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IMPROVING PRODUCTS AND SYSTEMS BY COMBINING AXIOMATIC DESIGN, QUALITY CONTROL-TOOLS AND DESIGNED EXPERIMENTS

Fredrik Engelhardt
fen@cadcam.kth.se
Dep. of Manufacturing Systems, KTH
Visiting scholar dep. Aeronautics and Astronautics, MIT

ABSTRACT

This paper presents an approach for solving design problems. A design analysis with Axiomatic Design, called Design Object Analysis, describes a product or a system in terms of customer needs (CNs), functional requirements (FRs), design parameters (DPs), and process variables (PVs), as well as their associated design matrices (DMs). In this paper the design analysis is combined with a thorough investigation of possible problems within the design, utilizing the seven quality tools, noise factor analysis, and designed experiments to form an approach for quality improvements and problem solving.

The Design Object Analysis helps secure valid input-factors to the designed experiments, and the designed experiments correct or improve the assumptions made in the Design Object Analysis. Thus, a combination of product modeling by Axiomatic Design and designed experiments overcomes shortcomings of the two methods.

The benefits of performing a Design Object Analysis, as compared to other methods, becomes clear when it comes to *evaluating* the results from the designed experiment, and *preventing* the problem. Once the critical parameters are confirmed, and the design matrices are updated, then suggested design improvements can be checked against the design matrices and the system effect of a design-change-order can be estimated.

The approach described in this paper was successfully applied and verified in a case study at a large automotive company.

Keywords: Design Object Analysis; Axiomatic Design; Design of Experiments; quality; Problem solving

1 LARGE AND COMPLEX DESIGN SOLUTIONS YIELD COMPLEX QUALITY PROBLEMS

Numerous design problems are difficult to solve due to the fact that many parameters may contribute to the problem. The internal relationships among these parameters are seldom fully understood. Such design problems could, for instance, be problems regarding car-suspension and its manufacturing, offset screen printing, or aircraft dynamics. Engineers have difficulties finding out which parameters to focus on, and how changes in certain parameters affect the product or system performance. Thus, *how* to perform design changes in complicated products, where a small engineering-change-order affects many other parts of the product, is also an important question that has to be addressed.

The ability to effectively deal with large and complex problems is becoming increasingly important since today's products are built up of many subsystems and more heterogeneous technologies than before, making it harder to gain in-depth understanding of the product. A comprehensive understanding is necessary to solve the design problems described above. The term product is used in this article, but it could also be a system, subsystem, or a process that is investigated.

Engineering design schools provide means for analyzing and understanding the product's design. However, they often rely on subjective engineering judgements when modeling product structure and behavior. When quality problems occur in large and complex products, common sense and engineering knowledge might not suffice to deal with such matters. There is a need for getting *new* knowledge about what parameters contribute to the functional performance of the product, and how they interrelate.

The designed experiment can provide new knowledge regarding product behavior and the effects of various components on performance. However, a designed experiment is dependent on the quality of the experimental input (i.e. the factors in the experiments) to yield good results.

A combination of product modeling by engineering design tools and designed experiments overcome weaknesses of the methods. Engineering design modeling of the product provides good input to the designed experiment, and the designed experiment can correct or improve the assumptions made in the product description phase. The benefit of combining engineering design and designed experiments becomes even clearer when it comes to *evaluating* the results from the designed experiment, and *preventing* the problem.

It is the author's belief that such a combined approach with problem solving in focus will allow faster solution of large and complex quality issues in industry.

The paper begins with a short introduction to engineering design, designed experiments, and Quality Control-tools in section 2. Section 3 presents the combined approach discussed above, and section 4 illustrates this with a case study. Finally, the conclusions are summarized in section 8.

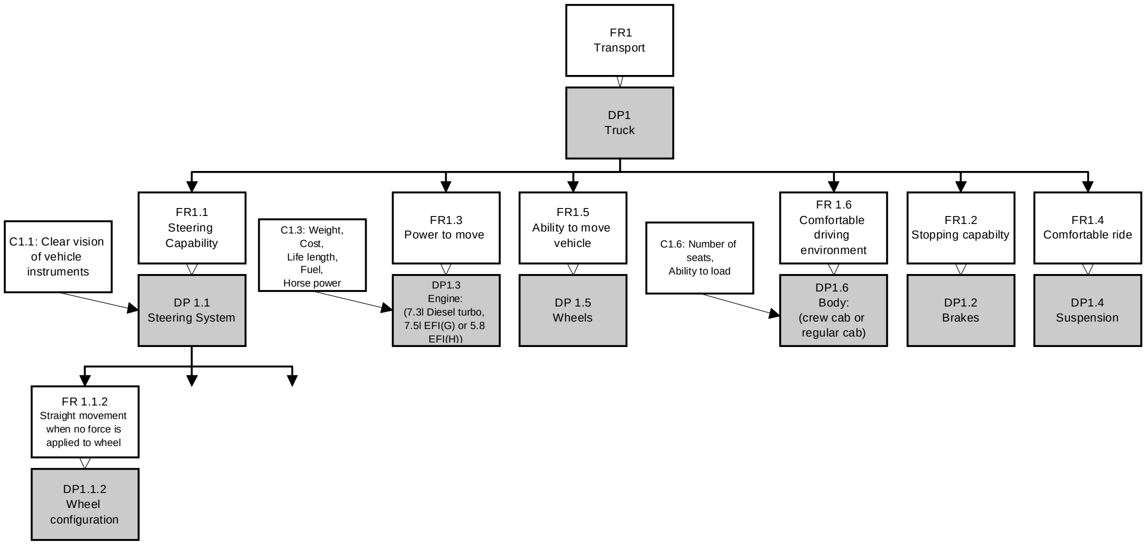

Figure 1. Part of function-means tree from a Design Object Analysis [1].

2 RELATED WORK

2.1 ENGINEERING DESIGN

Engineering design schools could provide part of the knowledge needed for quality improvements by providing engineers with tools necessary for setting up a model of the product. It is important to understand the product during the development phase [2], as well as to understand the completed product, before trying to fix any problems. Engineering design schools stress the importance of a systematic approach to design, as well as some kind of documentation of the product's design parameters and the underlying choices for their selection (see for instance [3-7]).

One way of creating a model of the product is by setting up a function-means tree [8]; see also [9]. The function-means tree is a top-down description of the product, starting with an overall functional requirement (FR; for instance "need of transportation") and the corresponding solution in terms of a design parameter (DP; for instance "truck"). This high-level concept (i.e. need for transportation – truck) is then decomposed into a tree of more detailed functions and design parameters. See Figure 1.

The function-means tree organizes information and provides an overview of the product, but does not facilitate investigation of how different design parameters and their corresponding functional requirements interact.

