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EXPLICIT MODELING OF TECHNOLOGY IMPROVEMENT OVER TIME IN CONCEPTUAL AIRCRAFT DESIGN

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Abstract

Given the fact that neither sufficient information nor time are available at the very early stages of aircraft design, conceptual aircraft design uses simplified analysis methods. Usually, these "handbook" methods take into account few parameters, e.g., the thrust specific fuel consumption of an engine depends only on the bypass ratio. The present study focused on the fact that technology improvement over time is not explicitly taken into account in conceptual design methods. Hence, in the simplified example, engines with a similar bypass ratio share a similar thrust specific fuel consumption regardless of their entry into service date. The present study is based on the following hypothesis: The systematic error of a conceptual design model when compared to a set of existing aircraft arises due to the fact that technology improvement over time is neglected. The present study then optimized different technology factors to minimize the systematic error and examined whether the technology factors correlate with the aircraft entry into service date. In few cases a correlation could be identified and a symbolic regression was performed to model the dependency between the technology factors and the entry into service date. Finally, the paper highlights possible sources of error in the conducted analysis.

1 Introduction

Sophisticated physical models can not be applied in the conceptual design of an aircraft, as neither sufficient input data nor computational power are available at the early design stages. For example, finite element models for mass estimation require detailed information on the aircraft geometry and loads, and furthermore, these models require high amounts of computational power. Hence, conceptual design models are based on simplified, so called, "handbook" methods.

Conceptual aircraft design can not explicitly reflect the impact of minor technology changes and secondary effects due to the low level of detail. For example, Raymer [9] presents equation 1 to quantify the thrust specific fuel consumption that takes into account the engine bypass ratio. Accordingly, it is sensitive to the major driver of the thrust specific fuel consumption, but can not catch secondary physic effects, e.g., due to a rise in the overall pressure ratio or an improved combustion. Hence, conceptual design methods are insensitive to technology improvement on a detailed level.

$$TSFC_{cr} = 0.88e^{-0.05BPR} \tag{1}$$

The methods that are applied in conceptual aircraft design build upon historic data. Although physics-based assumptions are the foundations of these methods, empiric, historic corrections are necessary to bridge the low level of detail. For example, Shevell [12] provides equation 2 to estimate the wing mass. The first part of the equation introduces empiric corrections scaled by the wing's reference area S, while the second part of the equation multiplied by K_2 reflects the physical effects of bending moments that act on the wing.

$$m_{wing} = K_1 S + K_2 \frac{n_{ult} b \sqrt{m_{TOM}\, m_{ZFM}}}{(t/c) cos(\varphi)^2 S} \frac{1+2\lambda}{1+\lambda} \quad (2)$$

Despite the fact that conceptual design methods are composed of historic-based data neither of the methods, for unknown reasons and with few exceptions, reflects on time or the entry into service date to choose a parameter more specific to aircraft design.

Two exceptions can be named: First, Jenkinson [5] distinguishes between *conventional* and *CFD* designed wings in his method to quantify the induced drag of an aircraft. Obviously, the method addresses time not explicitly, but a step function is introduced to separate modern designs. Second, Bräunling [2] provides a graph that correlates the turbine entry temperature of a turbofan engine with the entry into service date, as shown in figure 1.

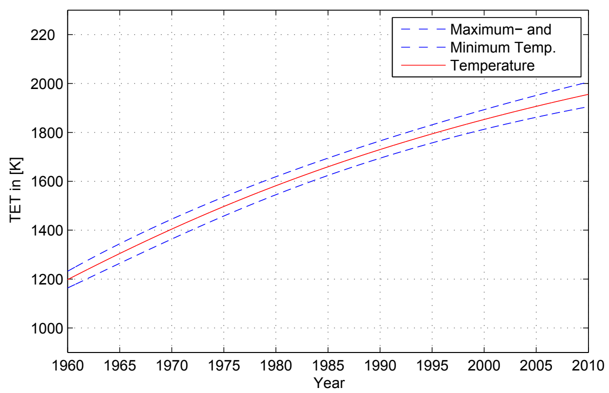

Fig. 1 : Turbine entry temperature over time, *in german* [2]

The hypothesis of the present study is that the systematic error that can be observed when a conceptual design model is verified to a database of existing aircraft arises because the technology improvement over time is not explicitly included.

