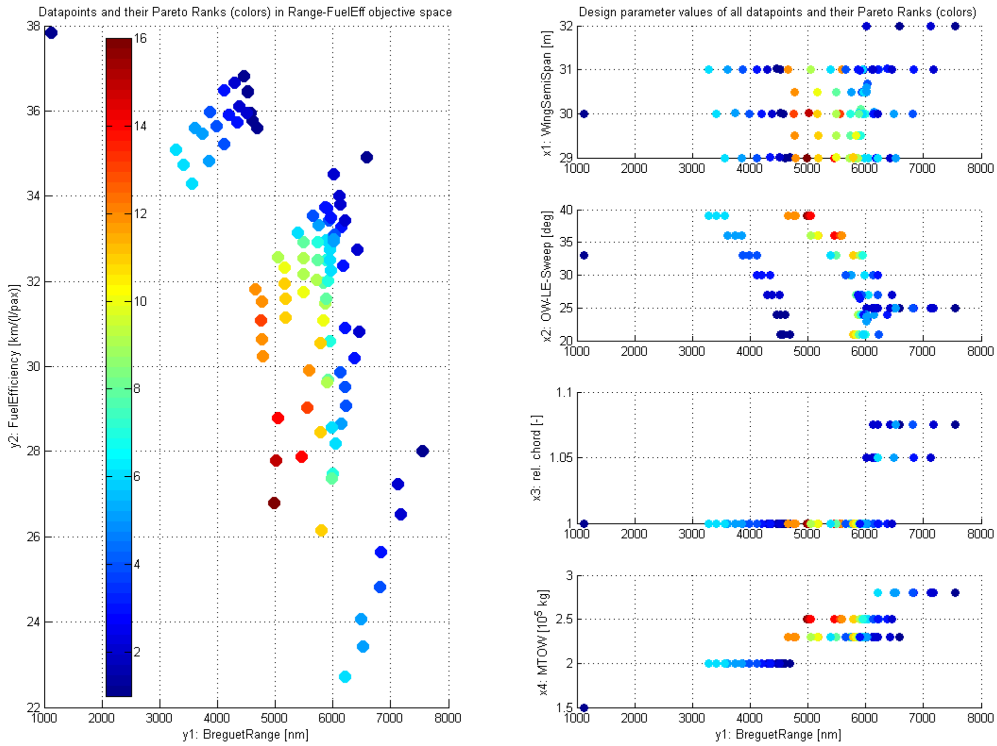

Fig. 4 The range and fuel results in the 99 design points in objective space (left) and in parameter space (right), coloured by their Pareto rank.

A number of different polynomial functions (polyn in Tab. 1 and Tab. 2), kriging models (kriging-xy in Tab. 1 and Tab. 2), neural networks (ann in Tab. 1 and Tab. 2) and radial basis functions (rbf in Tab. 1 and Tab. 2) are applied [1], and the best fit functions among these are determined. These best fit functions are found through various cross-validation assessments on the data set, such that these functions' predictions of the design objectives (range, fuel efficiency) have the smallest residuals. The residuals in these cross-validations are determined by separating one or a few points (validation points) from the data set, create the fits on the remaining points, predict with these fits the values in the validation points and compare these predictions with the actual values. Finally, the root mean squared (RMS) values of the residuals (or in other words, root mean squared errors, RMSE) in the validation points are calculated. Four different cross-validation assessments are performed by selecting different sets of validation points.

In a first cross-validation assessment the nine rank-one data points, i.e. those data points having the best (lowest) Pareto rank values for range and fuel efficiency (dark blue dots in Fig. 4), are used as validation points. The resulting RMS values indicate that the kriging-linear-Exponential (kle) [8] and second order polynomial (poly2) fit functions provide the best fits for range and fuel-efficiency, respectively (99/9-column in Tab. 1 and 2 below). However, this assessment represents the accuracy of the fits in only a local region around the rank-one data points. In order to obtain a more global accuracy assessment we include some more validation points by adding the 11 Pareto rank-two data points to the validation set (99/20-column in Tab. 1 and 2 below). Because this validation set is rather large (20 out of 99 points), the validation fits are made on relatively small data sets (79 points), and thus will differ significantly from the "full" fits made on the complete data set (99 points). Therefore we also evaluate the RMS-residuals from a leave-1-out experiment [9] of this validation set (99/1/20-column in Tab. 1 and 2 below). In this leave-1-out experiment, subsequently each point of the validation set is separated from the data set, a fit is made on the remaining 98 points, the residual in the validation point is evaluated, and the RMS of the 20 residuals is calculated. Finally, as a real global accuracy assessment, we also performed a leave-1-out experiment on the complete data set (99/1/99-column in Tab. 1 and 2 below). As an additional indication of the relative accuracy of the fits, we also include the Mean Absolute Percentage Error (MAPE) of the global leave-1-out residuals (99/1/99/%-column in Tab. 1 and 2 below).