2.1.1 Axiomatic Design

Using the concept of domains from Axiomatic Design [7] as a framework for developing a function-means tree in combination with design matrices is suitable for design problem solving, since Axiomatic Design specifically addresses the internal relationships between a product's components. Axiomatic Design is a principle-based design method. It is based around the concept of four design domains and the mapping between them, as depicted in Figure 2.

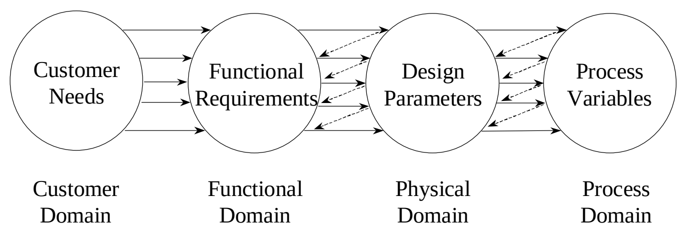

Figure 2. Design domains in Axiomatic Design.

The mapping is often performed between functional requirements (FRs) and design parameters (DPs), but could also be done between design parameters (DPs) and process variables (PVs). This mapping process can be described as in Figure 1, and is represented by the design equation with its associated design matrices (DMs):

$$\{\mathrm{FR}\} = [\mathrm{DM}]\{\mathrm{DP}\} \tag{1}$$

where

$$\mathrm{DM}_{\mathrm{ij}} = \frac{\partial FR_i}{\partial DP_j} \tag{2}$$

There are guidelines provided by axiomatic design theory (consisting of axioms, theorems, and corollaries) about the relations that should exist between the different domains. These guidelines answer the question—will a set of design parameters (DPs) satisfy the functional requirements (FRs) in an acceptable manner? This reasoning should also hold between DPs and process variables (PVs). The relationships between customer needs and FRs, however, are more loosely structured.

Analyzing an existing product with Axiomatic Design is called Design Object Analysis [1, 10, 11]. One major concern with Design Object Analysis and Axiomatic Design, is *how* to specify the design equations displayed in the design matrices (DMs). Often Engineering knowledge is used to define the interrelationships in the DMs, and a simple "X" in the DM indicates an effect, while a "0" indicates no effect.

Since the design equations are crucial steps that guide further design efforts it is important that the DMs are set up correctly. Often there exist different opinions among the engineers on how certain parameters are affecting other DPs and FRs. This phase of a design object analysis can be vastly improved with designed experiments.

2.2 THE DESIGNED EXPERIMENT

One frequently used way of getting information about how different parameters (i.e. DPs) in a product, or process, are related to one another, and to the performance measure of interest, is to use designed experiments. Designed experiments can be carried out in many different ways. For instance Design of Experiments (DoE, see Box et al., [12]), Taguchi Methods [13] or Response Surface Methods (RSM, see [14]) can be used. These methods all assume a set of given factors that may affect the performance measure of interest. Once the *possibly* important factors are selected, the designed experiment finds the active factors, optimum factor values for product performance, or factor settings for variance minimization, etc.

Statistical researchers in the field of designed experiments have put much effort into how best to identify factors that are actively affecting the performance measure, *once the test is carried out* (for instance [15, 16]).

Introducing domain knowledge when evaluating the experimental results has been found effective in selecting factors that are active [17, 18]. However, even though the selection of active factors from those incorporated in the designed experiment can be quite accurate, a poorly defined *input* to a designed experiment nevertheless yields a weak result! Thus, it is crucial to incorporate as much domain specific knowledge, i.e. engineering knowledge, as possible when *selecting* the parameters for the designed experiment.

In order to incorporate the right parameters one should carefully analyze the product.

2.2.1 Planning for a designed experiment

A 13-step approach for *planning* for a designed experiment that focuses on pre-design guide sheets is presented in [19], based on [20]. Coleman et al. acknowledge the importance of relevant background information, such as expert knowledge and physical laws etc., but very little is said about how to gather these relevant details. A drawback of both Montgomery's and Coleman's approach is that the designed experiment is not put in a problem-solving context. See also sections 3 and 3.5.

The designed experiment is put in a problem-solving context by Bergman [21]. Nevertheless, *how* to select factors for a designed experiment, and *how* to implement design changes based upon the result from the designed experiment, are rather neglected in literature.

2.3 THE SEVEN QUALITY CONTROL TOOLS

Another way of gathering knowledge in order to solve quality issues in products is to use the seven quality control tools (seven QC-tools, see [22]). The seven QC-tools are: (1) Data collection, (2) Histogram, (3) Pareto diagram, (4) Ishikawa diagram, (5) Stratification, (6) Graphs, and (7) Control charts.

The QC-tools are a set of simple, and effective, statistical and graphical tools for analyzing data. The seven QC-tools are complementary to designed experiments and can be used as a screening step, in between the Design Object Analysis and the designed experiment, in order to verify the statements from the Design Object Analysis. The root cause of the product's problem can often be found by using the QC-tools, making the designed experiment unnecessary. The seven QC-tools form an effective toolbox, and they should be used when appropriate.

3 AN INTEGRATED DESIGN PROBLEM SOLVING APPROACH

A combined nine-step approach for overcoming the weaknesses of the aforementioned methods is presented in Figure 3. This approach is similar to Bergman's problem solving approach [21], but focuses more on problem solving and the design activities in steps 1 through 4, as well as step 7.

The approach presented in Figure 3 can be summarized as follows: Once a product's problem is thoroughly understood, then Design Object Analysis, with help of Axiomatic Design, is combined with the seven QC-tools, Noise factor analysis, as well as designed experiments. Information gathered is then transferred back to the Design Object Analysis. Design matrices are updated, and redesign and optimization are performed according to the constraints given by the Design Object Analysis.

The approach enables continuous improvements by providing some of the means for organizational learning. Part of a learning organization is increasing corporate memory. A good way of increasing corporate memory is to use Design Object Analysis, and the ideas in Axiomatic Design, to record DPs, FRs and Constraints at component part level. Also the designed experiment and the seven QC-tools increase corporate memory and enable continuos learning.

Below is a description of the 9 steps in Figure 3.