The paper is then organized as follows: Section 2 describes an approach to determine whether the entry into service date correlates with the error of a conceptual design model and derives means to explicitly include technology improvement over time in conceptual design. Section 3 provides the results that were obtained when the proposed approach was applied to a database of 20 aircraft. Finally, section 4 draws a conclusion and outlines several possible error sources as well as items for future research.

2 Approach

This section provides an overview on the body of methods that is necessary to determine whether the entry into service date of aircraft correlates with the systematic error of historic-based, conceptual design methods. First, the overall process, as shown in figure 2, is outlined. Subsequently, each sub-section provides further details on specific aspects of the analysis. The process can be broken down into the following five steps.

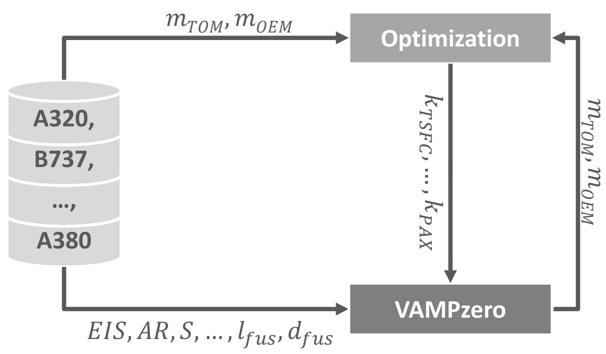

Fig. 2 : Analysis schematic

1. The key element of the body of methods is a conceptual aircraft design code, as described in section 2.1, that encompasses historic-based, conceptual design methods and provides several means to manipulate the design process.

2. A conceptual design is performed for several aircraft from an aircraft database, as outlined in section 2.2. The inputs for the design are the overall geometric characteristics of each aircraft and the transport task, i.e., range and cruise Mach number. The output includes among other parameters the maximum takeoff mass (m_{TOM}) and the operating empty mass (m_{OEM}) of each aircraft.

3. In a subsequent step, technology factors are introduced for each aircraft. Hereby, a technology factor scales the result of a single, historic-based, conceptual design method. In the present study technology factors are chosen that have a major impact on m_{TOM} and m_{OEM}. These are listed in table 1.

Factor	Description
k_{CD0}	zero lift drag; major driver fuel mass.
k_{TSFC}	thrust specific fuel consumption; major driver fuel mass.
k_{wing}	wing mass; major driver empty mass; depends on m_{TOM}.
$k_{fuselage}$	fuselage mass, major driver empty mass, independent from m_{TOM}.
k_{pax}	single passenger mass; major driver payload mass.

Table 1: Technology factors

4. For each aircraft in the database the technology factors are optimized to minimize the error of the conceptual design method. Hereby, the error metric is the sum of the relative errors of the m_{TOM} and the m_{OEM} and is written as in Eq. 3. Section 2.3 provides further details on the optimization.

$$e = \frac{(m_{TOM_{opt}} - m_{TOM_{ref}})^2}{m_{TOM_{ref}}} + \frac{(m_{OEM_{opt}} - m_{OEM_{ref}})^2}{m_{OEM_{ref}}} \tag{3}$$

5. Finally, simple correlation analysis shows whether the entry into service date correlates with the different, optimized technology factors. If a correlation can be identified then the correlation hypothetically provides a hint that the historic-based design method fails to reflect technology improvement over time. Furthermore, if a correlation can be identified then a symbolic regression approach is applied to connect the entry into service date and the technology factor. The symbolic regression can be included in the conceptual design model to establish a sensitivity towards time. Section 2.4 explains the symbolic regression approach applied in the present study.

2.1 Conceptual Aircraft Design

The present study needs to use a computer executable conceptual aircraft design model to conduct the necessary number of optimization runs. For this purpose the conceptual design model VAMPzero that has been developed in recent years by DLR [1] is chosen. VAMPzero makes use of handbook methods that have their origin in the established literature on aircraft design, e.g., by Roskam [10], Raymer [9] or Toreenbeek [13]. The applied handbook methods fall into the category of the already mentioned historic-based conceptual design methods.

