Mapping customer needs to engineering characteristics: an aerospace perspective for conceptual design

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Published online: 01 Apr 2014.

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Designing complex engineering systems, such as an aircraft or an aero-engine, is immensely challenging. Formal systems engineering practices are widely used in the aerospace industry throughout the overall design process to minimise the overall design effort, corrective re-work, and ultimately overall development and manufacturing costs. Incorporating the needs and requirements from customers and other stakeholders into the conceptual and early design process is vital for the success and viability of any development programme. This paper presents a formal methodology, the value-driven design (VDD) methodology that has been developed for collaborative and iterative use in the extended enterprise (EE) within the aerospace industry, and that has been applied using the concept design analysis (CODA) method to map captured customer needs into engineering characteristics and to model an overall 'design merit' metric to be used in design assessments, sensitivity analyses, and engineering design optimisation studies. Two different case studies with increasing complexity are presented to elucidate the application areas of the CODA method in the context of the VDD methodology for the EE within the aerospace sector.

Keywords: aerospace conceptual design; customer needs; design merit; design optimisation; value-driven design; extended enterprise

1. Introduction

The Advisory Council for Aeronautics Research in Europe (ACARE 2002) research agenda firmly states that world aeronautics now stands at the threshold of a third age of aviation. After the Pioneering Age and the Commercial Age, the sector is approaching a 'bright with opportunity, but heavy with risk' Age of Sustainable Growth, requiring 'more affordable, cleaner, quieter, safer and more secure air travel'. This age is characterised by the relentless increase in aviation traffic (IATA 2010) and by the evolution of the passengers' travel behaviour and core values. Hence it requires a fundamental change in the way engineering design activities are initiated, to balance the upward demand and the broader needs of the society for economic and social benefits.

These issues raise the order of magnitude and complexity of engineering tasks to a level that cannot be tackled only by improving existing design practices. Modern aircraft development programmes, such as the Airbus A350 XWB (eXtra Wide Body) programme (AIRBUS 2012), feature about 100 major work packages that are contracted to risk-sharing partners and key suppliers; these major work packages are further subcontracted to a large variety of other suppliers and subcontractors in the 'extended enterprise' (EE). One should no longer speak about a 'supply chain',

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because this would falsely imply a relatively simple structure; rather the term 'supply network' should be used, as it describes more accurately the complexity and global nature of the EE.

Systems engineering (SE) (Sage 1992) standards, such as ISO 15288 (ISO/IEC 2008) and the INCOSE SE Handbook (INCOSE 2011), help in structuring the necessary activities when dealing with a design problem of such complexity. One key discipline of SE is requirements management (RM) (Nuseibeh and Easterbrook 2000), in which contractual requirements are signed off between directly interfacing partners within the EE (Browne and Zhang 1999) and virtual enterprises (VE) (Davidow and Malone 1993). They represent the main reference for any work at any level of the EE and VE, ensuring robustness and quality of the development process outcome. However, to reduce development cycles and times-to-market, companies have to start working ever earlier in a programme context, long before mature requirements from the super system are made available to them.

Such organisations traditionally have a number of options regarding how they could deal with their situation: (1) they could wait and only start working after they have received their validated input requirements from the aircraft level; (2) using previous experience and a number of assumptions, they could start working at their level, without exactly knowing what their input requirements will be; or (3) they could ask for preliminary versions of their input requirements, in order to start their particular work based on those.

All of these options have some serious drawbacks. The first one ensures that the organisation will work on a sound basis, but it will not have much time to develop long lead items, thus resulting in delays for the overall aircraft programme. The second option is much riskier, prone to corrective rework that could lead to unplanned costs and delays, and would potentially lead to conservative rather than innovative design solutions. The third implies a high degree of risk, as the development efforts would be based on immature input requirements, invariably leading to high levels of corrective rework, which in turn will lead to unplanned costs and delays as well as conservative rather than innovative design solutions.

In order to mitigate the effects of these drawbacks and to gain competitive edge, aerospace manufacturers need to understand early on what drives the generation of customer and other stakeholder value in a given business context. Hence, context-specific, multidimensional value considerations should be in the focus of early, conceptual work for a new product or technology.

Within SE, 'Value' is an interesting concept to indicate early-stage solution strategies. Value, in fact, could be used to communicate the 'intent' of a design throughout the supply network or EE, preceding, enhancing, and complementing requirements-based information. However, in the current SE standards 'value' is not covered in much detail yet and it is usually rather considered in monetary terms only (INCOSE 2011). The ambition of the research work is, therefore, to enhance the way in which context-specific, multidimensional 'value' is used as the criterion to guide preliminary design assessments across the aerospace supply network. This encompasses the identification, development, and testing of new methodological and technological enablers to make 'value' a clear and well-understood driver of early decision-making activities.

The objective of this paper is to present the value-driven design (VDD) methodology and the supporting concept design analysis (CODA) method (Woolley, Scanlan, and Eveson 2000, 2001; Feneley et al. 2003) to map customer needs (CNs) – and in fact any other internal and external stakeholder needs – to high-level engineering characteristics (ECs) during conceptual and preliminary design phases of aerospace systems and components. The CODA method offers an enhancement of quality function deployment (QFD), providing a more sophisticated mapping between requirements and key product attributes (Woolley, Scanlan, and Eveson 2000, 2001; Feneley et al. 2003). This paper, therefore, describes: (1) the theoretical foundations of the CODA approach that makes it suitable to establish the link between CNs and ECs; (2) the application of the approach within an aerospace development problem context; and (3) the results of the validation activities conducted in collaboration with major players in the European aerospace industry.

2. Literature review

The engineering design process, within the overall context of product development, continues to draw interest from academia and industry, and a number of reference works describe systematic approaches to engineer designs in great detail (Hubka and Eder 1988; Pugh 1991; Pahl and Beitz 1996; Otto and Wood 2001; Ulrich and Eppinger 2008; Ullman 2009). These methodologies have been in use in manufacturing industries for decades and they certainly improved and expedited the design iterations during product development.

Implementing a systematic engineering design process is vitally important for large enterprises developing immensely complex products, such as in the aerospace industry. Structured guidelines are particularly crucial in early design: according to Blanchard (Blanchard 1978) about 75% of the life-cycle costs of any product are determined by the design decisions made during the conceptual design stages; also, implementing design changes later in the development programme gets more difficult and costly (Dowlatshahi 1992; Miles and Swift 1998). Hence, taking a decision on the best concept (or a small set of top-ranking concepts) which will be developed further in detailed design for manufacturing is one of the most difficult, sensitive, and critical problems when approaching engineering design (Pugh 1991).

2.1. *Decision-making in engineering design*

Decision-making is a central concept in the design of engineering systems. On one end, decision-making is considered by some as the 'fundamental construct of engineering design' (Chen, Hoyle, and Wassenaar 2013). On the other end, engineering design is sometime spelled out as 'the set of decision-making processes and activities used to determine the form of an object given the functions desired by the customer' (Eggert 2005).

Such a decision-making process, however, is often disconnected. As elaborated by Chen and others traditional engineering design is conducted primarily with an engineering-centric viewpoint, in which the objective is to achieve the best performance constrained by the available budget (Chen, Hoyle, and Wassenaar 2013). In general, this is true for each of the major functional domains within a firm, which seek to optimise a domain-specific objective with limited input from the other functional domains. This way of working, they conclude,

> cannot assure optimal decisions for an engineering system at the enterprise level: the engineering-centric approach does not consider customer demand, whereas the market-centric approach does not consider the intricacies of engineering attribute coupling, and the resulting influence upon cost, for a product or system design. (Chen, Hoyle, and Wassenaar 2013)

Decision-based design (DBD) methodology is proposed as an enterprise-driven, collaborative, and interdisciplinary approach that embraces decision theory, and its underlying mathematical principles, for making rigorous design decisions (Chen, Hoyle, and Wassenaar 2013). DBD includes a number of methods to systematically integrate heterogeneous consumer preference into engineering design. When it comes to purchasing a product, many decisions are based on other attributes rather than solely on the purchase price. For instance, when choosing a car, comfort, performance, reliability, size, safety, style, image, equipment, handling, noise, running costs are just a few of the attributes the customers value when making a purchasing decision (Donndelinger and Cook 1997; Pozar and Cook 1998). DBD is intended to facilitate the integration of such heterogeneous dimensions to guide the selection of the preferred alternative in a rigorous manner.