For the different cross validation assessments we find reasonably consistent accuracies for most fit functions (Tab. 1 and 2 below). The best RMS-residual found in each assessment is marked by the green shaded cell.

For the range data (Tab. 1), the radial basis function (rbf) fit provides the best results for the leave-1-out experiments, but very poor fit quality according to the 99/20 experiments, and is therefore not selected as best fit for range.

Based on the results of each of the 5 assessments performed, and in particular on the global accuracy as measured by the leave-1-out experiments (Tab. 1, columns 99/1/99 and 99/1/99/%), it is concluded that the best fit for range is found by the kriging-linear-Gauss (klg) fit function.

For fuel efficiency the poly2 fit performs quite well (Tab. 2), but its global accuracy as measured by the leave-1-out experiment (column 99/1/99/%) is worse than for some of the kriging fits. In addition, poly2 provides a least-squares regression (non-interpolating) fit on the data, whereas the kriging models provide exactly interpolating fits on the data. Because the data represents results of deterministic computer simulations, it is concluded that the best fit for fuel efficiency is found by the kriging-constant-Exponential (kce) fit function.

Tab. 1: For the range data: Accuracies of the different fit functions (identified in left column) for the different cross-validation assessments (identified in first row, by data set size and number of validation points). Values given are the root-mean-squares of the residuals (or prediction errors) in the validation points.

	RMSE				MAPE
fit function	99/9	99/20	99/1/20	99/1/99	99/1/99/%
poly0	1824.8	1450.2	1464.0	993.2	18.5785
poly1	789.0	720.6	541.0	401.6	6.7994
poly2	739.3	509.2	460.8	234.1	3.7504
kriging-cG	1386.0	1155.3	886.3	400.3	4.2159
kriging-cE	1297.2	730.4	913.8	414.1	4.2473
kriging-cC	1025.6	722.3	814.8	367.0	3.8202
kriging-lG	608.7	519.3	301.7	138.6	1.7258
kriging-lE	567.6	418.8	465.5	210.1	2.2546
kriging-lC	600.9	440.5	411.0	186.8	2.2124
ann	1175.3	1053.7	957.3	859.6	12.8121
rbf	784.1	5130.0	205.0	99.7	1.1252

Tab. 2: For the fuel-efficiency data: Accuracies of the different fit functions (identified in left column) for the different cross-validation assessments (identified in first row, by data set size and number of validation points). Values given are the root-mean-squares of the residuals (or prediction errors) in the validation points.

	RMSE				MAPE
fit function	99/9	99/20	99/1/20	99/1/99	99/1/99/%
poly0	4.648	4.182	3.909	3.259	8.4636
poly1	1.984	1.499	1.368	0.995	2.3676
poly2	0.722	0.544	0.258	0.264	0.6371
kriging-cG	1.746	1.422	0.830	0.421	0.6577
kriging-cE	2.435	1.289	0.947	0.430	0.3894
kriging-cC	2.103	2.251	1.198	0.576	0.7798
kriging-lG	1.590	1.358	0.939	0.443	0.4836
kriging-lE	1.692	1.378	1.187	0.539	0.4136
kriging-lC	1.778	1.404	1.305	0.607	0.6339
ann	1.886	1.393	0.672	1.179	3.7600
rbf	6.990	66.977	4.740	2.140	1.1210

5 Design optimisation

A Pareto front optimisation of the aircraft's range and fuel efficiency is performed using a multi-objective genetic algorithm (based on epsilon-NSGA-II as described in [5]), where the best fits for range and fuel efficiency are used as objective functions.

