Effective Product Design through Enhancing Robust Engineering Design and Quality Function Deployment

Mark Anthony Atherton

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To the memory

of

my mother

Irene Atherton

1939 - 1991

"For now we see in a mirror dimly, but then face to face;" 1 Corinthians 13:12

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Declaration

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Abstract

Systematic design methodologies can produce good products particularly where complexity, teamwork and avoiding costly errors are concerned. In this thesis two accepted methodologies have been developed and they are linked to improved design parameter selection in the context of four industrial case studies.

Robust Engineering Design of a product minimises performance variability over its lifecycle; this approach is dependent upon the appropriate selection and configuration of design parameters. Two energy-based approaches have been developed in this research and shown to provide valuable insights. The means for using parameter values from standard production runs have been demonstrated and has incorporated adjustments for unbalanced noise conditions. In addition, a technique for handling multiple objectives has been shown to provide an incentive for continuous improvement based upon competitive benchmarking.

Quality Function Deployment, which processes multiple objectives, has historically been underexploited in terms of the correlations between design parameters. In this thesis enhancements have been made to incorporate identification of causal relationships. This has enabled a graphical representation of the design procedure which clarifies information flow and deepens the understanding of the design problem. Design retrieval has also been enhanced since causal information about parameters can be stored in the correlation roof.

Mark Atherton

Haywards Heath, West Sussex

Chapter 1. Introduction

1.1 The Design Process

1.1.1 What is Design?

1.1.1(a) Definitions of design

Dieter (1983) views design as essentially creating something that has never been, requiring analysis (separating the problem into manageable parts) and synthesis ("pulling together").

Dieter adopts the definition of Blumrich (1970):

> "Design establishes and defines solutions to and pertinent structures for problems not solved before, or new solutions to problems which have previously been solved in a different way".

Pahl & Beitz (1988) define designing as:

> "the intellectual attempt to meet certain demands in the best possible way. It is an engineering activity that impinges on nearly every sphere of human life, relies on the discoveries and laws of science, and creates the conditions for applying these laws to the manufacture of useful products."

A recent review (Evbuomwan et al, 1996) of design philosophies, models, methods and systems summarises certain properties and features of design as opportunistic, incremental, exploratory, investigative, creative, rational, decision-making, iterative and interactive - dependent upon the nature of the design problem. Developing on several definitions the authors describe the design process as:

> "The process of establishing requirements based on human needs, transforming them into performance specification and functions, which are then mapped and converted (subject to constraints) into design solutions (using creativity, scientific principles and technical knowledge) that can be economically manufactured and produced".

Cross (1989) does not offer a definition but focuses on design in terms of ability:

> "ability to design depends ... upon being able to make external visualisations ... a kind of thinking aloud ... [and the ability to address] ... two complementary aspects of design - problem and solution - have to be developed side by side."

Design being accomplished in a heuristic fashion through improving the understanding of the problem and in turn finding a better solution.

1.1.1(b) The relation of design to art, science and engineering

Design as an intellectual discipline has been explored by several researchers in relation to art, science and engineering:

Pahl & Beitz (1988) place engineering design at the cross roads between a politics/art continuum and a science/production continuum (Fig. 1.1). Whereas Dieter (1983) views the ability to design as both a science (techniques and procedures) and an art (learned only by doing). Dieter compares basic research, applied research and development and taking development describes it as a multidisciplinary activity. Fig. 1.2 illustrates how Dieter draws comparisons between the scientific method and the design method where the impetus for science is curiosity while the impetus for design is the needs of society.

Cross (1989) working from research by Davies (1985) recognises that intuition is seen by many as marking out designers (and engineering designers) from engineers who are brought up on proof, whereas problem-solutions for both designers and engineers weave creativity, visualisation and uncertainty. Cross cites a further study by Lawson (1984) which compares the approach of designers and scientists to the same problem. Scientists tend to explore a problem looking for underlying rules - the so called analytical or problem-focused approach. The designers on the other hand suggest a variety of possible solutions - the so-called synthesis or solution-focused approach. To cope with the uncertainty of the problem the designer defines, redefines and maybe