In contrast to other conceptual aircraft design models, VAMPzero is based on an object-oriented approach, as shown in figure 3. Hence, the code is grouped hierarchically into components, e.g., the wing, and disciplines, e.g., aerodynamics. At the cross-section of components and disciplines, VAMPzero introduces one or more parameters, e.g., the wing reference area. Each parameter then holds one or more calculation methods. Given the object-oriented structure of VAMPzero, technology factors are available for each parameter and enable the present study.

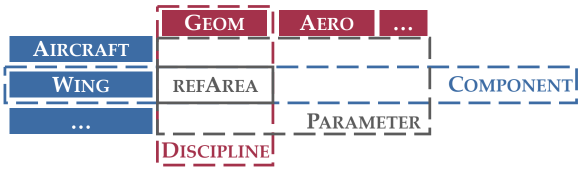

Fig. 3 : Object oriented conceptual design

Furthermore, VAMPzero is a code that is licensed under open-source[1]. Hence, the code is comparably transparent, and furthermore, changes to the code are possible that enable the integration of the results of the present study to enhance the quality of conceptual aircraft design.

A detailed description of the design method in VAMPzero certainly exceeds the scope of this paper. Instead a short list is provided that describes the calculation method for each parameter that is influenced by a technology factor. The thrust-specific fuel consumption is quantified by a simple thermodynamic cycle based on efficiency factors, as implemented by Dimchev and Goden [3]. The zero lift drag is a result of the Hoerner [4] method that is widely applied in conceptual aircraft design. Both the wing and fuselage

[1] http://software.dlr.de/p/VAMPzero

Model	Model EIS	Family EIS
A300-600	1983	1972
A310-308	1986	1984
A318-100	2002	1988
A319-100	1996	1988
A320-200	1988	1988
A321-100	1994	1988
A330-200	1998	1994
A330-300	1994	1994
A340-200	1993	1993
A340-500	2002	1993
A380-800	2007	2007
B737-400	1988	1968
B737-700	1998	1968
B737-800	1998	1968
B737-900	2001	1968
B747-400	1989	1969
B757-300	1999	1982
B767-200ER	1982	1982
B767-300ER	1986	1982
B777-200ER	1997	1995

Table 2: Aircraft entry into service dates

mass are quantified with the aid of the methods from the Luftfahrt Technisches Handbuch [7]. Finally, the single passenger mass including cargo is 95kg on short and medium range flights and is increased to 120kg on long-range flights.

2.2 Aircraft Database

In the second step of the proposed approach a database of existing aircraft is required. The databased needs to contain a) adequate information to trigger a conceptual design and b) a sufficient enough number of aircraft so that statistically, significant results can be obtained. The later criterion is hard to achieve given the limited number of aircraft that can be described by a given set of conceptual design methods and the limited applicability of the present study to aircraft from product families. Section 4 further elaborates on this topic.

The database in the present study includes 20 jet-transport aircraft, narrow- and wide-body, that operate on short to long range missions. The data is gathered from publicly available sources such as the *Aircraft Characteristics for Airport Planning* documents[2] and the *ICAO Aircraft Engine Emissions Databank*[3].

For each aircraft in the database two distinctive points in time can be identified: First, the entry into service date of the family, e.g., Airbus A320, and second, the entry into service date of the model, e.g., Airbus A321-200, need to be taken into account. The model entry into service date is related to fuselage stretches and often to different engines or at least engine ratings. Conversely, the family entry into service date is of relevance for aircraft components that are build into several aircraft models of the family and therefore are based on the technology level of the family rather than on the technology level of the model. For example, a similar wing design is often applied for several aircraft models in a family. Table 2 lists all aircraft in the database and their respective entry into service dates.

As already mentioned, the database needs to contain details on the characteristics of the aircraft and the transport task to enable a conceptual design as well as the maximum takeoff weight and operating empty weight to perform the optimization task. Table 3 lists all the parameters that are an input into the VAMPzero calculation. Furthermore, the database contains the m_{TOM} and the m_{OEM} for each aircraft model. If available, the high gross weight variants of each aircraft model are chosen as these should reflect the aircraft with the maximum loads on the structures. Hence, the aircraft high gross weight variants are supposed to be the driving variants that size the components of the aircraft, e.g., the wing. However, this

[2] http://www.airbus.com/support/maintenance-engineering/technical-data/aircraft-characteristics/, retrieved June 2014
http://www.boeing.com/boeing/-commercial/airports/plan_manuals.page, retrieved June 2014

[3] https://easa.europa.eu/document-library/icao-aircraft-engine-emissions-databank, retrieved June 2014

Component	Parameter
Aircraft	Take off field length
	Design range
	Cruise Mach number
	Initial cruise altitude
Fuselage	Height
	Width
	Length
Wing, HTP, VTP	Ref. area
	Sweep angle
	Aspect ratio
	Taper ratio
	Thickness to chord ratio
Engine	Bypass ratio
	Overall pressure ratio
	Turbine entry temperature

Table 3: Conceptual design parameters

is a subject of further discussion and will be highlighted in section 4.

