



NONLINEAR QUALITY FUNCTION DEPLOYMENT: AN EXPERIMENTAL ANALYSIS

Bertoni, Marco; Bertoni, Alessandro
Blekinge Institute of Technology, Sweden

Abstract

Quality Function Deployment (QFD) is a common model to frontload engineering design activities with, linking the characteristics of a product vs. the voice of the customer using linear relationships. This approximation is often claimed to be misleading when dealing with the design of complex engineering systems. The paper presents the results of experimental activities aimed at verifying usability and effectiveness of nonlinear functions as extension of the QFD logic. A total of 40 experiments was conducted in a given design episode, involving 139 participants, to analyse the trade-off between the benefit of introducing nonlinearity vs. effort and cost triggered by increased complexity in the modelling. The results show that nonlinear functions, while improving the granularity of the QFD mapping, keeps the method simple enough to work as ‘boundary object’ in cross-functional design teams, irrespectively from the experience of design team members. The experiments also highlight how users’ cognitive attention in the task is dependent from the format by which nonlinear merit functions are presented.

Keywords: Quality Function Deployment, Design methods, Decision making, Early design phases, Evaluation

Contact:

Dr. Marco Bertoni
Blekinge Institute of Technology
Department of Mechanical Engineering
Sweden
marco.bertoni@bth.se

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1 INTRODUCTION

Quality Function Deployment (QFD) (Akao 1990) is surveyed to be one of most popular methods to support early stage design decision-making (Cristiano et al. 2000; Kara et al. 2014). Literature values its ability to guide the establishment of appropriate system requirements from the initial Voice of the Customer (VoC) (Ullman, 1992, p.112; Roozenburg and Eekels, 1995, p. 155; Wright, 1998, p. 234; Volland, 2004, p.442; Ulrich and Eppinger, 2012, p. 75), and stresses the important role played by QFD during early design, a stage where the most influential decisions about a future system configuration are taken (Ullman, 1992; Krishnan and Ulrich, 2001; Ulrich and Eppinger, 2012).

QFD far-reaching popularity has not prevented authors (e.g., Eres et al., 2014, Zhang et al., 2015) to raise concerns about the lack of depth and detail of the method, which compromises its ability to effectively ‘front load’ the engineering design process. Frontloading refers to the activity of moving or ‘loading’ problem identification and solutions generation as much as possible backward in time, to what is called the “front” of the process (Thomke and Fujimoto, 2000), to mitigate the risk for corrective rework later in the process. A main reason for this is that QFD assumes the existence of a linear relationship between the characteristics of a product vs. customer desire (Busacca and Padula 2005), while this was demonstrated to be highly nonlinear (Thurston, 2001; Kim and Xirouchakis, 2010; Erginel, 2010). Informing the design team of the complex and rich nature of such dependencies is important to mitigate the risk of taking wrong decisions about which attributes should be offered to increase customer satisfaction (Huiskonen and Pirttilä, 1998; Tontini, 2007).

QFD extensions, in form of convex and concave merit functions, are often proposed (Bertoni et al., 2013, Eres et al., 2014; Khamuknin et al., 2015) to cope with the above issue; still their added value for the engineering design decision making process has not been assessed and verified with much detail. The paper objective is therefore to present the results of experimental activities intended to verify usability and effectiveness of nonlinear functions as extensions of the QFD logic. The experiments have focused on the trade-off between benefit of their introduction vs. effort and cost due to increased complexity, and aimed at testing the following two hypotheses:

- H1: The designers’ agreement on setting nonlinear merit functions does not differ from the agreement in setting traditional QFD correlations.
- H2: The outcomes of QFD obtained by setting nonlinear merit functions are independent from the previous experience of the design team members.

Based on the experimental results, the paper further discusses and elaborates on how to nonlinear QFD may be considered a suitable trade-off between simplicity and detail when mapping VoC and product/service attributes during early design.

2 NONLINEAR QFD: APPROACHES AND EXPERIMENTATIONS

The relationship between product requirements and customer satisfaction is often explained as: the more the performances of a product (hardware and related services) increase, the more customer satisfaction is achieved (Huiskonen and Pirttila, 1998; Busacca and Padula, 2005). The work of Kano (1995) claims that such relationship exhibits a nonlinear pattern, and that requirements may bring more than proportional satisfaction to customers: while customer satisfaction is linear with one-dimensional performance needs, basic needs and so-called attractive needs show a different behaviour.