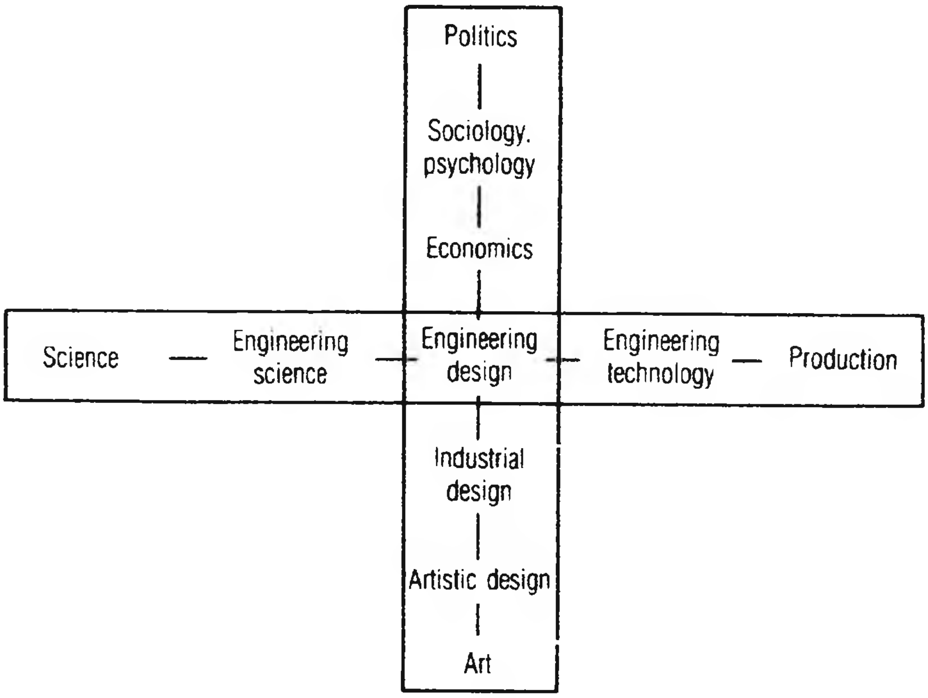


Fig. 1.1 **The central activity of engineering design according to Penny (Pahl & Beitz, 1988)**

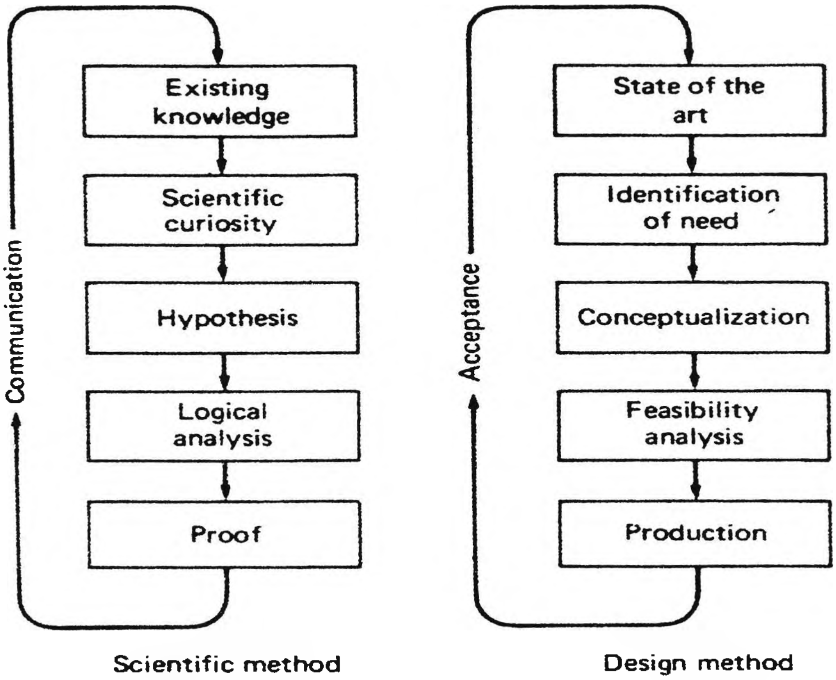


Fig. 1.2 **Comparison between the scientific method and the design method by Hill (Dieter, 1983)**

even changes the problem suggesting tentative solutions as a starting point. The problem-focused strategies used by designers probably reflect the nature of the problems that they normally tackle and also offers another way of defining design.

1.1.1(c) Defined by the type of problem

According to Cross (1989) design problems have three aspects a goal, a set of constraints and criteria for success. Unlike other types of problem the person setting the problem does not know what the answer is. Design problems are therefore regarded as ill-defined (or ill-structured) problems with the following characteristics:

(i) There is no definitive formulation of the problem.