Among the opportunities for enhancing DBD, Chen and others propose to investigate the intersection and interaction between engineering and marketing with social science, to cope with the inherent challenges related to modelling consumer choice behaviour early in the design process

(Chen, Hoyle, and Wassenaar 2013). Similar considerations led the authors of this paper to develop an approach that links customer satisfaction with a product's ECs.

2.2. *Decision-making for concept selection*

The conceptual design stage is the juncture in the entire design process, where vital decisions for the success of any design or mission tend to go wrong (Mattson, Mullur, and Messac 2009). A plethora of concept selection methods (CSMs) are then proposed in literature to mitigate such a problem. CSMs are broadly classified into four categories by Okudan and Tauhid (2008); however, the majority of the CSMs reported tend to use a blend of these in order to encapsulate the best of each. These are as follows:

- CSMs based on Decision Matrices, e.g. Pugh Charts (Pugh 1991) and QFD (Hauser and Clausing 1988; Akao 1990; Hjort, Hananel, and Lucas 1992; Park et al. 2008; Sorensen et al. 2010; Mayyas et al. 2011),
- CSMs based on analytic hierarchy process (AHP) (Zavbi and Duhovnik 1996; Saaty and Vargas 2001; Saaty 2005a, 2005b; Ayag and Ozdemir 2007; Afacan and Demirkan 2010; Mayyas et al. 2011; Remery, Mascle, and Agard 2012),
- CSMs based on uncertainty modelling, e.g. probabilistic methods, sensitivity analysis (Reddy and Mistree 1992),
- CSMs based on Decision Theory/Economics models, e.g. the Thurston–Locascio methodology (Thurston and Locascio 1994),
- CSMs based on optimisation concepts, e.g. Pareto optimality concept (Mattson and Messac 2005).

2.3. *Tools and methods to support concept selection*

One of the most widely accepted CSMs is the QFD method. QFD originated in 1972 at Mitsubishi's Kobe shipyard site (Hauser and Clausing 1988). Since its conception by Joji Akao and his colleagues, the QFD method has been widely used in the fields of product development, quality management, CN analysis, product design, planning, engineering, decision-making, and management (Chan and Wu 2002). QFD is arguably the most popular framework for the implementation of company- or enterprise-level design decision tools and it is basically a set of hierarchical matrices where the internal and external CNs are mapped into measurable or quantifiable ECs. There are a large number of review articles on the QFD method and recent developments in terms of QFD research, spanning more than four decades (Chan and Wu 2002; Sharma, Rawani, and Barahate 2008; Xu, Xun, and Xie 2010).

Quite a number of studies and various techniques have attempted to investigate the modelling of the relationship between CNs and ECs in QFD. It is widely recognised that QFD involves substantial subject judgement while constructing a house of quality; thus existence of fuzziness in QFD is unavoidable (Verma, Chilakapati, and Fabrycky 1998; Bouchereau and Rowlands 2000; Song, Ming, and Wu 2013). In order to address the fuzziness of the modelling, quite a few previous studies have adopted the fuzzy set theory on modelling the relationships between CNs and ECs (Thurston and Carnahan 1992; Fung, Popplewell, and Xie 1998; Park and Kim 1998; Verma, Chilakapati, and Fabrycky 1998; Wang 2001). As an alternative, a stepwise regression analysis method has been utilised to produce second-order polynomials to model the functional relationships between CNs and ECs in QFD (Dawson and Askin 1999).

More recently, these relationships have been modelled by employing a fuzzy rule-based systems approach with an asymmetric triangular fuzzy coefficient (Fung et al. 2003); by adopting a fuzzy rule-based approach to build models relating CNs to ECs (Chen et al. 2004; Park and

Han 2004; Fung, Chen, and Tang 2006); or by using a multi-criteria decision-making framework based on a fuzzy logic-based composite structure methodology on the evaluation of marine and offshore engineering design proposals (Sii et al. 2004). More recent examples include a multi-layer graph model that not only resolves the conflict of experts' opinion but also aggregates the layers corresponding to decision criteria into a single graph (Erginel 2010; Jenab, Sarfaraz, and Ameli 2013).

However, fuzzy logic is a rather lengthy methodology which offers a limited advantage when used as a design concept evaluation method (Ayag and Ozdemir 2007) as it makes decisions with mathematical equations (King and Sivaloganathan 1999), which are usually not known during the early stage of product development (Song, Ming, and Wu 2013). These limitations hinder the application of fuzzy approaches, asking for a more qualitative approach that fits within the time constraints as well as with data availability restrictions of preliminary design activities.

It is also widely recognised that the behaviour of the relationships between CNs and ECs is extremely complex and the dependencies can be non-linear (Thurston 2001; Duck Young and Xirouchakis 2010; Erginel 2010). Most of the aforementioned CSMs can only be used to develop models with linear terms, and generation of interaction terms and/or higher-order terms of models cannot be addressed (Chan, Kwong, and Wong 2011). QFD, for instance, uses a linear relationship (positive or negative) to map CNs to ECs, which simply makes it impossible to model more complex behaviours. For instance, the relationship between the CN of 'Ease of reading in the cockpit' and the EC of 'Illumination level [lux]' can only be modelled by using an optimisation-type function, which describes an optimum level of illumination in the cockpit at which the customer satisfaction level with respect to reading will be higher compared to both lower and higher levels of illumination.

Artificial neural networks have been used to develop non-linear models in other domains (Tong, Kwong, and Yu 2004); however, they normally require a large amount of precise and objective information regarding product concepts, which is not easily available at the early stage of the new product design process (Rosenman 1993), as the amount and the quality of data sets for developing these models are usually very limited (Fung, Chen, and Tang 2006; Xu and Yan 2006; Kwong et al. 2007; Song, Ming, and Wu 2013). This also hinders the application of methods that use real values (from appropriate databases) to model the relationship between the CNs and ECs (Brackin and Colton 2002). The lack of precise engineering data results in a more intuitive and less data-consuming approach to model the non-linearity in the functional relationships. Hence, the approach introduces non-linear optimisation-type functions, which are also intended to solve one of the major issues related to the use of QFD in design optimisation problems, i.e. the fact that QFD does not accommodate negatives – alternatives that detract from an attribute rather than contribute to it (Collopy 2009).

Another limitation of the QFD method is that the overall implication of design changes by varying ECs is not easily apparent; therefore, QFD is not really suitable for engineering design optimisation, trade-off studies, and sensitivity analyses. In order to alleviate these shortcomings, the CODA method was identified as a suitable candidate to link CNs to ECs during the representative preliminary design phases of aircraft development programmes.

3. Methodology

The paper's findings – which are the methodological and technological enablers for value assessment – have been developed within a European Commission's Seventh Framework (FP7) Programme project entitled 'Collaborative and Robust Engineering using Simulation Capability Enabling Next Design Optimisation' (CRESCENDO 2012).

Empirical and qualitative data have been mainly collected through the authors' active participation in physical and virtual work-meetings involving major European aircraft, aero-engine, and sub-systems manufacturers (Airbus, Rolls-Royce plc, and GKN Aerospace Engine Systems Sweden, respectively) between May 2009 and October 2012. The definition and clarification of the problem domain have been conducted in close collaboration with the industrial partners, featuring regular (bi-annual), multi-day physical workshops, which have involved a total of 35 participants from 12 different partners including manufacturers (aircraft, aero-engine, and sub-system), universities, research centres, and software vendors.

The gathering and analysing of the user needs as well as the definition of the methodological and technological enablers have been aided by regular multi-day visits to Airbus, Rolls-Royce plc, and GKN Aerospace Engine Systems Sweden. Data have been gathered through semi-structured interviews with managers, engineers, and information technology experts involved in the development of hardware, software, and services related to aerospace products.

Reflective learning has been aided by the continuous participation in regular debriefing activities, which have taken the form of weekly virtual meetings. The findings have been iteratively discussed and validated with the project partners, which have actively participated with their knowledge and expertise to the development of a preliminary mock-up for value assessment.

The validation of the research outcomes has been aided by three multi-day project reviews involving key stakeholders from a wide range of companies in the European aeronautical industry. Dissemination activities have also contributed in validating the generalisability of the approach, through the contribution of companies and universities that were not directly involved with the CRESCENDO project.