Integrating a Kano logic into QFD may therefore enhance designers’ understanding of the original customer needs (Tan and Shen, 2000, Sireli et al., 2007). However, QFD struggles to realistically model nonlinear phenomena (Erginel, 2010, Zhang et al., 2015); hence the use of artificial neural networks is often proposed as possible solution (e.g., Tong et al., 2004; Hassan et al., 2016). However, neural networks and derivatives require a large amount of precise and objective information about problems and possible solutions (Kwong et al., 2007), which are typically not available in early design (Rosenman, 1993).

An alternative approach is to replace QFD linear numeric relationships with nonlinear merit functions (Zhang et al., 2014), Eres et al. (2014) and Khamuknin et al. (2015) elaborate on what type of nonlinearity is the best fit-for-purpose to support early stage decisions. They prescribe the use of the three characteristic exponential curves proposed by Taguchi et al. (1989), indicating them as the most reasonable approximation of customers’ response to changes in a product attribute, These curves, which take the form of maximization (Max), minimization (Min), optimization (Opt) and avoidance (Avo)

functions, are intended to measure user dissatisfaction about a product performance that deviates from a target value (Belavendram, 1995), as well as to facilitate the use of numerical search techniques in the process (Feneley et al., 2003).

Figure 1 shows the exponential shape of the Max and Min functions. Max functions describe the increase in customer satisfaction with regards to the increase of the value of a requirement (ρ). This value equals 0 as far as $\rho=0$, and it asymptotically gets closer to 1 as far as ρ increases. The value of the neutral point η , which expresses the value of ρ by which customer satisfaction equals to 1/2, determines the slope of the function. Min functions work in a similar manner but with an opposite logic, going from a design merit of 1 to a design merit asymptotic to zero as far as the value of ρ increases. The shape of Opt and Avo functions mirrors that of a Gaussian distribution anchored on a preferred target value. This value indicates a customer satisfaction of 1 in the first case, and of 0 in the second case. Their shape is further regulated by a so-called tolerance point (τ), which works in a similar way as the neutral point η .

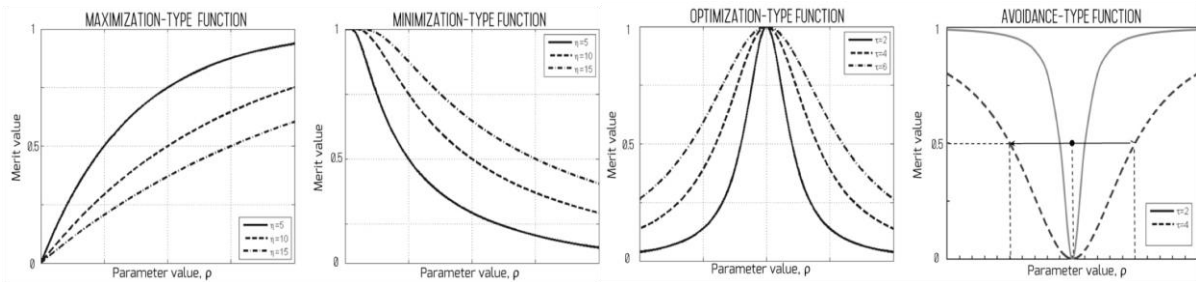


Figure 1. Nonlinear merit functions (Eres et al., 2014; Khamuknin et al. 2015)

2.1 Experimenting with QFD

Historically, QFD experimentations have had a twofold purpose. Most often testing activities aimed at verifying the intrinsic consistency of the QFD logic, for instance verifying the use of alternatives numerical values for the correlations populating the intersection in the matrix. Less often authors have investigated the effect QFD has on design decision making, and on the identification of the best possible design. Ghiya et al. (1999) fall in the first category. By using as example a real industrial case, they verified QFD robustness for small changes in the value of correlations and in the importance of customer demands. They concluded that the elimination of weak correlations, or the variation of the importance of a weight by one unit, makes little effect on the final QFD results. Olewnik and Lewis (2008) analysed the effect to the final weight and rank of a technical attribute triggered by a change in the density of a QFD column. Statistical evidence shows that there is no effect in the final quantitative results due to quantitative scale choice: while an effect was observed when changing from 2 over 5 to 3 over 5 the density of a column, the same effect is not present when changing the density from 3 over 5 to 4 over 5. The authors further apply random processes to simulate QFD results and verify: (1) the insertion of discrete uniform random numbers, (2) the arbitrary insertion of 3-number scoring scale, and (3) the arbitrary insertion of discrete uniform random numbers. The results indicate that the random numbers generation produced results numerically similar those scales typically used in the QFD. This brought them to question if the traditionally used scales are a meaningful representation of the relationships between customer needs and technical attributes. Iqbal et al. (2014) further demonstrated that, regardless of the choice of the rating scale applied, QFD results do not sensibly change: the final weights that are significant will generally remain so, independently from the scale applied.