(ii) Any problem formulation may embody inconsistencies.

(iii) Formulations of the problem are solution-dependent.

(iv) Proposing solutions is a means of understanding the problem.

(v) There is no definitive solution to the problem.

Not all problems are as ill-structured as they might appear since the boundary with well-structured problems is unclear and so a rigorous approach is therefore still possible. This is true even for so-called 'pernicious' problem structures such as with the cyclical problem structure shown in Fig. 1.3 and identified by Luckman (1984) where a decision loop is broken by incompatible options (e.g. direction of roof span, load and non-load bearing walls) (Fig. 1.4). Cross points out that a top-down approach using decision trees (Fig. 1.5) avoids cycling around the pernicious decision loops although there may still have to be some backtracking up and down the levels of hierarchy to undo sub-optimal decisions.

From the literature survey of Evbuomwan et al (1996) design problems fall into one of three general categories. The first are **Routine designs** which are considered to be derived from common prototypes or origins.

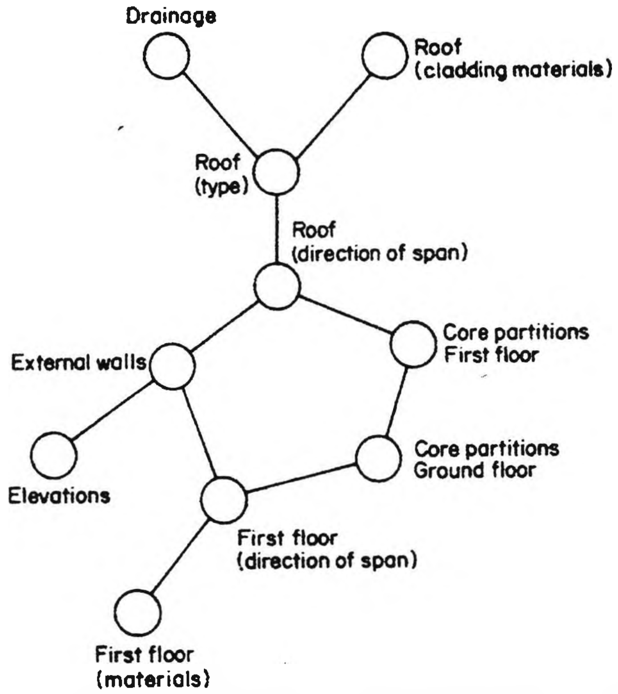


Fig. 1.3 **Problem structure in a housing design problem (Cross, 1989)**

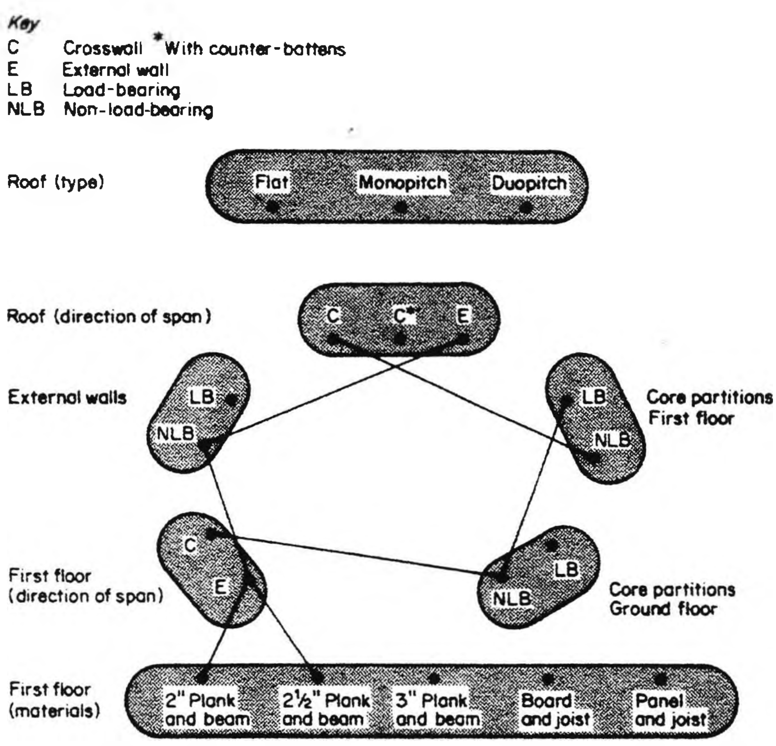


Fig. 1.4 **Expansion of the housing design problem structure, showing incompatible pairs of sub-solutions (Cross, 1989)**