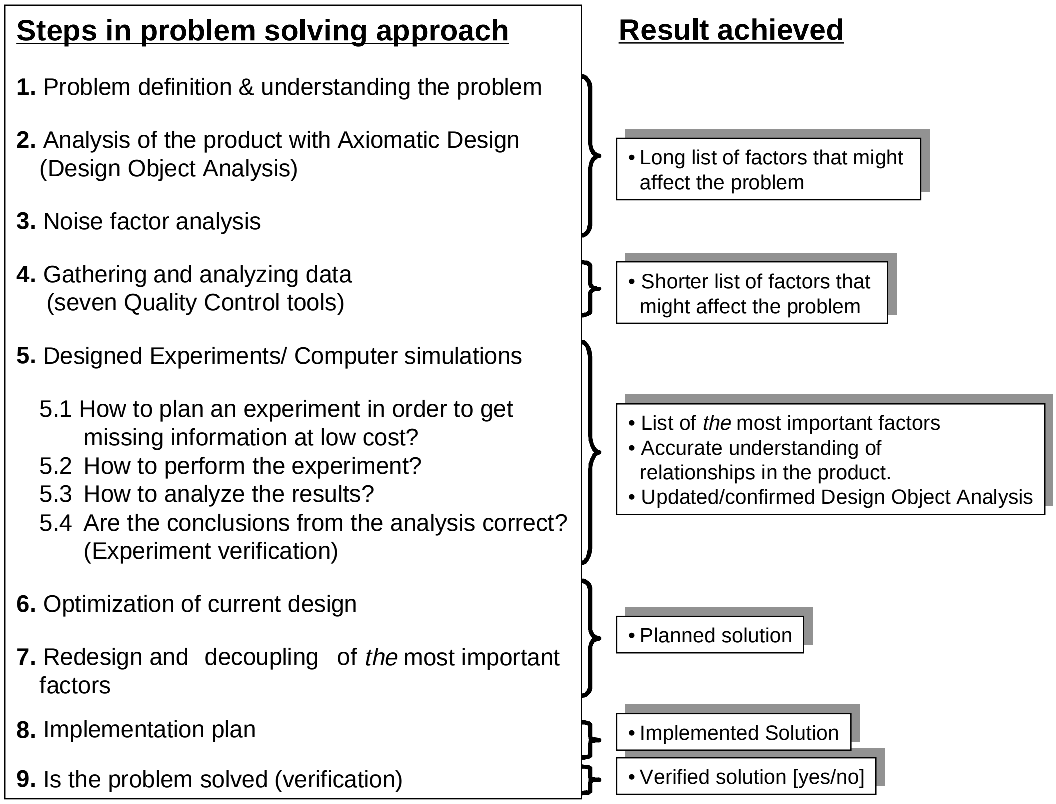

Figure 3. Approach in solving design problems by combining Axiomatic Design, Quality Control tools and designed experiments.

3.1 PROBLEM DEFINITION

Defining the problem correctly is an important and seldom trivial task. If the problem description is vague, then internal and external customer interviews, and Quality Function Deployment could be used to get a more precise problem description (see for instance [3]). The results of the problem definition should be a set of clearly stated objectives for use in the following improvement project. A thorough understanding of the problem is essential for finding a way to solve the problem.

3.2 THE DESIGN OBJECT ANALYSIS

For the design object analysis it is necessary to describe the product from the problem's perspective and set up a function-means tree. "From the problem's perspective" means that in the case of a car suspension problem, for example, the function-means tree will not describe FRs and DPs related to the cars rear light (e.g. elements that obviously not are part of the problem).

The *main* FR is the one FR that is *not* satisfied, thereby indicating the problem of interest. The main FR is one of the FRs in the tree.

Design matrices are set up for all the FR-DP relations at the different levels in each branch of the tree. Special focus is placed on how DPs are affecting the *main* FR. Typical questions that arise during the Design Object Analysis include the following: What are the FRs of this design? Does the design meet all its constraints? Are there any couplings in the design? What FRs do the different DPs (components or parts) satisfy? Does the manufacturing process match the optimal sequence from the design matrices? One interesting feature of a Design Object Analysis occurs when DPs affect a FR in another branch. See Figure 4.

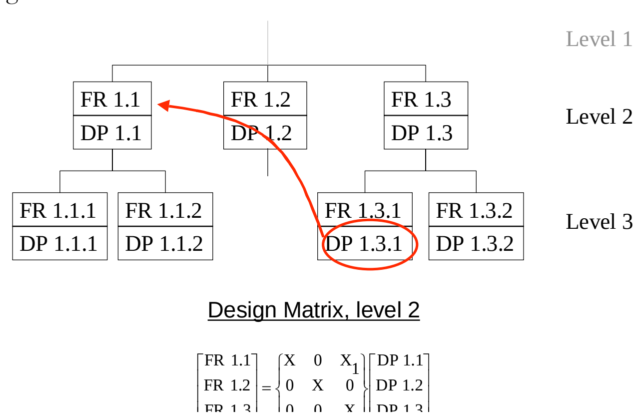

Figure 4. Design Matrix displaying cross-branches relationships.

In Figure 4 the cross-branch affect is displayed in the design matrix by an indexed X (X_1), indicating the indirect affect of DP1.3.1 on FR1.1. This is done at the level where the branches merge in a common design matrix (level 2). Indexed effects can then be described in more detail (origin, reasoning, physical laws, etc.).

To find the factors most likely to have caused the product's problem from the design tree, the design matrices should be examined, with particular attention paid to:

1. "0" elements on the diagonal. These are DPs that affect the main FR, or affect sub-FRs in the same branch as the main FR, and are believed to *not* satisfy their corresponding FRs.
2. Off-diagonal elements. Coupling effects that comes from DPs that affect the main FR without having the main FR as their corresponding FR (i.e. a component in the system that is supposed to have nothing to do with the main FR, but still somehow affects the main FR. For example, truck frame configuration might unintentionally affect truck suspension characteristics). The main FR can be affected directly or indirectly.
3. Sequencing of the DPs. Is the manufacturing system manufacturing the product according to the preferred sequence described by the design matrices and the independence axiom? If not, DPs that relate to such manufacturing processes are very sensitive to disturbances, which may yield quality problems. In other words, they are not robust. In this case, a new sequence of manufacturing operations that better satisfies the independence axiom in axiomatic design, and is more robust to process disturbances, should be found.

The first kind of factors above are related to Axiomatic Design's information axiom (i.e. increase the probability of success), and the second and third kinds of factors relate to the independence axiom (i.e. maintain the independence of FRs).

Gathering expert knowledge about the various components in the product, and how they affect one another, is of the utmost importance if the Design Object Analysis is to be successful. This can be done by interviews with experts, or expert panel groups, etc. The use of cross-functional teams is a good way of obtaining knowledge about the product from many different perspectives.

The function-means tree provides a good overview of the product's structure, which simplifies learning and understanding. This overview is especially important when dealing with large and complex design problems. It helps the team analyze the problem, and manages and displays the many possible roots of the problem and their relationships.