Moskowitz and Kim (1997) fall in the second category. They present a test with students and practitioners team on a computer-based extension of QFD, named ‘QFD optimizer’, to reveal if the use of QFD as a decision support system worked as a facilitator to find feasible designs. A so called ‘feasibility ratio’ was defined as key metrics: this was determined by the number of feasible designs vs. the number of design attempts. After observing and interpreting the results of group work, they concluded that QFD optimizer allowed to find feasible designs more rapidly and could also be used as an effective training tool.

A reflection from reviewing experimental efforts is that most of the verification activities on QFD have focused on applying numerical simulations on a set of predefined correlations, while less attention has been paid to the analysis of the performances of different design teams using QFD to face the same design challenge. While Moskowitz and Kim (1997) did perform a comparative experiment on the QFD

Optimizer, the aim of their work was neither to verify the QFD underlying logic, nor to test types of correlations more complex than traditional numerical linear scales.

3 EXPERIMENTING NONLINEAR MERIT FUNCTIONS USAGE: SETUP

Eres et al. (2014) report on the application of nonlinear merit functions in an educational example related to the conceptual design stage of a bicycle wheel. The example illustrates how nonlinear QFD is used to correlate requirements (e.g., the ‘diameter’ of a tire) with the higher-level needs (e.g. the concept of ‘stiffness’). The experimental activity is based on such example: the authors created a fictional design episode concerning the selection of a bike wheel concept from a set of available options. In the experiment, participants were tasked to populate 2 separate QFD matrixes: the first one only with correlation coefficients (0-0,1-0,3-0,9), and the second one with both correlation coefficients and nonlinear functions. An ‘experiment controller’ facilitated the design session as suggested by Cash et al. (2012). This two-step design (Figure 2) fulfils the purpose of letting participants to get acquainted with QFD logic, so to focus their attention on populating the matrix and setting relationships in the second iteration, rather than discussing the technicalities of the exercise.



Figure 2. Experiment setup, process and supporting tools

In the initial 10-minute introduction the facilitator explained the objectives of the session, the tasks, the features of the provided QFD template (in paper-based A3 format), and provided other contextual information about the component to be designed.

In the first QFD iteration, all teams were given a 20-minute time slot and were asked to populate with correlation coefficients each intersection between super-system level (see: Hubka and Eder, 1988) needs (i.e., related to the bike and its operational environment) and system needs (i.e., related to the bike wheel) (Table 1). Super-system needs are thought as keywords that mirror the customer usage experience of the bike along its lifecycle. System needs are attached and relate to how customers experience the bike wheel within such super-system. Importantly, both lists of needs are solution independent; hence they do not feature a unit of measure.

The 10-minute introduction to the second iteration was meant to verify the alignment between teams, as well as to clarify remaining issues about the task and about the use of the provided material. It was also meant to introduce the second QFD template, to explain the meaning of ‘system requirements’, and the concept of nonlinear merit functions.

In the second QFD iteration teams were given a 25-minute time slot and were asked to populate each intersection between system-level needs and system requirements (Table 1) with correlation coefficients and nonlinear functions. The latter (Max, Min and Opt) were taken from the original example proposed Eres et al. (2014), which did not feature Avo functions. At the end of the session, templates were collected from the groups and data were manually imported from the paper-based template to the software environment to be analysed.

Even if a longer session would have been beneficial for the study, previous research (Tsenn et al., 2014) has shown benefits in constraining experimental activities in design episodes shorter than 1 hour. Also, the experiment aimed at observing how intuitive the process of setting functions is, compared to a traditional QFD. In this spirit speed was more important than precision: the experiment emphasized how quickly teams agree on functions rather than numbers, and the constrained timeframe helped in this respect.