2.3 Optimization Strategy

The goal of the optimization strategy is to change the five technology factors mentioned above so that equation 3 is minimized. Thereby, each technology factor may not exceed an upper value of 1.3 and a lower value of 0.7 to ensure that a) the search for an optimum becomes easier due to a restricted design space and b) the optimizer ignores mathematically correct but physically unfeasible designs. For example, the optimizer might choose to lower the zero lift drag and instead raise the thrust specific fuel consumption to unreasonable values.

A global optimization strategy is necessary, as several local minima can be expected in the design space due to the coupling of the design variables. Hence, the optimization strategy in the present paper utilizes a combined global and local optimization. The global optimizer is basin-hopping; the local sequential least squares programming (SLSQP). In both cases the present study makes use of the implementation in Scipy [6].

Basin-hopping, as proposed by Wales and Doye [14], is a stochastic global optimization approach that explores the design space by local optimizations that begin at random locations. The algorithm starts from an initial location and performs a local optimization. Subsequently, new locations are chosen, and accepted or rejected based on the Metropolis acceptance criterion. Hereby, the temperature in the current study is set to 10^{-5} and the initial step size to 10^{-4}. The step size is subject to adaptive changes. If the number of rejected steps is too high then the step size is decreased. In addition, if the ratio of accepted steps is too high then the step size is increased to escape local minima. In addition, steps that violate the above mentioned boundaries are rejected by an auxiliary function. The algorithm is set to terminate after 30 iterations in which the global optimum remains unchanged.

At each iteration, basin hopping triggers a local optimization via the SLSQP algorithm, as proposed by Kraft [8]. SLSQP is an effective method for nonlinear constrained optimization problems. New steps are determined for a quadratic subproblem that is created from the initial design function. As with the global optimization, the local optimizer is not allowed to violate the above mentioned boundaries.

Figure 4 shows an optimization run for the A320-200. The lines display the path of the optimizer and each dot marks a local optimum, and furthermore the global optimum is marked in red. In this example, the optimization required 32 iterations of the global optimizer to converge. It can be observed that the global optimum was identified quickly, yet, more difficult cases were encountered in the database. Obviously, the number of function calls is large, and hence, it is questionable whether the search should be fastened by surrogate techniques. However, given the fact that several local optima are already present in the data, the additional inaccuracies from a surrogate model such as Kriging are suspected to restrain the optimization as they may add further false local minima. Furthermore, given the fact that numerical noise may hamper the optimization, the convergence criteria of the conceptual