Results achieved from the Design Object Analysis are: (1) a long list of potential factors that might cause the design problem, (2) capture and storage of engineering knowledge in a systematic way, and (3) internal relationships and couplings within the product and the manufacturing system are investigated.

3.3 NOISE FACTOR ANALYSIS

The quality of the product is increased when the product is insensitive (i.e. robust) to disturbances (i.e. noise factors). Robustness is an important aspect of quality, and it can only be addressed once the noise factors are known. In problem solving it is important to analyze how noise factors might be part of the problem. Three major classes of noise factors can be described [13]:

1. *External/Environmental*. Noise due to conditions in which the product is used.
2. *Unit-to-unit variation/Manufacturing variance*. Each unit of a product has unique settings of specific part parameters, and there are always small deviations from written specifications due to manufacturing variance.
3. *Deterioration/Wear*. As time passes individual components may change, leading to deterioration in product performance from specified targets.

The noise factor analysis broadens the long list of possible reasons for the product problem that was found in the Design Object Analysis.

Gathering the noise factors, according to the three classes mentioned above, often requires different kinds of expert knowledge. Knowledge about how the product is used could be acquired through interviews with customers and sales personnel. Unit-to-unit variation is often well understood by manufacturing engineers and other workers in manufacturing. Understanding how parts wear might be achieved in cooperation with reliability engineers. Talking to customers and checking warranty claims also increases the understanding of factors related to wear.

A result that might be achieved from noise factor analysis is, for instance, that noise factors that affect the problem are incorporated in the long list of potential factors that might affect the problem.

3.4 GATHERING AND ANALYZING INFORMATION; 7 QC-TOOLS

This step of the investigation aims at analyzing the long list of factors that might affect the problem. The data analysis and data gathering described in this section should be part of a continuous interplay with the Design Object Analysis. The Design Object Analysis is not a static solution. New information updates the design matrices in the Design Object Analysis. Data analysis is done by utilizing the seven simple but effective statistical quality control tools (QC-tools). The data is often company data related to production, product performance, warranty claims, etc.

Some results achieved from the use of the QC-tools are:

(1) The analysis of data concerned with the long list of parameters described in sections 3.2 and 3.3 excludes the

unimportant factors from the list and creates a shorter list of factors that might affect the problem. (2) It might be possible to identify the root cause of the problem by solely using the 7 QC tools together with the Design Object Analysis. If this is the case, then one may try to solve the problem directly by using Axiomatic Design combined with the already performed Design Object Analysis (see section 3.7). In this case the designed experiment would be ignored. (3) The Design Object Analysis is updated and/or verified by the new information provided by the use of the QC-tools.

3.5 THE DESIGNED EXPERIMENT

The root cause of the problem is now narrowed down to a short list of potential factors and designed experiments can be used to find which factor(s) most affect(s) the quality problem.

In quality improvement work the focus should be on improving the performance robustness, as well as setting the performance value to the target. For these purposes a series of designed experiments are carried out. A sequential approach enables knowledge gained from one experiment to influence the design of the following experiment.

When planning the details for the designed experiments the design matrices can be used as an interaction table, indicating interactions where severe coupling may exist. There are several different approaches for how to design the experiment. See section 2.2. Simpson et al. [23] provides a comprehensive overview of the different ways of using statistics in design, and also presents special circumstances that arise when using statistical experiments in computer simulations.

The specific planning steps 5.1 to 5.4, in Figure 3, are described in more detail in basic statistical and quality literature (see for instance [19, 21]), and will not be discussed in detail here.

It is important not to forget the goal of the experiments and simulations. No matter which method is chosen, one wants to achieve robust products that perform well. Or, in other words, products that perform well under many different conditions. Sometimes specially designed computer simulations can replace physical experimentation.

Some results that can be achieved in the designed experiment phase are:

(1) A list of *the* most important factors. (2) And, an accurate understanding of the physical relationships within the product. This new information facilitates an updated version of the design matrices in the Design Object Analysis.

3.6 OPTIMIZATION OF CURRENT PRODUCT

The result from the designed experiment is used not only to identify the most important factors regarding the quality problem but also suggests settings of parameter values for the most important factors, which will increase performance and robustness. Thus, it may be possible to optimize product performance and quality by implementing suggestions from the designed experiment. Sometimes such an optimization is enough to solve the product's quality problem and no major redesign efforts are necessary. All suggested design changes (redesign or optimization) have to pass the constraints or other trade-offs that prohibit a design change. See also section 3.7.

The results achieved from factor optimization:

New parameter values that optimize the product (if changes are allowed by constraints).

3.7 DESIGN CHANGES

Once the engineering team knows which parameters are most important, they can focus on these parameters and redesign them to solve the problem. The axioms, corollaries, and theorems from Axiomatic Design provide guidance in this effort.

It is important to evaluate how design changes affect related parts of the product, since trade-offs and limitations often are present. The design matrices express relationships between the product's parts, and enables easy tracking of effects resulting from suggested design changes. Limitations in the design often make both optimization and redesign necessary.

The results achieved from this step are planned design changes to solve the product's problem.

3.8 IMPLEMENTATION PLAN

In order to realize the planned improvements, an implementation plan has to be constructed. Some important questions to address are: Responsibilities? Time frame? Budget? Team members? etc.

An implementation plan results in a higher probability of success for the planned improvement efforts.

3.9 IS THE PROBLEM SOLVED?

Following up and confirming that the problem really is solved is important. This might consist of months of measurements and recording of customer feedback. Unless this step indicates that the problem is solved, uncertainty remains about whether or not the problem still is present.

4 AUTOMOTIVE CASE STUDY

The approach presented in this paper was used to deal with an ongoing and complex problem at a large automotive company [1]. How the problem was tackled using the steps presented in Figure 3 is described below.

4.1 PROBLEM DEFINITION

The problem in the study was called "Drift/Pull". A Drift/Pull *problem* is said to exist if a driver takes his hands off the steering wheel at 85 km/h and the vehicle changes lane in less than 10 seconds. Warranty claims due to Drift/Pull in the automotive company's light truck had incurred significant costs. In this case the problem was very precisely defined at the start of the project.

$$\begin{Bmatrix} \text{FR11221 Correct length of spring} \\ \text{FR11222 Correct placement of brackets} \\ \text{FR11223 Correct design of brackets} \end{Bmatrix} = \begin{bmatrix} X & 0 & 0 \\ 0 & X & 0 \\ 0 & 0 & X \end{bmatrix} \begin{Bmatrix} \text{DP11221 Springs horizontal distance X, bracket to steer knuckle bolt} \\ \text{DP11222 Frame distance Y, bracket holes on frame front to rear} \\ \text{DP11223 Placement of spring holes on bracket} \end{Bmatrix} \tag{3}$$

4.2 The Design Object Analysis

In this case the truck was modeled in terms of Axiomatic Design *from the Drift/Pull point of view*. It means that parts of the truck that were believed to be unimportant for Drift/Pull were either not included in the model, or not further decomposed in the function-means tree.