Within the CRESCENDO research project, an integrated scenario was used to apply and validate the VDD methodology (Kossmann et al. 2012; Isaksson et al. 2013). Figure 1 shows three simplified levels of the EE, i.e. the aircraft level, the engine level, and the sub-system level. The
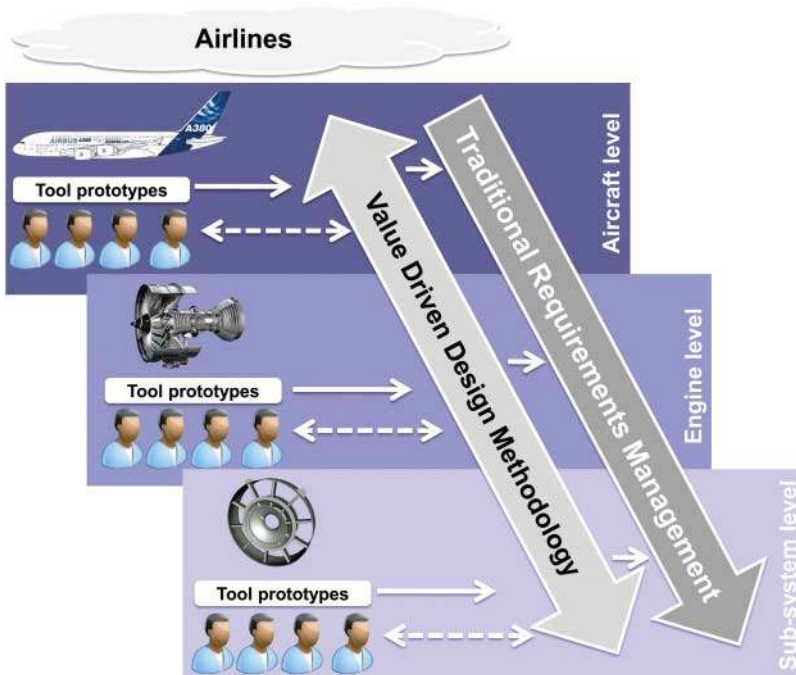

Figure 1.   Enhancing the traditional RM process.

VDD methodology is a generic, upfront, add-on (to the traditional RM process) activity that takes place iteratively, potentially across all levels of the EE to provide early context-specific, multidimensional value information throughout the EE, in order to:

- Enable the selection of early concepts and designs that represent the highest contribution in terms of their value;
- Enable the optimisation of the final product or system at the highest integration level (in terms of the overall value contribution) as opposed to local optimisation at one or different levels;
- Enhance the development of high-quality and value-driven requirements based on these value-generation activities.

For the purpose of validating the VDD methodology in the context of CRESCENDO, two iterations across the above-mentioned three simplified levels of the EE were considered. In reality, of course, there would be many more levels (vertical dimension) and teams in parallel (horizontal dimension), as well as multiple iterations. Figure 2 displays the integrated scenario over the three levels and two iterations.

For the first iteration at the aircraft level, based on captured, analysed, and validated expectations as well as other relevant context knowledge, a list of external and internal high-level needs is formulated for a given context. These needs are analysed, validated, and rank-weighted with the relevant stakeholders and a suitable value dimension is selected as an attribute of each need. Initial value drivers are identified for each need, as something which is expected to have a significant impact on the achievement of the corresponding stakeholder need. A first iteration of a value creation strategy (VCS) is formulated, containing a free context description, the list of rank-weighted needs, and the initial value drivers.

Similarly at the engine level, the first iteration involves formulating a list of external and internal high-level needs for the given context that is defined by the first-iteration VCS at the
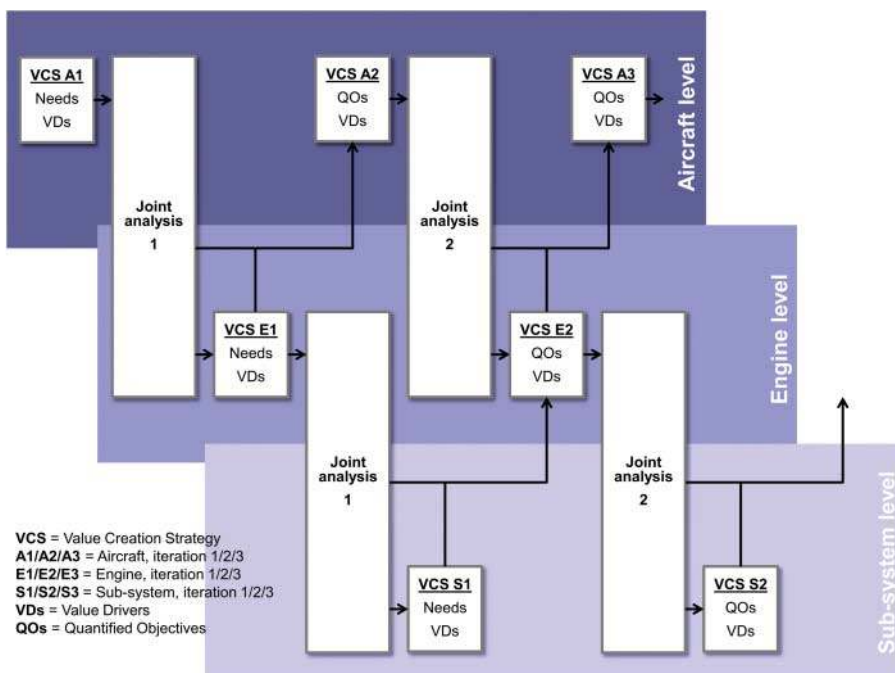

Figure 2.   The integrated VDD scenario (simplified).

aircraft level, other relevant context knowledge at the engine level including their own captured customer expectations, and a joint analysis between the aircraft and engine levels. These needs are analysed, validated, and rank-weighted with the relevant stakeholders and a suitable value dimension is selected as an attribute of each need. Initial value drivers are identified for each need. These value drivers are likely to differ at least partly from the value drivers defined at the aircraft level. Then, a first-iteration VCS is formulated, at the engine level, containing a free context description, the list of rank-weighted needs, and the initial value drivers.

The first iteration at the sub-system level is similar to the process at the engine level. Again, at least some of the value drivers at the sub-system level are likely to differ from the value drivers defined at the engine level regarding content and level of granularity and detail. Then a first-iteration VCS is formulated, at the sub-system level, containing a free context description, the list of rank-weighted needs, and the initial value drivers.

During the second iteration at the aircraft level, based on feedback from the joint analysis and in light of the first iteration of the VCS at the engine level, relevant quantified objectives are elaborated based on the previously identified value drivers that are expected to jointly satisfy the set of rank-weighted stakeholder needs. This set of quantified objectives will be subject to specific value-modelling activities by means of suitable methods and tools, in order to optimise the overall value contribution of the entire set of quantified objectives. Also, the initial set of value drivers is either confirmed or modified in light of the above value-modelling activities. A second-iteration VCS is then formulated at the aircraft level, containing a refined free context description, the list of rank-weighted needs, the confirmed or updated value drivers, and the set of rank-weighted quantified objectives.

Similarly during the second iteration at the engine level, based on feedback from the joint analysis and in light of the second iteration of the VCS at the aircraft level, relevant quantified objectives are elaborated that are expected to jointly satisfy the rank-weighted stakeholder needs. Again, this set of quantified objectives will be subject to specific value-modelling activities by means of suitable methods and tools, in order to optimise the overall value contribution of the entire set of quantified objectives. The initial set of value drivers is either confirmed or modified in light of the above value-modelling activities. Then, a second-iteration VCS is formulated at the engine level, containing a refined free context description, the list of rank-weighted needs, the confirmed or updated value drivers, and the set of rank-weighted quantified objectives.

Finally, during the second iteration at the sub-system level, based on feedback from the joint analysis and in light of the second iteration of the VCS at the engine level, relevant quantified objectives are elaborated that are expected to jointly satisfy the rank-weighted stakeholder needs. Again, this set of quantified objectives will be subject to specific value-modelling activities by means of suitable methods and tools, in order to optimise the overall value contribution of the entire set of quantified objectives. The initial set of value drivers is either confirmed or modified in light of the above value-modelling activities. Finally, a second-iteration VCS is formulated at the sub-system level, containing a refined free context description, the list of rank-weighted needs, the confirmed or updated value drivers, and the set of rank-weighted quantified objectives.