In this optimisation a population size of 99 individuals is used, where the 99 design points from the data set are used as the initial generation. The bounds of the search domain for the optimisation are set to the minimum and maximum values of the design parameters of the 99 design points. In a first run 3 generations, so about 300 objective functions evaluations are run with the genetic algorithm. The resulting population is indicated by the green circles in Fig. 5 in order to give some illustration of the convergence history of the genetic algorithm. Then this resulting population is used as the initial population for an extensive run of about 100 generations with the genetic algorithm. The total number of objective function evaluations in this extensive optimisation is about 10.000, and takes about 20 seconds computational time on a standard PC (P-4, 2.8 GHz). The resulting Pareto front solution (red diamonds in Fig. 5) provides a set of clearly improved designs, as compared to the initial set of designs in the data set (black dots).

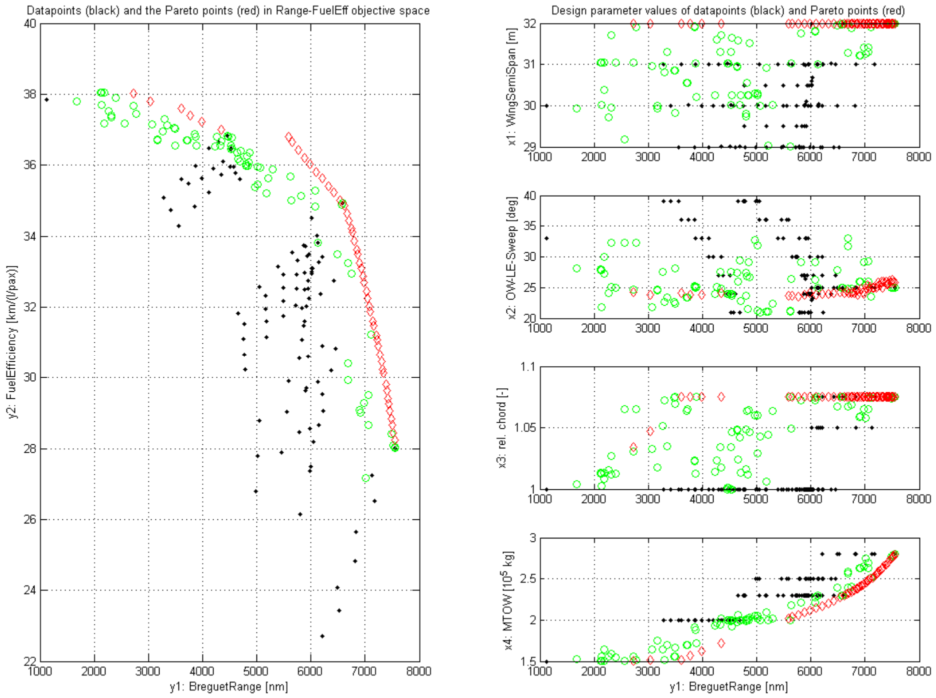

Fig. 5 Design points of data set (black dots), population after 3 generations (green circles), and Pareto front after 100 additional generations (red diamonds) for maximum range versus maximum fuel efficiency found with the kriging-linear-Gauss and kriging-constant-Exponential meta-models, respectively, for range and fuel efficiency. Results presented in objective space (left) and in the range-parameter sub-spaces (right) for each of the four design parameters.