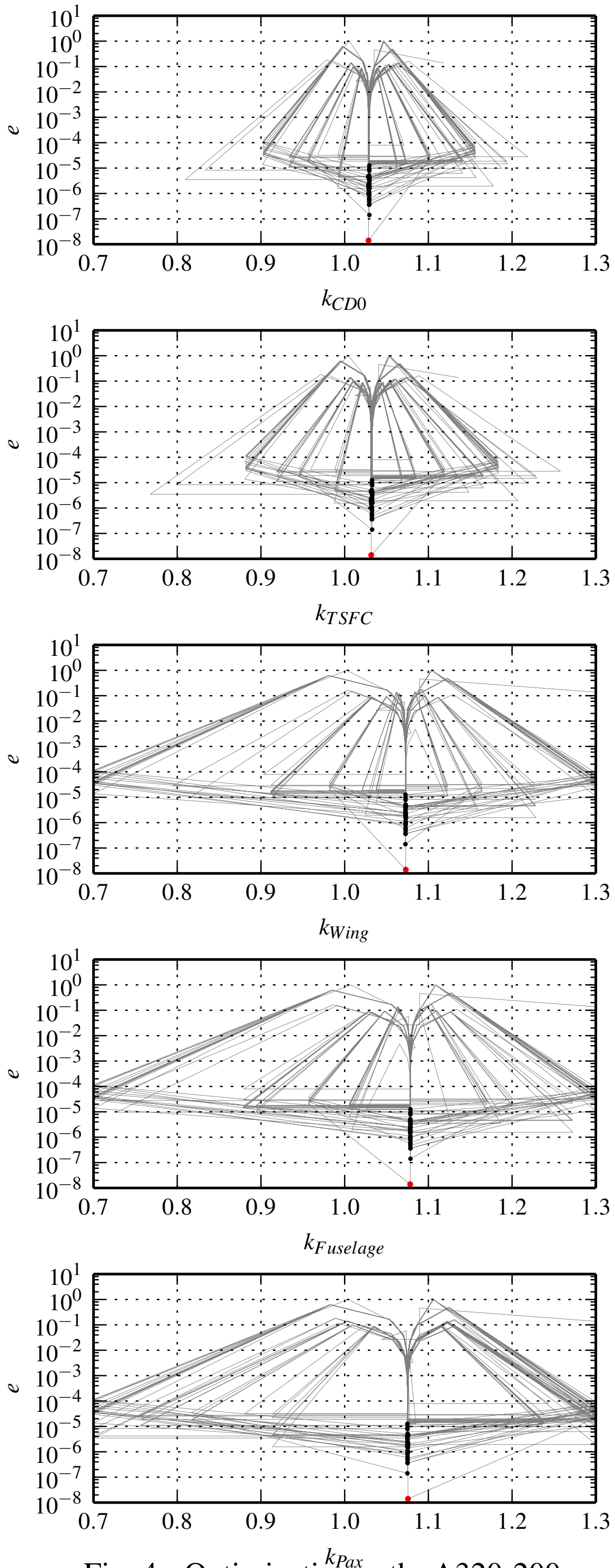

Fig. 4 : Optimization path: A320-200

design model needs to be fine and in this case is set to 10^{-8}.

Instead, the optimization is fastened by a tweak in the conceptual design model. Each conceptual design in an iteration of the optimizer is based on the previous design rather than performing a new design. The conceptual design model is forced to carry out at least five iterations per optimizer iteration to circumvent early convergence. Hereby, each iteration of the local optimizer takes much less than a second on a low-performance computer.

2.4 Symbolic Regression

If a correlation between the respective technology factors that minimize e and the entry into service dates can be found then the goal of the present study is to model this correlation so that it may be combined with the conceptual design model. As most handbook methods are comparably simple and often base on a single equation, the correlation model should be as simple as possible as well. Hence, the present study applies symbolic regression which is elaborated in the following paragraphs.

In 2009, Schmidt and Lipson [11] distilled the equations for the laws of momentum conservation by applying symbolic regression to the measurements of angles and angular velocities of a double pendulum. No prior knowledge of geometry, physics, or kinematics was provided to the algorithm. Through the monitoring of a physical system, a formulation could be derived that not only described the behavior of the system but also granted insight into the physical coherence.

Fig. 5 : Schematic symbolic regression approach

Figure 5 shows a schematic of a symbolic regression approach. The goal is to find an equation $f(x)$ that fits to a set of experimental data that may originate either from a physical or a software experiment. Subsequently, an iterative process in the fashion of a genetic algorithm mutates and matches equations to the experimental data. Symbolic regression aims to combine parameters via mathematical operators to fit the experimental data as well as possible. For example, if an equation for the technology factor k_{TSFC} is requested then a database with the technology factor and the entry into service dates is used as the input for the symbolic regression. In addition, the permitted mathematical operators such as addition, subtraction, division, multiplication, and cosine, are specified. A genetic algorithm generates new sets of equations from the characteristics and operators and further modifies the most promising ones. The result is a Pareto front that includes both the accuracy and the complexity of the equations.

3 Results

The methods decribed in the previous chapter are applied and this section provides an overview on the findings. That is to say, an optimization was performed for each aircraft within the database to minimize e.

Figure 6 shows the optimum technology factors for each aircraft. The technology factors are plotted once over the model entry into service date and once over the family entry into service date. Hence, effects can be distinguished that have their origin in the initial family design or are specific to the model. For reasons of clarity, the plots are restricted to the distribution of k_{Pax} and k_{TSFC} over time.