The VDD methodology as described in this section of the paper is independent from the methods and tools that are used to carry out the described value-modelling activities. In the following section, the CODA method will be described in more detail, which was used as one of the suitable methods to support the VDD methodology.

4. Theoretical foundations

The CODA method can be used in assessing the value generated by improving the customer satisfaction level during the conceptual design phase of a new product. A CODA model allows

the designers to systematically modify tangible and measurable ECs and to immediately see their effects on the customer satisfaction level of the product. This approach enables designers to perform a wide range of analyses, such as trade-off and what-if studies, sensitivity analysis, and engineering design optimisation.

In order to calculate the overall value of a new design two orthogonal measures are usually needed. These are:

(1) *The total cost of the product*: For disposable products the total cost involves just the development and manufacturing costs; on the other hand, for a repairable and revenue generating product, the total cost may also involve operating costs, maintenance costs, and attrition costs. The calculation of unit costs is relatively straightforward and a wide range of parametric costing tools exists in the manufacturing industry. Similarly, high-fidelity models on operating, maintenance, and life-cycle costs are commonly used in the aerospace industry.
(2) *Performance*: This is not merely the physical performance of the product, but how well the product meets the needs of the customers. Compared to total costs, many performance measures are less tangible and more difficult to quantify for early product designers.

The CODA method employs three different merit functions to calculate a performance metric (or a customer satisfaction level) of a new product. These are:

(1) Maximising function
(2) Minimising function
(3) Optimising function

Representative merit functions for various ECs are presented in Figure 3. The maximum take-off weight of an aircraft or the sea level static thrust of engines can be modelled with a maximising function as higher values of these ECs correspond to higher customer satisfaction levels. On the contrary, specific fuel consumption of engines or the cabin noise level of an aircraft needs to use a minimising function as lower levels of these ECs are more desirable. For some other ECs, such as the cockpit illumination level or the legroom in the economy class cabin, a target setting may

1) Maximum take off weight of the aircraft
2) Seal level static thrust of the engines
3) Specific fuel consumption of the engines
4) Cruise viscous drag coefficient of the aircraft
5) Cockpit illumination level
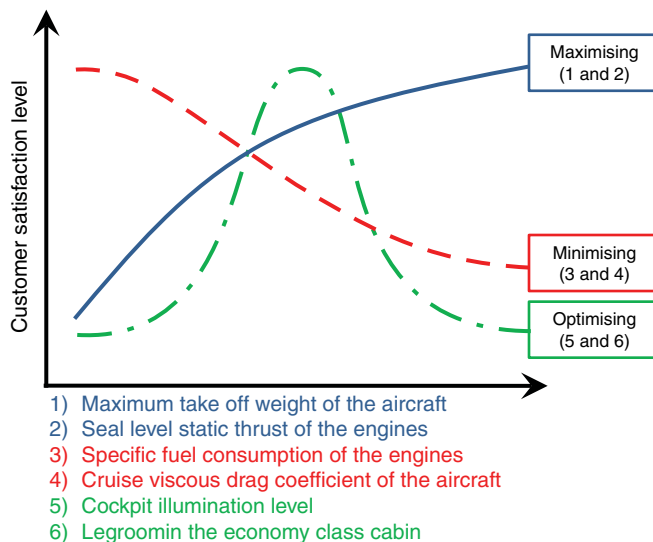6) Legroom in the economy class cabin

Figure 3.   Representative merit functions for various ECs showing their effects on customer satisfaction levels.
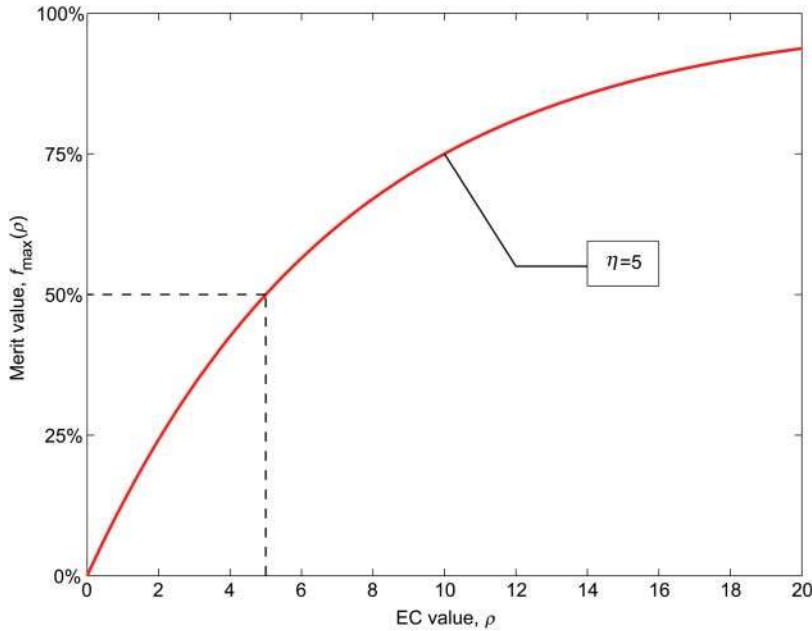
Figure 4.   The effect of neutral point η on the merit value for the maximising function.

be more appropriate and the optimising function offers a more viable alternative than minimising and maximising functions.

The maximising function describes the increasing nature of the customer satisfaction level with increasing EC and it has the following mathematical form:

$$f_{\text{Max}}(\rho) = 1 - \frac{1}{2^{\rho/\eta}}. \tag{1}$$

Here, ρ is the value of the EC and η is the neutral point of the EC. When the value of the EC is equal to the neutral point value, the merit function has the value of 0.5 (see Figure 4), representing a 50% customer satisfaction level. When the EC value ρ for a design alternative is greater than the neutral point η the customer satisfaction level increases.

Conversely, the minimising function describes the decreasing nature of the customer satisfaction level with increasing EC and it has the following mathematical form:

$$f_{\text{Min}}(\rho) = 1 - \frac{1}{2^{\eta/\rho}}. \tag{2}$$

In the minimising function, when the value of the EC, i.e. ρ, is equal to the neutral point value, i.e. η, the merit function has the value of 0.5 (see Figure 5). In contrast to the maximising function, when the EC value ρ for a design alternative is smaller than the neutral point η the customer satisfaction level reaches values above 50%.

Finally, the optimising function describes dependencies where an optimum value of an EC is more suitable. The optimising function has the following mathematical form:

$$f_{\text{Opt}}(\rho) = \frac{1}{1 + \left(\frac{\rho - \eta}{\tau}\right)^2}. \tag{3}$$

Here, ρ is the value of the EC, η is the neutral point, and τ is the tolerance. When the EC is equal to the neutral point value ($\rho = \eta$), by definition the optimising function has the optimum value
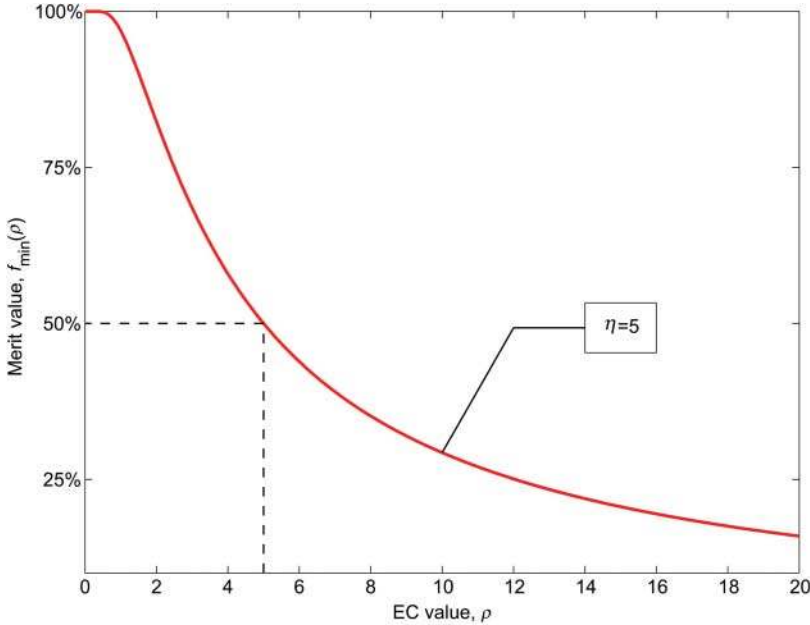
Figure 5. The effect neutral point η on the merit function for the minimising function.

of 1.0 as shown below

$$f_{\text{Opt}}(\rho = \eta) = \frac{1}{1 + \left(\frac{\eta - \eta}{\tau}\right)^2} = \frac{1}{1 + \left(\frac{0}{\tau}\right)^2} = 1.$$

This behaviour describes that the maximum merit is reached when the EC reaches the target neutral value. When the EC is equal to one of the tolerance values ($\rho = \eta \pm \tau$), again, by definition the optimising function has the value of 0.5 as shown below

$$f_{\text{Opt}}(\rho = \eta \pm \tau) = \frac{1}{1 + \left(\frac{\eta \pm \tau - \eta}{\tau}\right)^2} = \frac{1}{1 + \left(\frac{\pm \tau}{\tau}\right)^2} = 0.5.$$

The neutral point and tolerance parameters in the optimising function enable model builders to approximate customer satisfaction levels for certain ECs. Figure 6 shows the functional behaviour of the optimising function for $\eta = 10$ and $\tau = 2$.