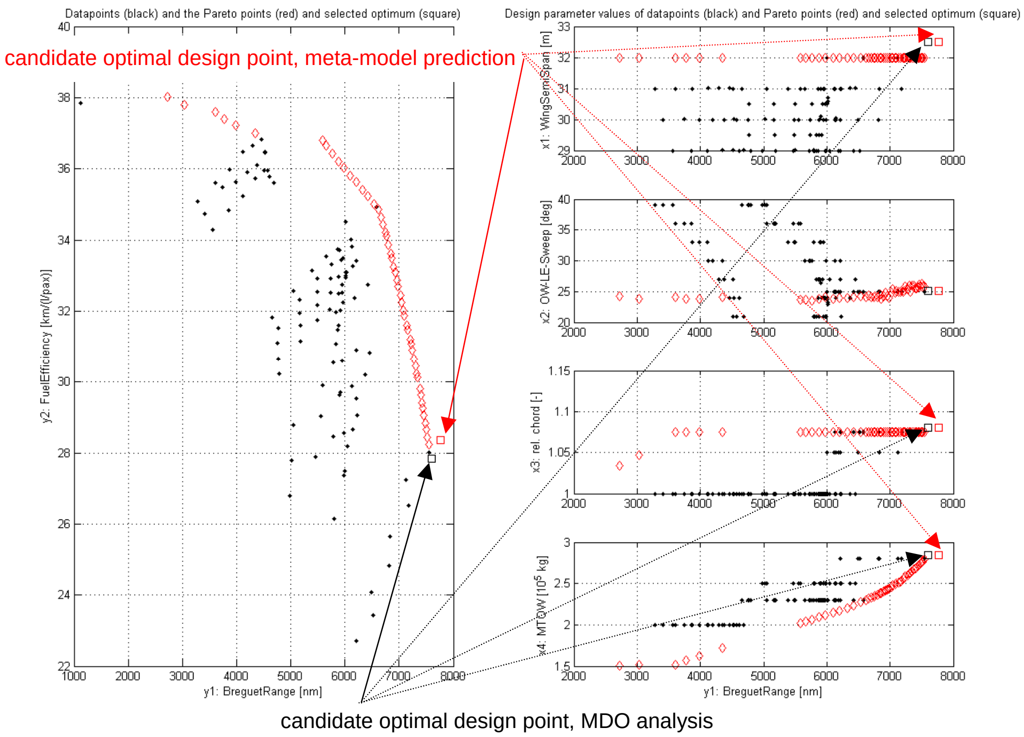

Fig. 6 Pareto front found with initial meta-model (red diamonds), data set (black dots), and MDO analysis and meta-model predictions for candidate optimal design point (black and red squares).

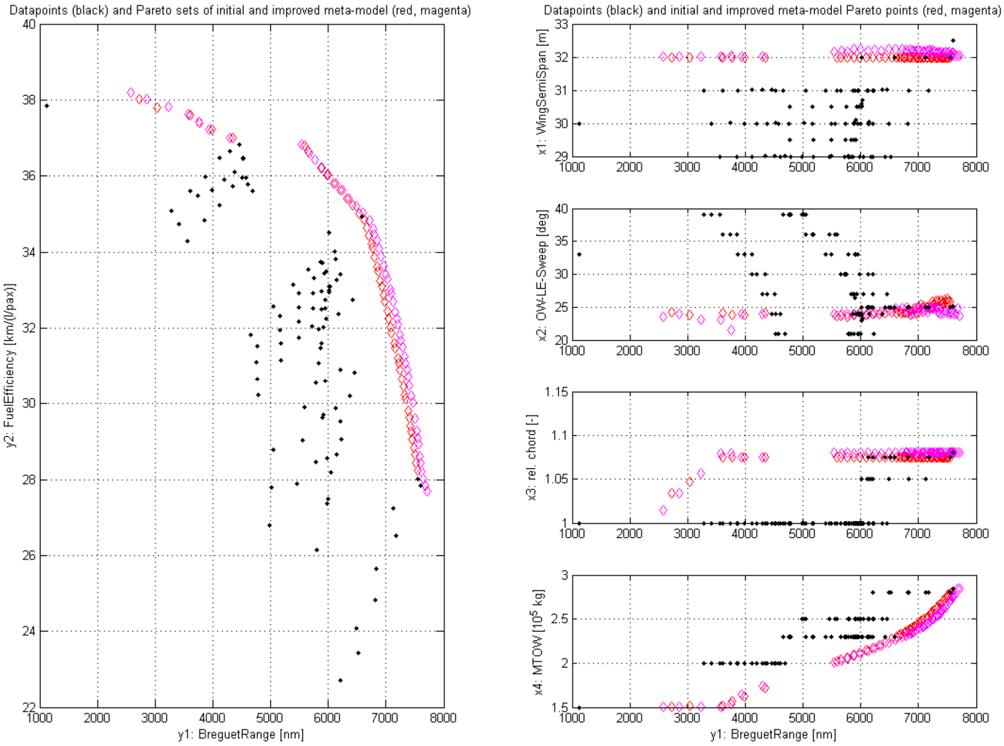

Fig. 7 Pareto fronts found with the initial meta-models (red diamonds) and the improved meta-models (magenta diamonds).