The truck was modeled from above and the system concept was laid out as shown in Figure 1. In parallel, the various design parameters in the assembly drawing were analyzed and their corresponding functional requirements were identified. This "bottom up"-analysis of the assembly drawings was then combined with the "top down" description of the truck concept, and the parts that are interesting from a Drift/Pull perspective build up the function-means tree.

Figure 6 sketches the entire function-means tree, and highlights a close-up of the Drift/Pull branch.

Drift/Pull is related to *not* satisfying the main FR1.1.2 (Straight movement when no force is applied to wheel). In the design the FRs and DPs of the FR1.1.2-branch is meant to satisfy FR1.1.2. In reality many other DPs of the design affect FR1.1.2 too. Various factors affecting FR1.1.2 were identified through a careful investigation of all branches of the function-means tree, and their effects on FR1.1.2. The leaves of the branches in the function-means tree are often physical parts, or parameter values, that can be found in the design drawings or assembly drawings.

Knowledge used for this design analysis came from engineering experts, physical laws, theoretical studies of car suspension, warranty statistics, and product data, etc. Teamwork, and cooperation with experts, were two important aspects in getting an accurate understanding of the truck and the Drift/Pull issue, as well as for correctly defining the function-means tree and the design matrices. The researchers in this study had support from a quality-conscious manager at a high company level. Results achieved in the case study would not have been possible in the relatively short project time-frame (three months) without this managerial support.

4.2.1 Design Matrices

Design matrices were set up for the different levels of the function-means tree. A simple example of a design matrix is given in equation (3), which shows the design matrix 1.1.2.2.x (Front and rear axles parallel) from Figure 6.

In design matrices where non-diagonal elements exist, these elements were indexed (i.e. $X_1, X_2 \ldots X_n$) and explained separately. DPs believed to have some problem fulfilling their corresponding FRs were also discussed separately. Constraints were added for clarity and for making future design changes and trade-off decisions easier.

Factors providing couplings(directly or indirectly), or believed not to fulfill their corresponding FRs, were added to the list of potential factors affecting Drift/Pull.

4.2.2 Manufacturing process analysis

For all design matrices that were created, the corresponding manufacturing processes were studied. It was found that the manufacturing process was seldom adjusted according to the optimal sequence suggested by the equation systems in the design equations, thus making the trucks' Drift/Pull performance sensitive to deviations within the manufacturing process. Some factors were added to the list of potential problem-causing factors due to the manufacturing process analysis, in combination with input from regular suspension theory (for instance the factor: non-parallel axles).

4.2.3 Transformation of factors into a set of more experiment-friendly factors

Thirty-three factors were first identified from the design matrices as being of interest for further investigation. Many of these parameters are related and yield the same kind of affect when changed from their original value. For instance, the DPs that build up (or affect) the axle parallelism are: (1) DP11221 Spring horizontal distance X, "wrap" holes to steer knuckle bolts, (2) DP11222 Frame distance X, bracket holes front to rear, (3) DP11223 Placement of spring holes on bracket. Together these factors form the compound factor "axles not parallel". See Figure 5 for the setup of the DPs above. By combining factors, the long list could be reduced to 16 factors that described the result from the design matrices.

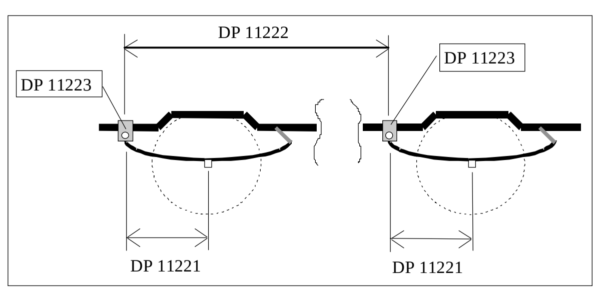

Figure 5. Design parameters (DPs) building up the front to rear axle distance.