These merit functions are utilised to establish the mapping between CNs and ECs of the product. However, not every CN should have the exact same effect on the design concepts and usually CNs are assigned different weights to capture this variable influence. These weights on CNs can come from a variety of sources, such as customer surveys, customer focus groups, or maintenance data of a previous product, and so on. In this study, a binary weighting method has been utilised. Assuming there are M distinct CNs, a binary weighting matrix, W, with a size of $M \times M$, is used to model the relative importance of every CN to each other. By definition the binary weighting matrix W is an upper triangular square matrix, and if the CN on the row is inherently more important than the one in the column, a numerical value of one is used. Similarly, when the CN on a row is decided to be less important than the one in the column, a numerical value of zero is used. This method allows the designer to assess the importance of CNs in pairs and the overall process requires $M \times (M - 1)/2$ number of decisions to be made. Hence, if the number of CNs in the analysis becomes very large, the management of binary weighting model can be demanding. A simplified example of a binary weighting model for an aircraft is presented in Figure 7.
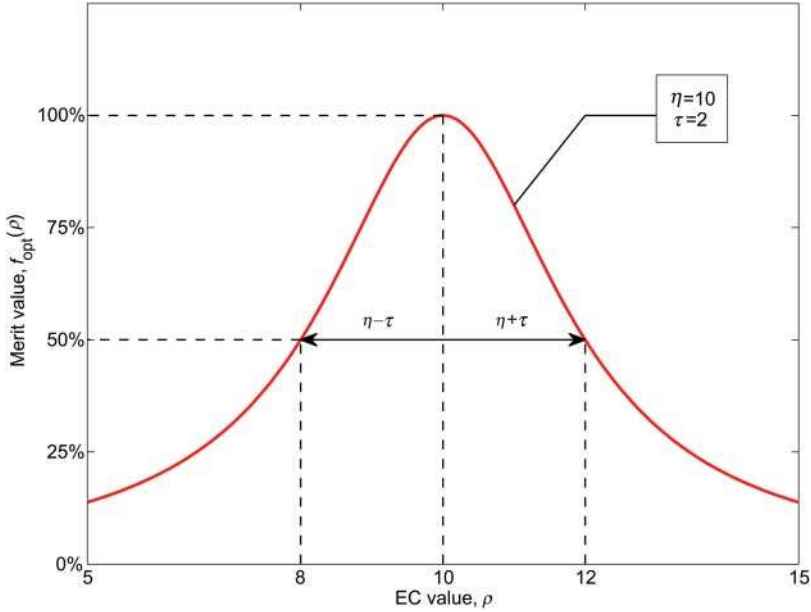
Figure 6.   The effect of neutral point, η, and tolerance, τ, on the optimising function.

	Easy to extend operational life	Green aircraft	Easy to operate	Cheap to maintain and repair	Lowest consumption per PAX-km	No A/C on ground	Unlimited use of Internet	Extremely comfortable	Sufficient range	X Scores	Y Scores	Total score	Biased score	Normalised score
Easy to extend operational life		0	1	1	0	1	1	1	0	5	0	5	6	13%
Green aircraft			0	1	1	1	1	1	0	5	1	6	7	16%
Easy to operate				1	1	0	1	1	0	4	1	5	6	13%
Cheap to maintain and repair					1	0	0	0	0	1	0	1	2	4%
Lowest consumption per PAX-km						1	1	1	1	4	1	5	6	13%
No A/C on ground							1	0	0	1	2	3	4	9%
Unlimited use of Internet								1	0	1	1	2	3	7%
Extremely comfortable									1	1	2	3	4	9%
Sufficient range										0	6	6	7	16%
	0	1	1	0	1	2	1	2	6				45	100%

Figure 7.   A simplified version of an aircraft-level binary weighting model.

When all the pairwise decisions on all CNs are performed, the overall normalised weights, N_i, can be calculated by using the following formula.

$$N_i = \frac{X_i + Y_i + 1}{\sum_{i=1}^{M} (X_i + Y_i + 1)}. \tag{4}$$

Here, X_i values are the total number of ones for each row of CNs and they are calculated as follows:

$$X_i = \sum_{j=i+1}^{M} W_{ij} \quad \text{for} \quad i = 1 \cdots (M-1) \quad \text{and} \quad X_M \equiv 0. \tag{5}$$

Similarly, Y_i values are the total number of zeroes for each column of CNs and they are calculated as follows:

$$Y_1 \equiv 0 \quad \text{and} \quad Y_i = \sum_{j=1}^{i-1} \left(1 - W_{ji}\right) \quad \text{for} \quad i = 2 \cdots M. \tag{6}$$

Note that in Figure 7 the Y_i scores (highlighted row at the bottom) are transposed next to the scores in order to calculate the biased scores $X_i + Y_i + 1$. Finally each biased score is normalised with the sum of all biased scores to yield a percentage weight for each CN. These normalised scores are then transferred to the main overall design merit (ODM) calculation model as shown in Figure 8.

In order to model the ODM, a functional relationship between each EC and corresponding CN is assumed. These functional relationships are in the form of minimisation, maximisation, or optimisation form and they are functions of each EC's parameter value. If there are N ECs and M CNs, the individual customer satisfaction level for each CN CS_i, is calculated by using the following formula:

$$CS_i = \frac{N_i}{SCF_i} \sum_{j=1}^{N} MV_{ij} \cdot CF_{ij}. \tag{7}$$

Here, $MV_{ij} = F_{ij}(\rho_j)$ is a function of each EC's parameter value, CF_{ij} is the correlation matrix between ECs and CNs (numeric values 0.1, 0.3, and 0.9 are used for weak, medium, and strong correlations), and SCF_i is the sum of all correlation factors for each CN. Finally, the ODM is simply the sum of all design merits corresponding to each CN:

$$ODM = \sum_{i=1}^{M} CS_i. \tag{8}$$

Here, it is assumed that CNs are sufficiently analysed and they meet the independence conditions (Zhang et al. 2013). For a step-by-step example the user is referred to our first case study in Section 5.

The proposed CODA method involves the following steps:

(1) Identify the needs of the customers and other stakeholders. These can be done by employing individual surveys, customer focus groups, expert panels, and similar processes.
(2) Calculate the percentage weights of each identified customer or other stakeholder need. In this paper a binary weighting method is used; however, other analytical models, such as the AHP (Saaty 2005a, Saaty and Sodenkamp 2010), can be employed.
(3) Identify ECs of the design along with their lower and upper limits that have an effect on any number of CNs. The 'Engineering characteristics should describe the product in measurable terms and should directly affect customer perceptions'. (Hauser and Clausing 1988)
(4) Decide on the functional relationships between each CN and the corresponding EC. This step requires the following steps:
    (a) Is there a strong (0.9), medium (0.3), weak (0.1), or no correlation?
    (b) If there is a correlation, decide which relationship function (minimisation, maximisation, or optimisation type) to use.