The behaviour of the aircraft in the parameter space around the Pareto optimal design points (which were predicted on the basis of the meta-models) was further explored and interpreted by aircraft design experts. One candidate optimal design point was selected and accurately evaluated by the MDO simulation system. The results from this evaluation are given in Tab. 3 and Fig. 6.

Tab. 3: MDO analysis result and meta-model prediction for the candidate optimal design point.

parameters				MDO analysis		meta model	
span	sweep	chord	MTOW	range	FuEff.	range	FuEff.
32.5	25.1	1.08	285000	7594.6	27.8	7761.9	28.4

When considering these results more closely, we can conclude from the MDO analysis results that this point is an additional Pareto optimal design point (Fig. 6). The meta-models predicted somewhat over-estimated values for range and fuel efficiency for this point (Tab. 3).

Furthermore, this new design point provides a valuable additional point for the data set on which the meta-models are created, and hence the meta-models can be further improved and used again in the multi-objective optimisation. Therefore the meta-models for range and fuel efficiency were regenerated using the same kriging models as before (kcg for range, and kle for fuel efficiency). In this optimisation the 100 design points from the new data set are used as the initial generation and the bounds of the search domain are set to the minimum and maximum values of the design parameters of the 100 design points.

The resulting Pareto front (magenta diamonds in Fig. 7) found with these improved meta-models provides a slight improvement compared to the Pareto front (red diamonds in Fig. 7) found with the previous meta-models, as is shown in Fig. 7. The Pareto front again helps to further guide the computationally expensive full MDO evaluations to the most interesting designs for the team of expert designers.

6 Conclusions

The meta-modelling approach presented in this paper allows for efficient and extensive assessment of the investigated aircraft behaviour in the considered design domain. The predictive accuracy differs amongst the different meta-models that are used. For this data set the most appropriate accuracies were found for the kriging-linear-Gauss and kriging-constant-Exponential models. The multi-objective Pareto front results directly provide the design information on which further design trade-off considerations can be based by the team of design experts involved. Additionally the Pareto front allows the design team to use the computationally expensive MDO design evaluations to those designs with relevance to the team.

The results found, indicate that the largest range is found for the highest MTOW, which is comprehensible because most fuel can then be carried by the aircraft. On the other hand, fuel efficiency, expressed as range per unit of burnt fuel per passenger, decreases with increasing MTOW, which is also a plausible result. However, the Pareto points indicate that the best design points for range and fuel efficiency are quite consistently found for the maximum values for span and chord, and a sweep angle of about 25 degrees.

7 Discussion

The creation of the various meta-models in this study is computationally efficient, easily allowing for the use of a variety of meta-models based on polynomial functions, kriging models, neural networks and radial basis functions. The meta-models, in particular when used in combination with the optimisation algorithms, consume much less computational resources then the MDO design evaluations.

The results of combining meta-models with optimisers provide the multidisciplinary team of design experts with the desired information on the designs being considered. In this case the results directly suggest the optimal values for the sweep angle, semi-span and chord, and allow for a roughly continuous trade-off between range and fuel efficiency.

When additional data comes available, for example as demonstrated by the candidate optimum design point that was evaluated with the MDO simulation system, the meta-model can be extended easily to incorporate such additional data at low computational costs. When the expert team wants to consider different objectives, new meta-models can be produced easily based on all the information available in the integrated design model.

The use of the integrated design model allows for the selection of other objectives and performing optimisations in a computationally efficient manner. This efficiency allows the multidisciplinary team of design experts to obtain more knowledge about the behaviour of their design in the considered parameter space, in a consistent way, i.e. the consequences of a change in one discipline are automatically taken into account by the other disciplines. This provides a more robust design.

The innovative capability described above supports the design team when considering future design variants, complying with the requirement for product families, common for large civil aircraft designs.

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