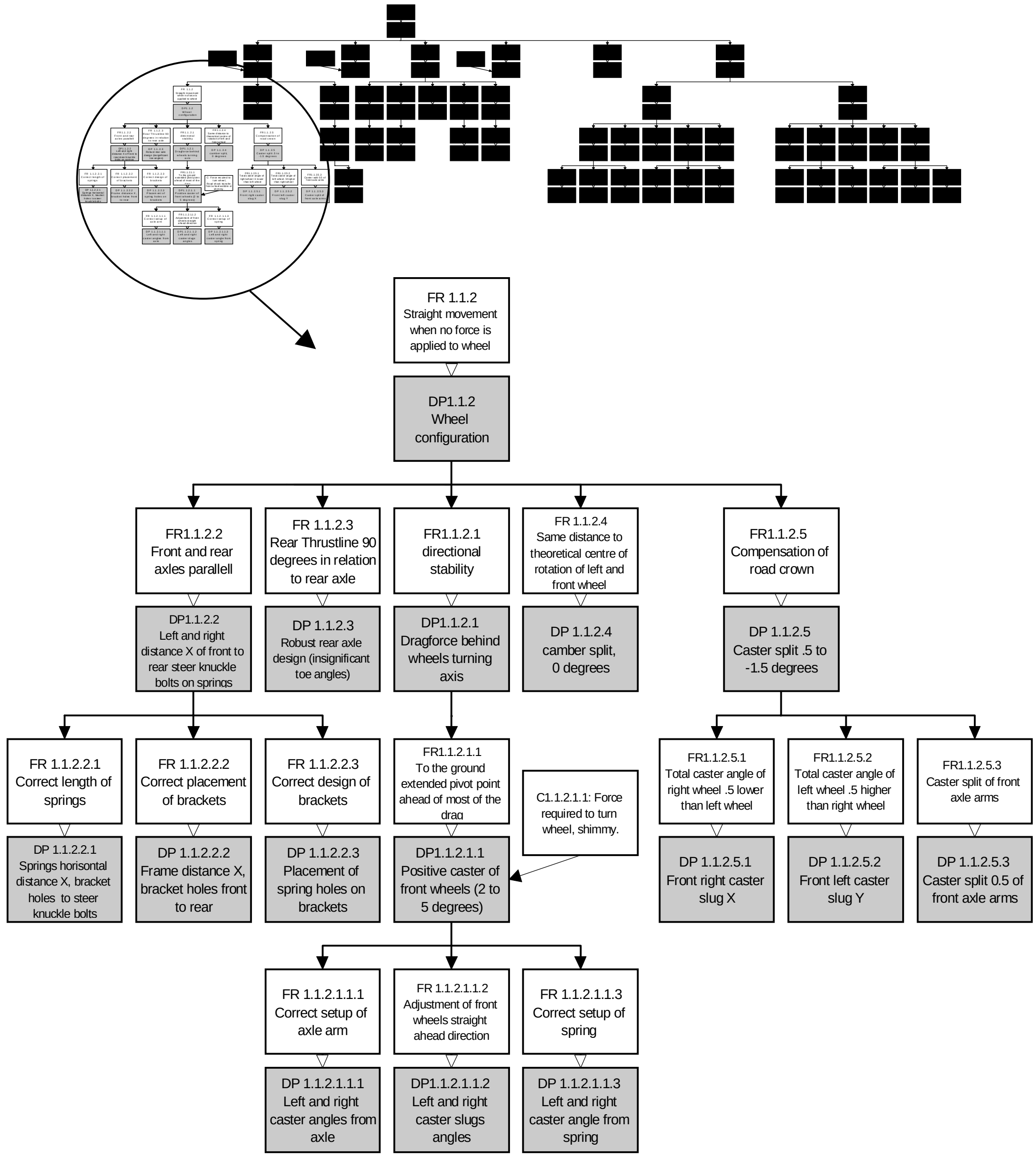

Figure 6. Drift/Pull branch of FR-DP-tree

Result from Design Object Analysis:

A long list of factors that might be the fundamental reason for the Drift/Pull problem. See Table 1. Many of the terms in Table 1 are automotive suspension terms that are explained in [1, 24], for instance.

Table 1. Parameters important to analyze.

1.	Caster angle, front wheels
2.	Caster split angle, front wheels
3.	Camber angle, front wheels
4.	Camber split angle, front wheels
5.	Wheel base
6.	Front and rear axles not parallel
7.	Toe angle, front wheels
8.	SAI angle, front wheels
9.	SAI split angle, front wheels
10.	Different loads on front and rear wheel-pair
11.	Different loads on left and right wheel in the wheel-pairs
12.	Tire RSAT
13.	Tire RSAT split
14.	Tire CRF
15.	Tire CRF split
16.	Different brake force applied to individual wheels without driver braking

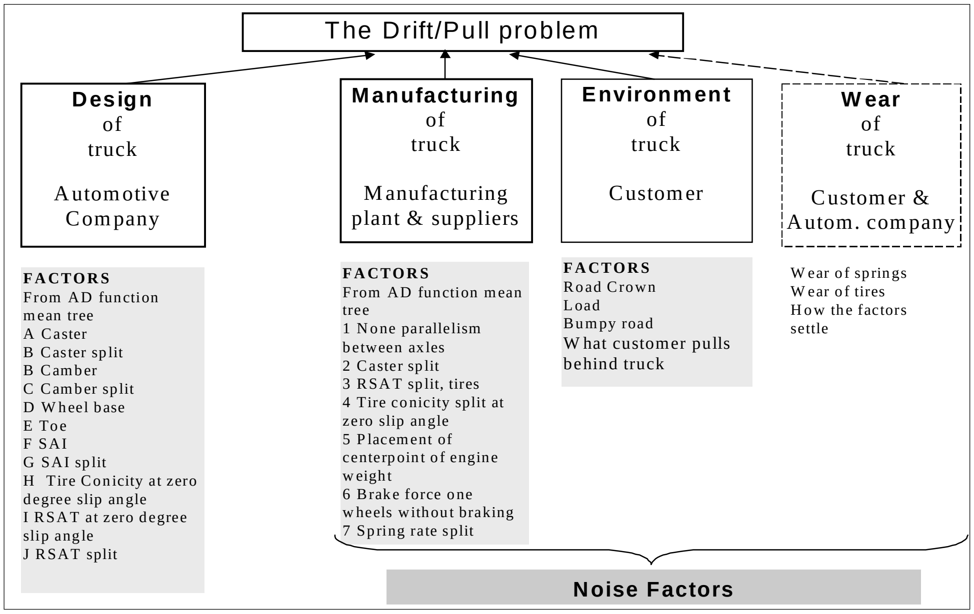

Figure 7. Different noise factors: Manufacturing, Environment, and Wear

4.3 NOISE FACTOR ANALYSIS

The analysis of how noise factors affect Drift/Pull is presented in Figure 7. In order to understand how the environment is influencing Drift/Pull, through customer usage of the truck, it is very important to know the behavior of the customers. In this case the subsequent analysis of company data excluded wear and most of the environmental noise factors from affecting Drift/Pull problem. See section 4.4. The noise factor analysis further extends the long list of factors from the Design Object Analysis. See Figure 7.

4.4 ANALYZING RECORDED TRUCK DATA AND WARRANTY CLAIMS WITH THE 7 QC-TOOLS

Existing data about trucks that were reported as incurring Drift/Pull warranty costs were examined in order to find out which parameters of these trucks might have caused the problem. In doing so, the company's database for warranty claims, and the corresponding data from the manufacturing process, were utilized. Below is a summary of the conclusions achieved. When QC-tools were used it will be indicated by writing the QC-tool in italic.

It was found that the Drift/Pull problem was manufacturing plant related. *Data collection* and construction of *graphs* similar to Figure 8 yielded the conclusion that a very large proportion of the trucks causing Drift/Pull problems exhibited them after low mileage.

Often the problems were apparent at the plant, after leaving the manufacturing line, or after low mileage incurred by either the truck dealer or when the vehicle was first driven by the customer.

This conclusion eliminated the noise factors related to wear of parts, as well as most of the noise factors related to the truck's usage environment. See Figure 8.

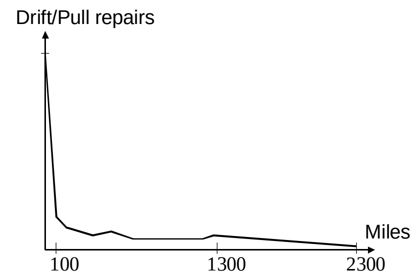

Figure 8. Drift/Pull warranty claims as a function of truck mileage

Suspension parameters were recorded for some of the trucks that caused Drift/Pull. *Graphs* and *histograms* revealed that the settings of classical suspension parameters were not the sole explanation for the Drift/Pull problem. Caster split, for instance, was regarded as the single most important factor to control Drift/Pull, and the only truck that had excessive caster split, out of the ones that caused Drift/Pull drifted the wrong way according to suspension theory. The conclusion from this part of the study was that none of the classical suspension parameters (i.e. caster, caster split, camber, camber split, toe, and toe split) alone cause the Drift/Pull problem.