				Customer Needs (CNs)								
Overall Design Merit 48.16%				Easy to extend operational life	Green aircraft	Easy to operate	Cheap to maintain and repair	Lowest consumption per PAX-km	No A/C on ground	Unlimited use of Internet	Extremely comfortable	Sufficient range
		Normalised Weights		13%	16%	13%	4%	13%	9%	7%	9%	16%
Level of Automation [%]			Correlation	0.9		0.3	0.1					
	Value	60%	Neutral or optimum point	0.55		0.6	0.7					
	Upper Limit	90%	Tolerance									
	Lower Limit	50%	Relationship Type	Max		Max	Min					
			Merit value	53%	0%	50%	55%	0%	0%	0%	0%	0%
Aircraft Drag Coefficient			Correlation					0.9				0.9
	Value	0.085	Neutral or optimum point					0.07				0.06
	Upper Limit	0.1	Tolerance									
	Lower Limit	0.01	Relationship Type					Min				Min
			Merit value	0%	0%	0%	0%	43%	0%	0%	0%	39%
Nominal electricity consumption [MW]			Correlation		0.9	0.1		0.3		0.3		0.3
	Value	50.00	Neutral or optimum point		60	80		70		100		75
	Upper Limit	150.00	Tolerance									
	Lower Limit	10.00	Relationship Type		Min	Min		Min		Max		Min
			Merit value	0%	56%	67%	0%	62%	0%	29%	0%	65%

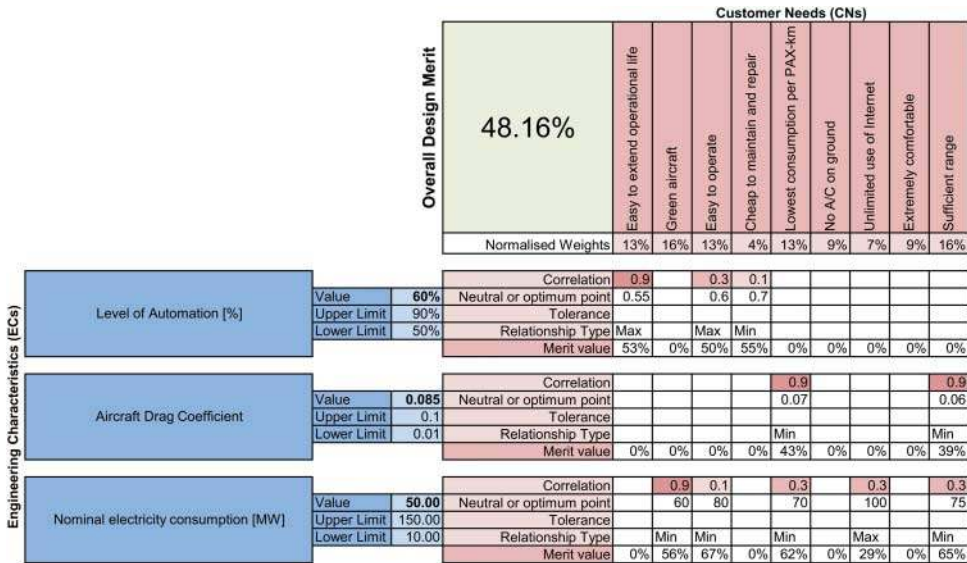*(Left margin label: Engineering Characteristics (ECs))*

Figure 8.   An excerpt from the ODM calculation model for an aircraft.

- (c) Depending on the functional relationship, decide the values of neutral point, optimal point, and tolerance.
- (d) Calculate the individual merit value.
- (5) Repeat step 4 for each CN and EC. Note that, if there is an EC which has no effect on any of the CNs, it may be removed from the model. Similarly, if there is a CN which is not affected by any EC, step 3 is used to find further possible ECs to improve the model.
- (6) Calculate the ODM by adding individual merit values.

Note that it is not always possible to map every EC to a CN and there will be entries with zero correlation values in the mapping. However, after following step 4 in the aforementioned methodology, if there is an EC which cannot be mapped to any CN, it is either redundant or a CN might have been overlooked at step 1 (Hauser and Clausing 1988). Similarly, there might be a case of a CN that cannot be mapped from any EC. In this case, it is very likely that step 3 in the method is incomplete and further analysis is needed in order to identify at least one EC that can influence that particular CN (Hauser and Clausing 1988).

After successfully building and verifying the CODA model, the mappings between the ECs and CNs are frozen and the model becomes a scalar function of N ECs, $ODM(\rho_1, \rho_2, \ldots, \rho_N)$, that calculates the ODM (or customer satisfaction level) on a normalised scale from zero to unity. This N-dimensional merit function can easily be used as a scalar metric in assessing different design options. Furthermore, the design merit function can be used in design optimisation studies and sensitivity analyses.

5.   Case studies

5.1.   *Case study 1: a bicycle wheel design selection model*

In order to elucidate the CODA method and the practical aspects of the modelling effort, a simple bicycle wheel selection model is selected. For the sake of brevity, this model has five simple CNs with equal importance weights, i.e. 20% and they are: (1) Stiffness, (2) Friction, (3) Weight, (4)

Table 1. Details of ECs of the bicycle wheel model.

ECs	Value	Lower limit	Upper limit
Tyre diameter (inches)	24	24	29
Tyre width (mm)	13	11	18
Spoke thickness (mm)	4.3	2.8	5
Use of composites (%)	20	5	80

Manufacturability, and (5) Repairability. These CNs are identified through CODA steps 1 and 2. Next, there are four relevant ECs identified for these CNs (CODA step 3), and these are: (1) Tyre diameter, (2) Tyre width, (3) Spoke thickness, and (4) Use of composites. Sample values, lower and upper limits, and units of these ECs are given in Table 1.

The bicycle wheel CODA model needs to be filled according to CODA step 4. The experts have to span through all ECs in the model and identify any correlation between them and the CNs. For the current model, the process starts with the EC 'Tyre Diameter' and CN 'Stiffness'. The first step (CODA step 4a) is to decide if there is a correlation between 'Tyre Diameter' and 'Stiffness' and, if so, to decide the level of the correlation (weak, medium, or high). For this particular case, a strong (0.9) correlation between the 'Tyre Diameter' and 'Stiffness' is chosen. If a stiffer wheel is preferred for the design, smaller tyre diameters will generate better customer satisfaction. Hence, a minimisation-type relationship is chosen (CODA step 4b) which only needs a neutral point to identify where in the solution domain 50% customer satisfaction is achieved (CODA step 4c). For this example the neutral point is chosen to be 29 inches. Using the minimisation function from Equation (2)

$$f_{\text{Min}} \, (24 \text{ inches}) = 1 - \frac{1}{2^{(29 \text{ inches}/24 \text{ inches})}} = 57\%,$$

the individual merit value or customer satisfaction for a specific 'Tyre Diameter' of 24 inches can be found. This process is repeated for all CN and EC combinations in the model. As expected some ECs do not have any effect on some of the CNs, and the correlation value for those are set to be zero. These mappings are also highlighted in yellow (see 'Tyre Diameter' on 'Manufacturability' and 'Reparability' in Figure 9) as a graphical feedback to the users.

After all the sub-steps in CODA step 4 have been finished, the sums of correlation factors, SCF_i, for each CN can be calculated. For instance, the SCF_1 for 'Stiffness' simply is

$$\text{SCF}_1 = 0.9 + 0.3 + 0.9 + 0.3 = 2.4.$$

This process is repeated for the rest of the CNs to populate the 'Sums of Correlations' row in the model (see Figure 9).