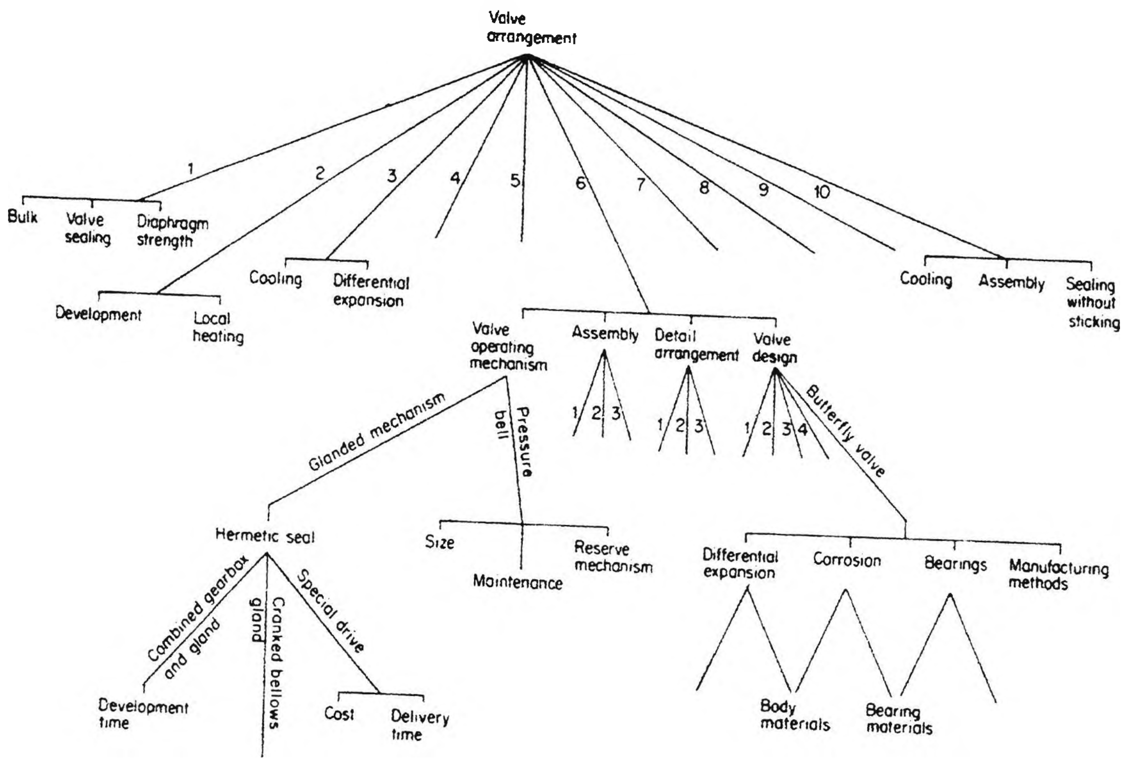


Fig. 1.5 **Part of the problem structure in a nuclear reactor valve design problem (Cross, 1989)**

Secondly **Redesigns** which involve modifying an existing design and may be considered as; *adaptive* when for instance a known system is applied to a changed task or undergoes a series of detail refinements; or *variant* when for example a proven design is used as the basis for generating further geometrically similar designs of different capacities. Thirdly **Non-routine, original or new designs** - which may be classified as; *innovative*, involving some new variables or features; or *creative* when radically new variables or features are introduced.

This is a marked development on the categories of Pahl & Beitz (1988) who distinguished between three types of design; **Original design** - which involves elaborating an original solution principle for a system. **Adaptive design** in which a known system is adapted to a changed task, often involving original design of sub-systems. **Variant design** in which certain aspects of a known system are varied in size and/or arrangement but where the solution principle remains unchanged. For the first two types of design the designer has to be highly creative and flexible. Pahl & Beitz cite a survey amongst German mechanical engineering companies that indicates the proportions of products falling into these categories as 25%, 55% and 20% respectively, and emphasises that the boundaries are imprecise.