Table 1. Super-system/system needs and system requirements used in the experiment

| Super-system needs | Phase 1 QFD mapping | System needs | Phase 2 QFD mapping | System requirements |
|--------------------|--|-------------------|---|-------------------------|
| Vibrations | Correlation coefficients (0-0.1-0.3-0.9) | Stiffness | Correlation coefficients (0-0.1-0.3-0.9) | Tire diameter (inches) |
| Noise | | Drag/Friction | | |
| Top speed | | Weight | | Spoke thickness (mm) |
| Grip | | Manufacturability | | |
| All-terrain | | Reparability | Nonlinear functions (none, Max, Min, Opt) | Reuse of composite (mm) |
| Robustness | | | | |
| Maintenance | | | | Tire width (mm) |

The experiment was repeated in the same fashion in 6 different events, involving students and practitioners from industry. A total of 139 people were involved: 61 Master programme students at the authors' home university, 45 engineers/managers working for an aerospace manufacturing company, 24 engineers/managers working for a telecommunication company, and 9 researchers and practitioners from industry and academia. The participants were divided into teams of 3 to 4 people, with care of avoiding mixing practitioners from different companies in the same team, or to mix students with practitioners. This rendered a total of 40 teams: 13 teams of aerospace practitioners, 7 teams from the telecommunication sector, 3 teams of industrial-academic practitioners, and 17 teams of students. All teams received the same task to be performed in the same timeframe. Each team worked on the task independently without interaction with other teams. To avoid biases in their performances, participants were unaware of the purpose of the experiment for the part that concerned comparing the use of nonlinear merit functions against the correlation coefficients.

4 EXPERIMENTING NONLINEAR MERIT FUNCTIONS USAGE: RESULTS

4.1 Verification of H1

H1 was verified by comparing coefficients (0-0,1-0,3-0,9) and functions (none, Max, Min, Opt) entered by the teams in the provided template during the second phase of the experiment. Initially, the authors spotlighted the most popular coefficients/functions at each intersection of the matrix, to calculate the percentage of teams agreeing on the most popular choice. This is defined as the level of agreement on an 'unique coefficient' (UC) and on an 'unique function' (UF).

Table 2 shows the results for both UC and UF during phase 2. The average agreement on UC along the 20 QFD matrix intersections is 55.2%, with a standard deviation of 16.3%. The highest registered agreement is 95%, meaning that in one specific intersection 38 out of 40 teams selected the same coefficient, while the remaining 2 chose differently. The lowest registered agreement is 37.5 %, which corresponds to 15 out of 40 teams. The average agreement on a UF is 58.1% with a standard deviation of 11.3%. The highest registered agreement is 75%, while the lowest is 39.3 %.

The Fleiss' Kappa value (Fleiss, 1971), which reflects the level of agreement in a classification over those agreements that could have happened by chance, was used to verify the statistical significance of the result. The value is suited for calculation in which many 'raters' (the 40 teams in this case) express ratings by binary or categorical variables. While there is not agreement on the significance of the Fleiss' Kappa values in the domain of engineering design, work in the medical field (Altman, 1991) suggest defining values of Kappa between 0.0 and 0.2 as poor agreement, between 0.2 and 0.4 as fair agreement, between 0.4 and 0.6 as moderate agreement, between 0.6 and 0.8 as substantial agreement, and between 0.8 and 1 as almost perfect agreement.

Table 2 shows a Kappa value of 0.2188 for the QFD correlations and of 0.1564 for the nonlinear functions. After eliminating the random component, this shows that the level of agreement in setting correlations is higher than functions. To verify if the difference between the two Kappas coefficients had a statistical significance, the Two-sample Z test was applied to verify the null hypothesis that the expected values of the kappa statistics are equal (with a confidence level of 95%). The obtained P-value is < 0.00001 , which provides a strong evidence to reject the null hypothesis, thus stating that the two Kappas are significantly different.

Table 2. Level of agreement on a unique value

| Correlations in QFD | | Nonlinear functions in QFD | |
|-------------------------------------|--------------------|----------------------------|--------------------|
| Average | Standard deviation | Average | Standard deviation |
| 55.2% | 16.3% | 58.1% | 11.3% |
| Fleiss' Kappa | Standard Error | Fleiss' Kappa | Standard Error |
| 0.2188 | 0.0047 | 0.1564 | 0.0048 |
| Two-sample Z test ($\alpha=95\%$) | | Z= 9.19 | |
| P-value is < 0.00001 | | | |

The distribution of values across all the range of possible choices (0-0,1-0,3-0,9) for the coefficients, Max, Min, Opt for the functions) suggested the authors to further aggregate the data and observe situations where the teams pointed to opposite relationships. The latter was considered a good proxy to assess to what extent the underlying logic of the ‘functions’ was easy to grasp by the participants. Also in this case, the analysis was comparative: the authors considered the most popular value chosen at each intersection, and measured the number of teams aligning with the most popular choice, plus those selecting consecutive/non-opposite values. The authors defined ‘consecutive correlations’ (CC) the following pairs: 0.9-0.3, 0.3-0.1 and 0.1-0, while ‘consecutive functions’ (CF) the Max-Opt and Min-Op pairs. Also in this case the agreement on CC and CF was represented as a percentage of the total answers.