The sums of design merits, CS_i, for each CN are calculated by using equation 7. Again, for the 'Stiffness' column, the sum of design merits is as follows:

$$\text{CS}_1 = \frac{N_1}{\text{SCF}_1} \sum_{j=1}^{4} \text{MV}_{1j} \cdot \text{CF}_{1j},$$

$$\text{CS}_1 = \frac{20\%}{2.4} \, (0.9 \times 57\% + 0.3 \times 53\% + 0.9 \times 63\% + 0.3 \times 31\%) = 11.07\%.$$

This calculation is performed for the remainder of all CNs in the model. And, finally, the ODM is the sum of all individual design merits for each CN as given in Equation (8). For the current
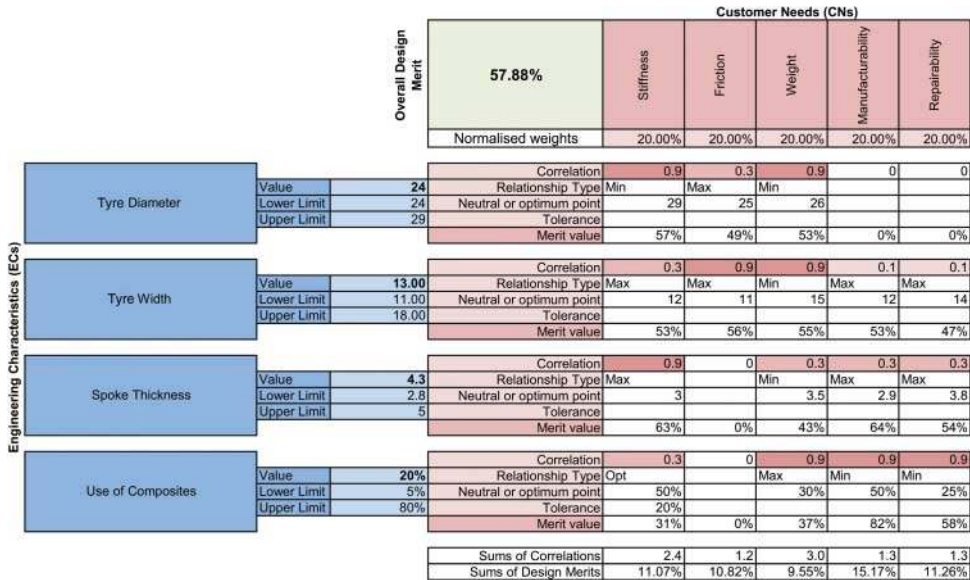
Figure 9.   Simple CODA model for a bicycle wheel design selection (example).

model the ODM is:

$$ODM = 11.07\% + 10.82\% + 9.55\% + 15.17\% + 11.26\% = 57.88\%.$$

When all the correlation factors, functional relationships, and relevant parameters in the CODA model have been decided upon, the CODA model becomes a function of the actual values of the ECs. For the current model, the designers can vary the values for tyre diameter and thickness, spoke thickness, and use of composites in design decisions or engineering design optimisation studies. For example, the non-linear dependencies between the ECs and the ODM (see Figure 10) and surrogate models of the design landscape (see Figure 11) provide valuable information to early concept designers.

5.2.   *Case study 2: development of an aero-engine component*

The CODA method was demonstrated in a case study related to the development of an aero-engine intermediate compressor case (IMC) technology. The IMC is one of the biggest static components in an aero-engine. Its main function is to support surrounding parts, keep the two airflows separated, and transfer the thrust from the engine to the airframe (see Table 2).

These CNs are identified in the very early beginning of the design process, and represent the main criteria upon which the value of an IMC concept will be assessed. The number of 10 CNs was considered as a good trade-off between simplicity and detail, allowing the drivers to be managed without being overwhelmed with too many details. A binary weighting was used to model the relative importance of these CNs, on the basis of the information provided by the aero-engine manufacturer.

The purpose of the demonstration activity was to benchmark two innovative design concepts against an existing product baseline. Option #1 embodied a fully casted design featuring 8–10 inner struts and 16–20 outer struts. It also included a casted hub that implements a bleed off-take function. Option #2 featured a more radical design, characterised by an increased use of composite material, but not featuring a bleed air off-take function.
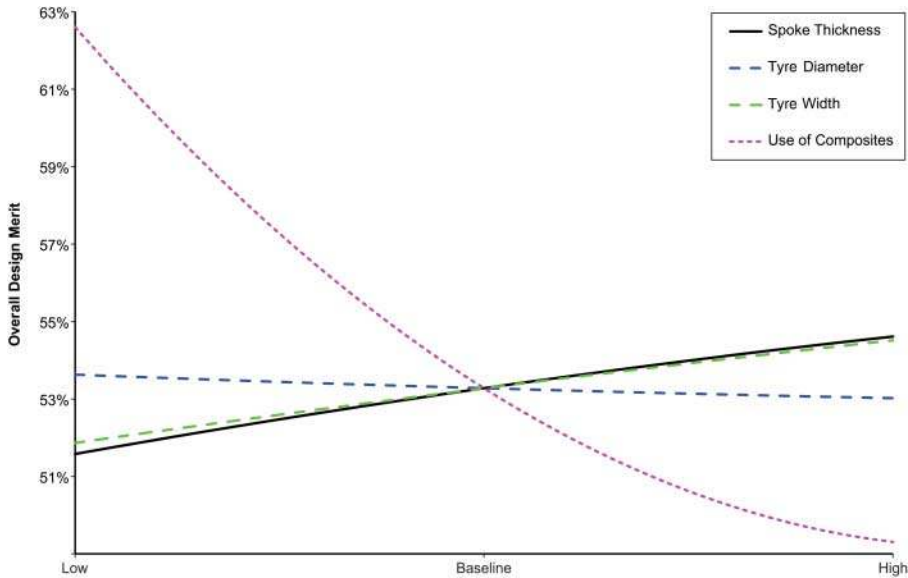
Figure 10. Main effects graph showing the non-linear dependencies between ECs and the ODM for the following baseline values: spoke thickness 5 mm, tyre diameter of 28 inches, tyre width of 15 mm, and use of composites 66%. The actual ranges (±10% of the baseline values) of the ECs on the horizontal axis are marked as 'Low' and 'High'.
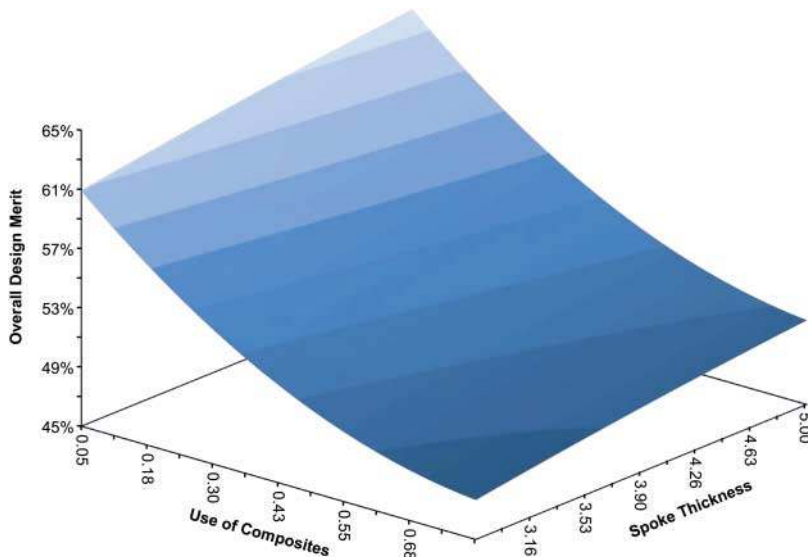

Figure 11. Surface contour plot of ODM versus spoke thickness and use of composites for tyre diameter of 28 inches and tyre width of 15 mm.

To detail the ECs of these options (and of the baseline design), the IMC was split into six main constituent parts (see Figure 12): mount lugs, outer fan case, outlet guide vanes, thrust lugs support, hub outer wall (HOW), and hub inner wall.

These parts have been detailed with information about, for instance, geometry, shape, material, production lead-time, reuse of technology, or accessibility to experts. An example of ECs for the HOW is shown in Table 3.

Table 2.　List of CNs for an IMC technology.

Customer needs	Abbreviation
High temperature in the component is desired	Temperature
High pressure in the component is desired	Pressure
The component must be lightweight	Weight
The air drag in the component must be minimised	Drag
The component must be reliable	Reliability
High availability of the component is desired	Availability
It should be possible to adapt the component to different operational conditions	Adaptability
It should be possible to manufacture the component with low effort and cost	Manufacturability
It should be possible to easily weld the component	Weldability
It should be possible to reuse knowledge from previous projects	Knowledge reuse

Figure 12.　Main parts used to define the IMC ECs.

Table 3.　List of ECs for the IMC HOW.