To evaluate what other factors might be part of the problem, different versions of the truck were investigated. *Stratification* of the warranty data regarding truck model (i.e. different cabs, different wheelbase, different tires, etc.) was performed. Different versions of the trucks turned out to cause different amounts of Drift/Pull warranty claims. In order to understand why this could be, the fundamental differences between the models were examined. These fundamental differences were then related back to the Design Object Analysis and specific factors in the design matrices. For instance, trucks equipped with one brand of tires caused more Drift/Pull problems than trucks equipped with the other tire brand, suggesting that tire characteristics could be an important parameter in the Drift/Pull issue.

Control charts were also made in order to view the impact of previous design changes on the Drift/Pull statistics. It was confirmed that a change in caster split affects the ratio of drift-right and drift-lefts, according to the suspension theory.

Results achieved from using the QC-tools were:

(1) Drift/Pull was, to a large extent, manufacturing-plant related, thus eliminating many possible factors from the noise factors analysis. (2) The long list of potential factors from section 4.3 was shortened and (3) the design matrices from the Design Object Analysis were updated.

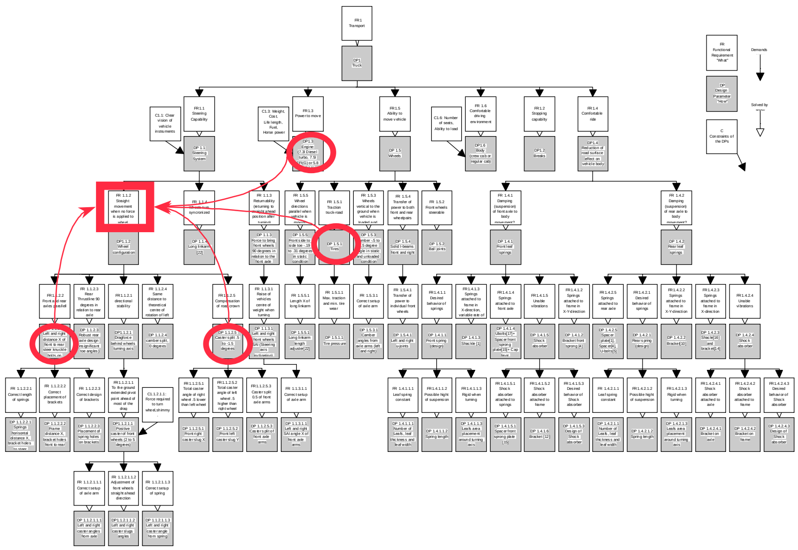

Figure 9. The four most important factors affecting Drift/Pull, displayed in the function-means tree.

4.5 THE DESIGNED EXPERIMENT; IMPROVING MODEL ACCURACY

To find out more about the factors that cause the variation in truck Drift/Pull, it was decided to perform a designed experiment. A computer model of the truck's dynamic behavior was available at the automotive company's Vehicle Dynamics department. This computer model had been verified and constructed with real-life trucks. No simulation regarding Drift/Pull was previously done. The choice of experimental design was the Response Surface Method. The objective was to find out how deviations of the factors in the short list of factors (see section 4.4 and Figure 7) affected Drift/Pull distance and Drift/Pull variance. Since the degrees of freedom for the simulation were limited, all factors could not be included. The factors included in the initial simulation are displayed in Table 2.

A second simulation was performed to evaluate the effect of non-parallel axles.

The result from the designed computer simulation was a short list of *the* most important factors:

1. Caster split

2. Tires, in terms of:
   a) Residual Self-Aligning Torque (RSAT), at zero degree slip angle
   b) Residual Conicity Lateral Force (CRF), at zero degree slip angle

3. Axle parallelism

4. Front weight (center of gravity) bias

The most important factors can also be found in the function-means tree. See Figure 9.
Further results achieved from the computer simulation:

The improved truck model provided by the computer simulation also enabled a *pareto diagram* (see section 2.3) to indicate the relative importance of the 4 factors to Drift/Pull. A spin-off of the computer simulation was a software package, delivered to the manufacturing plant, that allows one to change the settings of the factors included in the test and get the response in terms of new drifting distance and drifting variance. This software can be used as an indicator of the impact of future design changes on Drift/Pull. The designed experiment provided updating and validation of the design matrices from the Design Object Analysis.

Table 2. Factors taken in consideration in computer simulation (Response Surface Method)

FACTORS	Level	Testing Range
1. Average Caster	4°	+/- 1°
2. Caster split	-0.5°	+/- 1°
3. Average Camber	0°	+ 0.6°
4. Camber split	0°	+/- 0.3°
5. Total toe	0.06	+/- 0.2°
6. SAI Left	0°	+/- 0.15 mm
7. SAI Right	0°	+/- 0.15 mm
8. RSAT , at zero ° slip angle	-18 Nm	max. =-5, min. =-1 Nm
9. Conicity (lateral force tire), at zero ° slip angle	100 LB	+/-25 LB for each tire at 0° slip angle
10. Wheel Base	157 inches	- 20 inches
11. Road Crown	0°	+/- 3°
12. Front weight bias	40 LB	max. =-25 LB at curve condition

4.6 OPTIMIZATION OF CURRENT PRODUCT

Some optima were found from analyzing the designed experiments, but they were outside limitations set by other design constraints. The computer model of truck behavior suggested, for instance, the use of increased caster angle for robust straight-ahead movement. This suggested optimization would, however, lead to a large trade-off with other steering features, such as force needed to turn the wheels, etc. Optimization and design changes were closely interrelated and had to be jointly evaluated. See section 4.7.

4.7 DESIGN AND PROCESS CHANGES OF MOST IMPORTANT FACTORS

The pareto-rule was used to focus design improvements on the four most important factors (see section 4.5). The multiple constraints and trade-offs that were present in the truck's design made investigating design changes before implementing them even more important. By utilizing the previously completed Design Object Analysis, it was possible to see how the four most important factors were built up of other factors. For an example see Figure 5. The design matrices were also used to trace the affects of suggested design changes. Time could then be spent on minimizing variance in these factors. Redesign was simplified by using the design support in Axiomatic Design theory.