In addition, table 4 summarizes the results of the optimization. The mean μ of each technology factor could be applied to calibrate the conceptual design model without any reference to technology improvement over time. However, the significant values of the standard deviation σ provide reason that this approach is inappropriate. Furthermore, the table lists the correlation between the technology factors and the respective entry into service dates.

Larger correlation is only present in the data for the family entry into service date and the passenger mass, and the thrust specific fuel consumption and the model entry into service date. Albeit, it must be noted that the correlation is far from being without any doubt, and section 4 further elaborates on this topic. Hence, this data is forwarded to the symbolic regression. Instead of the actual entry into service date, for numerical reasons, the symbolic regression is based on a normalized entry into service date k_{EIS} where k_{EIS} is defined as in equation 4. The family entry into service date of each aircraft is noted as a_{EIS} and referenced by the youngest (A380) and oldest aircraft (B737) in the database.

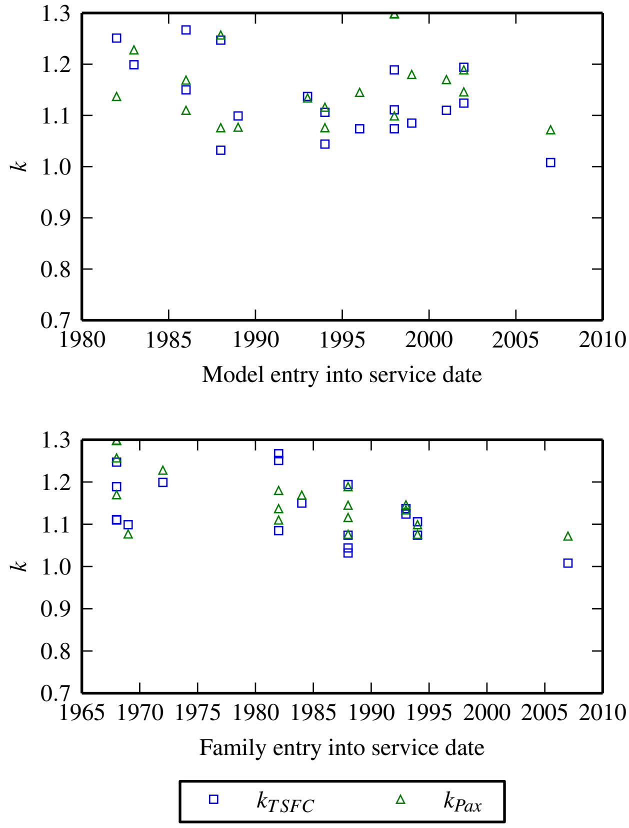

Fig. 6 : Technology factor distribution

	k_{CD0}	k_{TSFC}	k_{Wing}	$k_{Fuselage}$	k_{Pax}
μ	1.11	1.13	1.10	1.12	1.15
σ	0.06	0.07	0.08	0.09	0.07
C_{Model}	-0.26	-0.53	0.38	0.16	0.00
C_{Family}	-0.41	-0.48	0.21	0.20	-0.70

Table 4: Entry into service correlation

$$k_{EIS} = \frac{a_{EIS} - 1968}{2007 - 1968} \tag{4}$$

Given the fact that significant noise exists in the distribution of the technology factors and it is hard to extract meaningful information, the symbolic regression is limited to one application. The symbolic regression is configured to find a regression between k_{PAX} and k_{EIS} where k_{EIS} is available both for the family and model entry into service date. The mathematical operations allowed for the symbolic regression include addition, subtraction, negation, division, multiplication, power, log and exponential. Figure 7 shows the distribution of equations derived by the symbolic regression. Here, each equation has a given complexity that expresses the order and number of mathematical operations and the error of the fit.