HOW	Baseline	Option #1	Option #2	Upper limit	Lower limit
Thickness (mm)	7	7	5	8	3
Surface finishing (R_a)	0.11	0.05	0.02	0.15	0.005
Young's modulus (M·lbf/in^2)	18	18	14	25	10
Discharge of cooling fluid (m^3/s)	8	8	12	15	5
Heat transfer coefficient (W/m^{2}K)	20	19	23	50	5
Bleed air off-take (m^3/s)	6.7	7.1	0.01	10	0.01
Reuse of technology (%)	37.00	35.00	30.00	80.00	25.00
Access to experts (%)	56.00	50.00	29.00	75.00	25.00
Production lead-time (h)	72	80	32	120	25
Line commonality (%)	32.00	30.00	60.00	70.00	10.00

　　CODA has been used to link ECs to CNs and to calculate the merit value of the two proposed options as well as of the baseline design. The design team was first asked to define strong (0.9), medium (0.3), and weak (0.1) correlations between ECs and CNs, which expressed the extent to which a CN is positively or negatively impacted by a change in the value of an EC. In the example (see Figure 13), *Surface finishing* (which is expressed as friction coefficient) features

				Drag	Knowledge reuse	Manufacturability
			Normalised weights	17.54%	3.89%	13.22%

				Drag	Knowledge reuse	Manufacturability
			Correlation (0–0.1–0.3–0.9)	0.90	0.30	0.10
Surface finishing	Value	**0.11**	Neutral or optimum point	0.08	0.03	0.08
	Upper limit	0.15	Tolerance (only for OPT)			
	Lower limit	0.01	Relationship Type (MAX-MIN-OPT)	MIN	MAX	MAX
			Merit value	**39.60%**	**92.13%**	**61.44%**

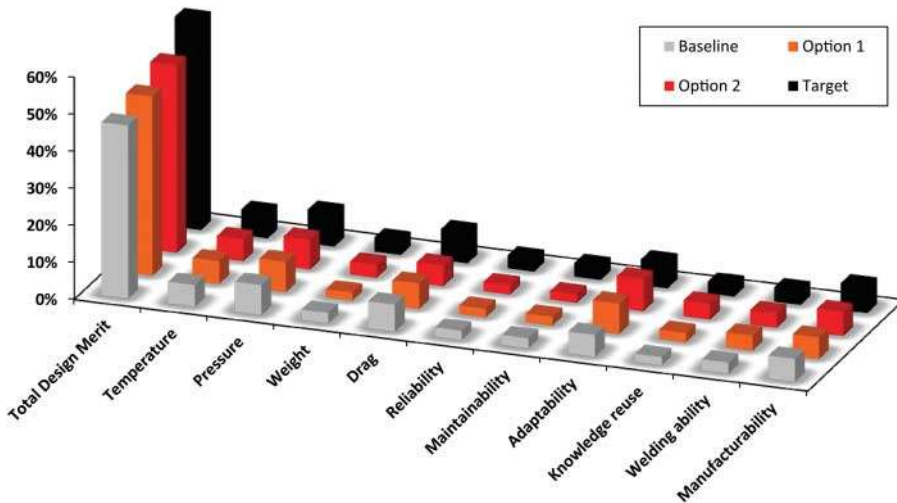Figure 13. Extract from the CODA model developed in case study 2.

Figure 14. Results of the CODA model for case study 2 (fictitious data).

a strong correlation (0.9) with *Drag*, a medium correlation (0.3) with *Manufacturability*, and a weak correlation (0.1) with *Knowledge Reuse*. A Relationship Type (Maximise, Minimise, and Optimise) further defines the link between ECs and CNs. In the example, *Drag* is improved when the friction coefficient is minimised, while *Manufacturability* and *Knowledge Reuse* are maximised, because a better surface finishing causes longer production lead-time and requires a higher level of expertise to be executed.

Eventually, the CODA method rendered an ODM for each option. These ODMs are the sums of the merits calculated for the different parts (of each Design Option) and for the different CNs. Figure 14 summarises the outcome of the CODA model for the considered IMC configurations. It is also possible to further define a Target option, which expresses the desirable outcome of the design task. The empirical study has shown that such target reflects a vision emerging from long-term forecasts. In the example shown in Figure 14, the Target option value is calculated as 120% of the baseline value contribution.

6. Discussion

There is an increasing level of awareness and interest in value assessment as being an integral part of SE practices in the aerospace industry. Discussions with aerospace companies have highlighted the opportunity to apply the CODA method as a means to use multiple value dimensions and value drivers to guide design trade-offs that deal with multiple levels of customers (customers of the customer) in the EE, and to use them both when mature requirements are not yet available, and even later on in the development cycle when value-driven requirements have been cascaded throughout the EE. In this perspective, the CODA method has been acknowledged to represent a step forward in terms of a more robust approach to capture, consolidate, and prioritise external and internal stakeholder needs (that may be based on concrete customer expectations) and to link them to the product's ECs.

Validation activities have been conducted with the industrial partners to assess the feasibility of the approach, in training sessions involving about 50 people (engineers, designers, managers). By means of live demonstrations and small-scale exercises, which were followed up by a questionnaire, the authors have received qualitative feedback from engineers and project stakeholders about strengths and opportunities related to the implementation of CODA for aero-engine component design. As main findings from these activities, the authors observed that the approach can enhance awareness on:

- The relative importance of the needs cascaded down from the system integrators, enabling the design teams to better identify the most important dimension to prioritise from the beginning of the design activity and thereby reduce corrective rework in later design phases.
- The relations between system-level needs and the ECs of the specific components to be designed, mainly because non-linear merit functions are believed to better approximate the customer response to changes in product attributes compared to QFD or other approaches.
- The reliability of the value analysis, through the use of knowledge maturity assessments as part of the conceptual trade-off analysis.

In the long run, the implementation of approaches like CODA that emphasise and support the early exchange of value-related information between organisations within the EE need to be followed by radical changes in the way in which such companies collaborate, including legal aspects of their relationships. A higher degree of openness and trust between the collaborating partners is a prerequisite to prepare the necessary context for the effective and efficient application of such value models for the benefit of all participating organisations. From a technological perspective, the degree of interoperability between systems has to be improved to enable access to value models at different levels of the EE in order to support overall value optimisation at the integrated product or system level, based on joint value analyses with different parts of the supply network.

The behavioural digital aircraft (BDA) developed in the EU FP7 CRESCENDO project (CRESCENDO 2012) is a significant step forward in this direction. The BDA can be viewed as a federated information system that, among other purposes, can be used by the partners in the EE in order to interact with value models across the network with seamless interoperability, including hierarchical, cross-functional, and contextual associativity.

Last but not least, all these changes will have to be accompanied by a deep cultural shift. Nowadays, design and development activities are challenged by a company culture that encourages working with structured information only. The qualitative nature of the value analysis is a main obstacle for its widespread adoption in product development activities; hence the actors in the design process have to become more acquainted with working with qualitative inputs and have to be prepared to deal with ambiguities better than is often the case today.

7. Conclusions

Value models were a curiosity in this sector in the 1990s, while nowadays they seem to have become a standard feature of aerospace programmes. Meanwhile, a plethora of value-driven approaches have been described, with the majority focusing on the economic aspects of value only. Very few real-life examples, however, can be observed, and most of the approaches remain only at a conceptual level of maturity.

The VDD methodology described in this paper is a multidimensional, value-driven, iterative, context-specific approach to optimising the overall value contributions of an integrated system or product at the highest integration level as opposed to local levels.

This paper further presented the CODA method, one example of a suitable method that is capable of supporting the described VDD methodology. The CODA was described in detail and its applicability demonstrated in two different case studies of increasing complexity. The method requires a number of educated guesses, group decisions, and assumptions to be made during the mapping of CNs into ECs. If there are N ECs and M CNs in a model, there will be $M \times (M-1)/2$ decisions to be made while calculating the normalised weights of the CNs in the binary weighting method and potentially $4 \times N \times M$ decisions during the mapping process. However, the number of decisions to be made for a CODA model is comparable to any QFD model with similar number of CNs and ECs. And, the CODA method provides a single normalised scalar output (i.e. the ODM) which is a function of N ECs of the design. This ODM metric simply becomes the objective function and it can easily be used in design assessments, trade-off studies, sensitivity analyses, and engineering design optimisation studies.

One of the biggest obstacles to the implementation of innovative approaches such as the VDD methodology – that enables the early, iterative, and concurrent development of context-specific, multidimensional, value-driven requirements throughout the EE – is the current way companies relate to each other at least in the aerospace industry. In other words, the proposed way of working depends to a large extent on the presence of 'strategic' partnerships between companies of the EE because sensitive information has to be exchanged across several levels of the EE very early in a development programme, whereas such exchanges were previously not possible before detailed contracts including requirements had been signed.

Acknowledgements

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