Table 3 shows that the average agreement of the teams in choosing the most popular coefficient or a consecutive one is equal to 82.5%, with a standard deviation of 11.8%. The maximum value recorded across the experiment is 93.3%, while the minimum is 69.3%. At the same time, the average agreement of the teams in choosing the most popular function or a consecutive one is equal to 82.8%, with a standard deviation of 7.0%. These results spotlight that the difference in both average and standard deviation between the two variables is reduced compared with the agreement on a unique value.

Table 3. Level of agreement on two consecutive correlations or non-opposite functions

| Correlations in QFD | | Nonlinear functions in QFD | |
|---------------------|--------------------|----------------------------|--------------------|
| Average | Standard deviation | Average | Standard deviation |
| Average | Standard deviation | Average | Standard deviation |
| 82.5% | 11.8% | 82.8% | 7.0% |

4.2 Verification of H2

The experiment aimed at verifying H2, which is at observing if the participants’ previous experience had an impact on the way teams set the nonlinear merit functions. Sample data were divided between ‘students’ and ‘practitioners’, with the first consisting of 17 teams and the second one consisting of 23 teams. Being a practitioner was considered as a good proxy for ‘previous experience’, under the assumption that students knew about the use of QFD through their academic courses, while practitioners could count, in addition to this, on a larger set of lessons learned emerging from previous case studies at the company.

Differently from the activities aiming at verifying H1, which featured the use of the Fleiss Kappa to express the level of agreement in a classification in the presence on many raters, H2 was corroborated by computing the p-value of the Pearson Chi-Square (Table 4), to verify if there was a statistically significant variation in the answers of the two categories

A 95% confidence level was considered as suitable for the analysis. None of the correlations listed in Table 4 showed a p-value lower than the confidence level (i.e. <0.05). This suggests the absence of a correlation between the team composition and how the teams have set the nonlinear merit functions. From the results of this analysis, it is possible to state with good level of confidence that the previous experience of the team members did not affect the way nonlinear merit functions were set during the second phase of the experiment.

Table 4. P-Value obtained at each matrix intersection (Chi-Square test)

| Intersection | | P-value of Pearson Chi-Square | |
|--------------------------------|-------|-------------------------------------|-------|
| Stiffness - Diameter | 0.414 | Stiffness - Spoke Thickness | 0.415 |
| Friction - Diameter | 0.582 | Friction - Spoke Thickness | 0.109 |
| Weight - Diameter | 0.412 | Weight - Spoke Thickness | 0.641 |
| Manufacturability - Diameter | 0.645 | Manufacturability - Spoke Thickness | 0.628 |
| Reparability - Diameter | 0.601 | Reparability - Spoke Thickness | 0.884 |
| Stiffness - Tire width | 0.634 | Stiffness - Composite | 0.776 |
| Friction- Tire width | 0.676 | Friction - Composite | 0.241 |
| Weight - Tire width | 0.963 | Weigh - Composite | 0.468 |
| Manufacturability - Tire width | 0.619 | Manufacturability - Composite | 0.238 |
| Reparability - Tire width | 0.910 | Reparability - Composite | 0.112 |
| Stiffness - Diameter | 0.414 | Stiffness - Spoke Thickness | 0.415 |

5 DISCUSSION

5.1 H1 is rejected, needing further verification

While design teams successfully manage to set both correlations and functions under time pressure, Fleiss' Kappa analysis shows that, after removing the statistical random component, the agreement on setting an UF statistically differs from that of an UC, the latter featuring a higher score (0.2188 vs. 0.1564). It is hard to state with certainty how relevant this difference is in practice, and the level of 'disagreement' that can be accepted in a preliminary design context. It shall also be noticed that, when extending the analysis to CC and CF, functions shows higher average agreement with a lower standard deviation than correlations, something apparently in contrast with the Fleiss K calculation. This might imply that functions increase the complexity of the QFD analysis only to a limited extent, most likely without sensibly affecting the results of the analysis. Nevertheless, such statement cannot be supported by strong empirical evidence and shall be deeper verified in future research.