Examples of some suggested design changes resulting from the redesign phase were:

i. Design changes such as: (1) Switching the loose end of the leaf spring (shackle) from the front end of the leaf spring to the rear end of the spring, making it harder for road shocks to transfer to the vehicle body; (2) A longer stabilizer bar for the front axle will decrease the chance of vibrations (shimmy). (1) and (2) will together ease the constraints on caster angle value, and allow a *larger positive caster angle*, which increases directional stability. Directional stability decreases Drift/Pull.

ii. The forces and torque of the tires at zero degrees slip angle was not considered by tire suppliers. The analysis of the tire values indicates that this has to be done, thus changing the manufacturing process at the supplier and/or at the automotive company.

iii. Spring rate of the leaf springs was found to be part of the front weight bias. One suggested way of minimizing front weight bias was to group the leaf springs according to their spring rate. Springs with approximately the same spring rate are then mounted on one wheel pair, thereby removing the side-to-side difference in spring rate.

iv. A method to maintain the manufacturing process mean centered around a target value of zero trucks with Drift/Pull, was designed by using Drift/Pull warranty data in combination with caster slug changes. Necessary online manufacturing measurements were not possible with the equipment available at the manufacturing plant. This made it necessary to rely on warranty data.

4.8 IMPLEMENTATION PLAN

A formal implementation plan was not set up, since the duration of the author's stay at the automotive company was limited. It was only possible for the author to indirectly affect the implementation plan thorough suggestions. However, the findings from the case study were used by the automotive company to improve Statistical Process Control at the manufacturing plant. This decreased the Drift/Pull problems. Some of the design changes suggested were also implemented in the following model of the truck.

4.9 IS THE PROBLEM SOLVED?

The automotive company was pleased with the new knowledge gained through the case study, as well as with the suggestions made. The problem with Drift/Pull was an ongoing problem that had occurred for 18 years (!), and a drop in Drift/Pull warranty claims has been noticed since the time of the case study. A project follow up in 1999 showed that the case study has successfully been used as a model for Drift/Pull improvements in also other car and truck models with similar suspension made by the company. Results from the case study's designed experiments have also served as a basis for other experiments regarding Drift/Pull issues, and the findings from the case study have been verified. Yet another result from the case study is that it is one of the reasons for the automotive company's decision to completely redesign the front suspension of future trucks.

5 SOME COMPARISONS WITH OTHER METHODS

A competing tool for design analysis is the Design Structure Matrix (DSM, [25]). The DSM investigates how the product's different parameters (i.e. DPs) are related to each other in a way similar to how Design Object Analysis investigates FR-DP relationships in the design matrices. However, some fundamental differences exist.

Axiomatic Design checks that each DP in the product fulfills some kind of function. The Design Structure Matrix checks the relationships among parameters in *what is already designed*, in the product/process (i.e. Strategy-Strategy or DP-DP matrix). This means that the DSM approach takes the design parameters for granted and does not reflect on whether they fulfill any purpose or not. If some DPs are present in the design, but are not needed any more due to repeated carry-overs, for instance, then Axiomatic Design's Design Object Analysis would spot this fact, but DSM would not. DSM has the advantage of displaying the design relationships in a single matrix. This improves the matrix overview. Axiomatic Design is a designing tool and a design analysis tool, whereas DSM is primarily a process/task analysis tool. DSM is descriptive whereas Axiomatic Design is prescriptive.

The Ishikawa diagram is another frequently used tool to structure causes and effects related to quality characteristics (see section 2.3). One major drawback with the Ishikawa diagram, compared with the Design Object Analysis presented in this paper, is that it does not investigate how the causes in the diagram are interrelated. The strength of the Ishikawa diagram is its simplicity. One should not see the Design Object Analysis and the Ishikawa diagrams as opponents.

If the Design Object Analysis is set up to include only the technical and physical aspects of the product, then the Ishikawa diagram might provide means for analyzing the human-factors of the problem. It would still be important to incorporate interrelationship analysis in the Ishikawa diagram, though.

Axiomatic Design has been used to integrate reliability analysis in terms of fault-tree analysis (FTA; see [26] with the overall product design process [27]). The fault-tree analysis itself does not analyze how design changes of certain DPs affects other FRs and DPs of the product, other than that the fault-tree analysis investigates the impact on the fault-probabilities in the fault tree. Fault-tree analysis provides the Design Object Analysis with a tool for measuring performance *over time* (i.e. reliability). Teng et al. use the Military standards for estimating failure probabilities for the various components in the fault tree [28]. The nine-step approach described by the author of this paper could be complemented with a fault-tree analysis in the case when reliability is of special interest. The “top-down” construction of a fault-tree could be complemented with the related “bottom-up” construction of a Failure Mode and Effect Analysis (see for instance [29]).

6 LIMITATIONS OF THE PROPOSED APPROACH

The approach to quality improvements suggested in this paper is developed only for single performance criteria. Another limiting aspect is that the approach is developed for quality issues only in existing products or processes.

7 FURTHER RESEARCH

One interesting topic might be to investigate how the framework of TRIZ [30] could be used to improve step 7 of the suggested approach (redesign and decoupling of the most important factors). Another interesting question to address is the case when multiple quality characteristics are present. How do multiple quality characteristics affect the Design Object Analysis, the use of the QC-tools, and the noise factor analysis?

The approach presented is mainly developed for hardware analysis. It would be interesting to further explore the man-machine interactions in design problem solving, especially when including human-factors in the Design Object Analysis, and thereby mixing man- and machine-parameters in the presented approach. In this case, implications regarding the use of the axioms, corollaries, and theorems from the Axiomatic Design theory are interesting. Applying and adopting the proposed approach to new product development would be exciting. Of course, more case studies have to be performed to further secure the findings presented in this paper.

8 CONCLUSIONS

This paper suggests an approach for combining engineering design theory and designed experiments in order to improve product quality. The approach presented consists of nine steps: (1) Problem definition, (2) Design Object Analysis with Axiomatic Design, (3) Noise factor analysis, (4) Gathering and analyzing data with the seven Quality Control-tools, (5) Designed experiments or computer simulations, (6) Optimization of current design, (7) Redesign and decoupling of *the* most important factors, (8) Implementation plan, (9) Verification of problem solution.

The product analysis, in terms of Design Object Analysis (step 2), is strengthened by knowledge gained from the designed experiment or computer simulation (step 5). The designed experiment, on the other hand, is strengthened by the domain specific product knowledge gathered in the Design Object Analysis, which increases the probability of selecting active factors for the experiment. The two major components of the approach complement each other.

Compared with other approaches to quality improvements, which also promote the use of designed experiments, the approach presented in this paper focuses more on utilizing engineering knowledge in order to select active factors for the experiment. This approach also puts more emphasis on, and provides means for, problem solving once the root causes of the problem are identified. This is done by utilizing the axioms, corollaries, and theorems in Axiomatic Design, in combination with the completed Design Object Analysis, when redesigning the product’s factors or process steps that most affect the quality problem..

This approach should not be followed blindly. It is a *suggested* workflow. The circumstances present in the specific study must be carefully analyzed.

The presented approach was successfully tested on a non-trivial problem, in a case study at an automotive company. The findings from the case study helped to resolve the problem and were verified by subsequent investigations.

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