Cross (1989) describes a 'design strategy' for addressing design problems in terms of a general plan of action and a realistic sequence of particular activities (i.e. design methods) within the constraints of time, and other resources. One extreme design strategy may involve a 'random search' and is allowable in novel design situations of great uncertainty where the widest possible search for solutions is being made. This represents a *divergent* design approach. The other extreme design strategy may use a 'prefabricated' sequence of well-tried-and-tested actions appropriate to designing another variant of a familiar product. This represents a predominantly *convergent* approach. In practice, most design projects require a strategy that lies somewhere between the two extremes but containing elements of both. Overall, the design process is convergent with varying degrees of divergence. Psychologists suggest that people tend towards either convergent or divergent thinking, and that this dichotomy is linked respectively with serialist/holist thinking, linear/lateral thinking and left brain/right brain thinking. Thus convergent and divergent thinking should play different roles at different design stages and it is therefore important to be able to change from one to the other. Many models of the design process tend to present a linear, serialist process which may be unhelpful to those designers with a predominantly *divergent* approach. Thus a design strategy should provide both a *framework* of intended actions and a *control* function enabling actions to be adapted as more is learned about the design problem.

1.1.2 Emergence of design methodologies

Defining Design and an outline of its execution, is considered to be design theory and leads to descriptive models of design. Design methodology on the other hand is concerned with how to design and leads to prescriptive methods.

Cross (1989) cites Jones' work (Jones, 1981) on design methodology, which groups the many methods into four groups: Methods for exploring design situations, methods of searching for ideas, methods of exploring problem structure and methods of evaluation. Cross uses just two broad groups: *creative* methods and *rational* methods. Creative methods try to increase the flow of ideas through removing mental blocks that inhibit creativity or by widening the search for solutions. Rational methods are more commonly regarded as design methods as they encourage a systematic approach to design. Cross recognises six main stages (Fig. 1.6) for both creative and rational methods. These stages are; clarifying objectives, establishing functions, setting requirements, generating

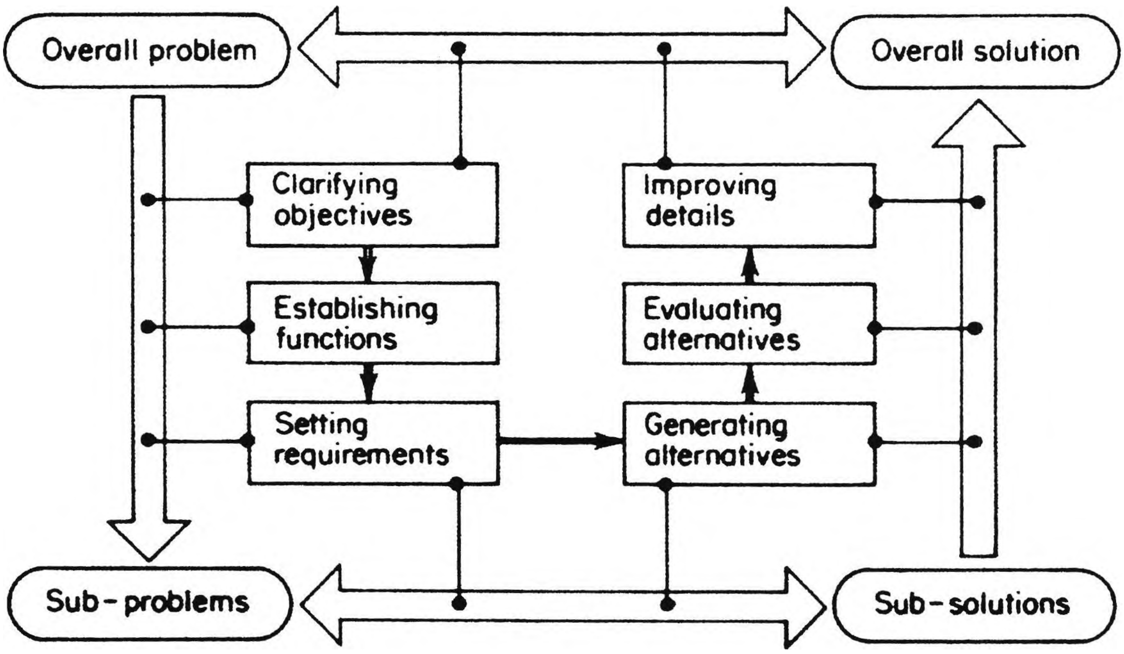


Fig. 1.6 **The six stages of the design process positioned within the symmetrical problem solution model (Cross, 1989)**