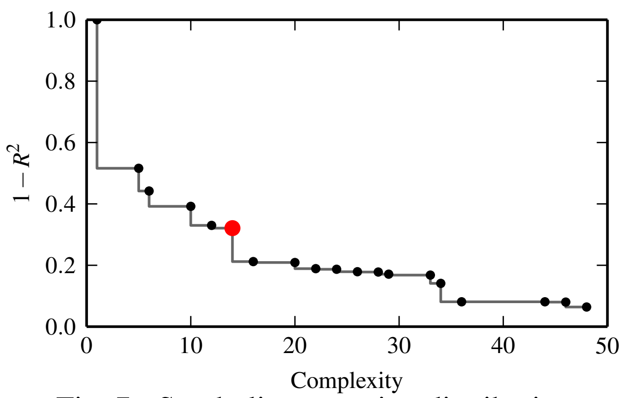

Fig. 7 : Symbolic regression distribution

Several equations are provided by the symbolic regression that fit the data, as shown in figure 6. However, as mentioned above, these equations reproduce the noisy data rather than provide a meaningful regression. Hence, equation 5 is chosen to describe the dependency of the single passenger mass in conceptual design over the family entry into service date. The equations is a compromise between accuracy and complexity.

$$\begin{aligned} k_{PAX} = &1.256 + 3.063 k_{EIS,Family}^{0.039} \\ &-0.271 k_{EIS,Family} - 3.003 k_{EIS,Family}^{0.0195} \end{aligned} \tag{5}$$

If one accepts a low accuracy of the symbolic regression to ignore most of the noise effects that it is capable of providing mathematical formulations that outperform the usual linear or polynomial regression approaches. However, the different sources of error remain an issue in the present study and the following section elaborates some of the possible sources.

4 Conclusion

The previous section outlined the results of the conducted optimization study and special attention needs to be paid to the correlation between the technology factors and entry into service dates, as listed in table 4. As already mentioned, a significant correlation is present only for few data pairs and even then the correlation values are not too high, i.e., close to one. It must be noted, that very high correlation values are not inevitable for a valid causation in the sense of the study's hypothesis. For example, if the improved design and production techniques lead to a decreased skin roughness then the zero lift drag is subject to technology improvement over time. However, if this effect stagnates over time rather than develops linearly then the correlation must not be close to one.

In the following paragraphs possible error sources are further discussed. These can be related to the conceptual design model, the aircraft database, and the optimization strategy. The hypothesis of this study is that the systematic error of the conceptual design model is due to the fact that technology improvement over time is not explicitly taken into account. Conversely, the hypothesis implies that no other systematic error remains within the conceptual design model and the aircraft database; a contentious statement.

Of course, unidentified systematic errors may remain within the conceptual design model. One hint is the correlation of the wing mass and the entry into service date. In contrast to the results of the optimization study, the standalone LTH [7] method provides lower errors. This may either be due to a systematic error within VAMPzero or due to an additional item in the mass breakdown, e.g., systems mass, that depends on m_{TOM}, is sen-

	k_{CD0}	k_{TSFC}	k_{Wing}	$k_{Fuselage}$	k_{Pax}
μ	1.10	1.12	1.09	1.10	1.13
σ	0.05	0.07	0.09	0.11	0.05
C_{Model}	-0.52	-0.72	0.52	0.35	-0.30
C_{Family}	-0.24	-0.43	0.50	0.41	-0.52

Table 5: Limited database correlation

sitive to technology improvement over time, and was not available to the optimizer as a design variable.

Furthermore, systematic errors are likely to appear in the aircraft database. First, given the fact that the aircraft database holds data from public sources, the accuracy is questionable. Second, the number of aircraft and manufacturers is sufficient for an initial study, especially if the computational cost is taken into account, but may be increased to obtain a more representative set of samples. Third, the aircraft database lists several aircraft from product families. As these aircraft are seldom the design drivers, components may be over sized and compromise the correlation analysis. For example, the wing of the A330s and early A340s is sized to withstand the loads of the higher gross weight variants of the A340. Table 5 illustrates this effect as it shows again the results of the optimization study, but excludes minor aircraft versions, i.e., A318, A319, A320, A330-200, B737-400, B737-700, B737-800, and B767-200ER. It can be observed that the correlation increases for this reduced data set compared to the initial results presented in table 4.

In addition, it must be noted that a stochastic global optimization approach must not find the global minimum. However, this effect could only be fully excluded if significant computational resources are available, e.g., for brute force analysis.

Finally, the present study shows an approach to determine whether the entry into service date correlates with the error of a conceptual design model. It proves that the process can be applied to introduce entry into service in conceptual design. However, several sources of error exist that produce significant noise in the data, and this noise is higher than initially expected. Hence, future research needs to broaden the available data in the aircraft database and reduce numerical errors to further enhance the results of the proposed approach.

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