5.2 H2 is accepted

The behaviour of students compared to practitioners didn't shown any statistically relevant difference. The authors conclude that the outcomes of setting of nonlinear merit functions are independent from the previous experience of the design teams' members. The proposed template was equally understood by experts and non-experts, indicating that previous experience does not play a relevant role in the use of the QFD extension. More in general, results seem to support the hypothesis that nonlinear merit functions are intuitive enough to be used by both experts and non-experts and that their integration in system design would not negatively affect the easiness of use of the QFD.

5.3 Validity of the method

The experiments were conducted in an artificial setting, which is common when testing new design methods and tools (Ellis and Dix, 2006). Master students have been considered as 'advanced beginners' that understand how to design and take situational factors into account (Kleinsmann et al., 2012). They can also be considered the target population for the development of new methods and tools, as they are soon becoming novice engineers in industry, and they will be actively involved in development projects featuring similar boundary conditions (intensity of teamwork, limitations in the knowledge baseline, deadlines) and problem statements (Bertoni, 2013).

The experiments were run in the same format in each event, which were timely distributed along a period of two years. All groups taking part to the experiments followed a preliminary introduction about the use of QFD and nonlinear merit functions. Practitioners were all enrolled on a voluntary basis: the experiment in this case was part of a course activity (or training session) on the topic of value-driven requirements establishment. Students approached the experiments as an activity in the frame of an academic course in the topic of innovation and value engineering. To mitigate the risk of different levels of motivation between the groups the students' presence to the activity was not mandatory and the results were not considered as part of the course grading.

5.4 Some considerations on the experimental results

The presented experiments aimed at identifying the trade-off between the benefit generated by improving the quality of the QFD mapping process (hence increasing the realism of modelling results) vs. the complexity added by introducing new constructs in its logic. Overall, the experimental results seem to indicate a positive benefit/cost ratio when implementing nonlinear merit functions in the exercise: at each intersection design teams seem able to deal with correlations and functions in similar way, which is the latter does not appear to be detrimental for the first. However, the analysis of the agreement in setting UF and CF raise concerns with regards to possible different interpretations of the meaning of ‘functions’.

It shall be noticed that both students and practitioners were facing a design problem that was somewhat new, apart from generic awareness of the mechanics of a bicycle. The underlying physical laws governing the dynamic of the system might not have been self-evident for everyone, as well as the link between the product and the operations (e.g. the relation between the spoke thickness and its reparability could have been difficult to grasp by some). In a real-world scenario, such ambiguity would be realistically addressed by accessing available knowledge, either through a search in databases or by making use of expert judgment, especially for the parts concerning manufacturability or reliability. Since the intuitiveness of the approach was in the focus of the experiments, the high tempo of the exercise did not allow the teams to search for information.

6 CONCLUSIONS AND FUTURE WORK

The assumption that requirements bring more than proportional satisfaction to customers calls for new methods to seamlessly introduce nonlinearity when translating the VoC into engineering characteristics of a design. The experimental verification sheds a light on usability and effectiveness of nonlinear functions as extensions of the QFD logic. The outcomes of the QFD mapping process is found to be independent from the previous experience of the design team members, which seem to indicate that the proposed extension, while able improve the granularity of the mapping, is kept simple enough to work as ‘boundary object’ in cross-functional design teams. The experiments are unable to confirm, however, that designers’ agreement on setting nonlinear merit functions is close to that of setting traditional correlations.

Current research is focused on the implementation of the proposed QFD extension in industrial case studies, with the objective to measure its effectiveness against the main key performance indicators for engineering design, such as time, cost and quality. Experimentation in these case studies is ongoing, and mainly relate to the design of aero engine sub-systems and components.

A main area of future development concerns improving the rationale capture capability of QFD (Reich, 2000). This is found to be critical to support the definition of neutral values, tolerances, upper limits and lower limits of the proposed exponential functions. The use of the Issue Based Information System (IBIS) technique to build the underlying knowledge base for setting these parameters is currently under investigation.

The experiments also highlighted the role of the format by which nonlinear merit functions are presented, so to capture users’ cognitive attention. Future activities will aim to determine what is the most effective way to complement the traditional QFD matrix-based representation with advanced visualizations, to take advantage of associative processing. The use of an interactive environment providing easy-to-use interfaces to allow engineers to ‘play with the data/functions’ and display the impact of a change in the coefficients and functions is another area of further exploration.

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