solutions, evaluating alternatives and improving details. Rational methods are not the opposite of creative methods according to Cross, they have similar aims such as widening the search space for potential solutions, facilitating teamwork and group decision-making. Yet many designers are distrustful of design methods because they appear too systematic even though this is countered by the need for handling complexity, working in teams and avoiding costly errors. This is a misunderstanding of the intentions of systematic design, which is meant to improve the quality of design decisions and hence of the end product. Systematic design is therefore "Not a straightjacket more of a lifejacket". There are two principal common features. Firstly, design methods *formalise* certain procedures and secondly they *externalise* design thinking through use of drawings and charts which again is important in dealing with complexity and also a necessary part of teamwork communication.

Thus it can be argued that systematic design methods are not against creativity, imagination and intuition. They are perhaps more likely to lead to novel design solutions than informal, internal and often incoherent thinking procedures of the conventional design process.

1.1.3 Descriptive models of the design process

Some design methods are specifically for aiding creative thought. Evbuomwan et al (1996) have reviewed descriptive models of the design process covering the work of Matchett et al (1966), Gero (1973) and March (1984) and confirm that descriptive models are often based upon cognitive processes (as highlighted by Cross (1989)). For example, March proposes that the design process comprises productive reasoning, deductive reasoning and inductive reasoning. This 'PDI' design process operates with *productive* reasoning used to establish an initial design proposal from the problem statement and solution presuppositions. This proposal is then *deductively* analysed to predict its performance. Finally it is then possible to *inductively* evaluate further design opportunities. This cycle is then repeated. Matchett's Fundamental Design Method is concerned with enabling the designer to perceive and control the pattern of their thoughts and relate it to the design situation. However, Gero's design process is seen as a series of transformations from one state of the design to another.

According to Cross (1989) descriptive models of the design process usually emphasise the importance of generating a solution concept early in the process reflecting the solution-focused nature. He proposes a simple three-stage model of the design process, consisting of generation, evaluation and communication (Fig. 1.7). A more detailed descriptive model by French (1985) highlights typical activities involved engineering design. Interestingly, Cross quotes that according to French, conceptual design is...."the phase where engineering science, practical knowledge, production methods and commercial aspects need to be brought together, and where the most important decisions are made." Cross also highlights how the activities of design and manufacture became separated as industry developed from craft-based approaches to large volume production - thus the focus of design shifted from being simultaneous with the creation of the artefact onto the description of it prior to its manufacture. Dieter (1983) sees this tendency to separate design and manufacturing into separate organisational units as a serious problem because the resulting barriers that emerge between the two can inhibit the close interaction that these two engineering functions should have.

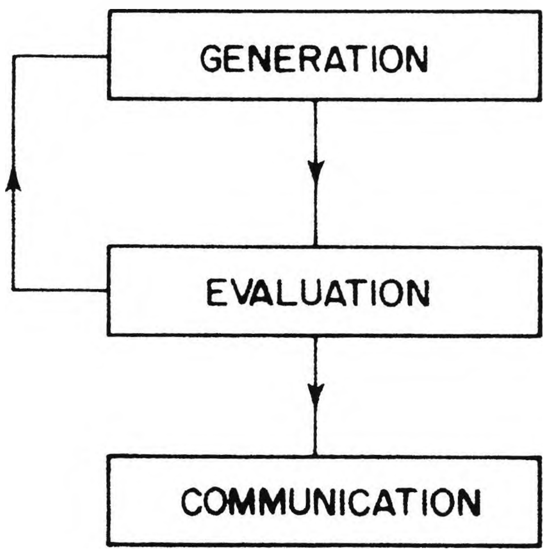


Fig. 1.7 **A simple three-stage model of the design process (Cross, 1989)**

1.1.4 Prescriptive design methodologies

There are numerous prescriptive design methodologies that have been proposed in the literature, sharing features represented by the ten methodologies addressed below.

Pahl & Beitz (1988) conclude that a design method must have seven important features.

(i) Encourage a problem-directed approach (applicable to every type of design activity).

(ii) Foster inventiveness and understanding (facilitating the search for optimal solutions).

(iii) Be compatible with concepts, methods and findings of other disciplines.

(iv) Not rely on chance.

(v) Facilitate the application of known solutions to related tasks.

(vi) Be easily taught and learned.

(vii) Reflect modern management-science thinking.

They suggest design methods are inextricably linked to the spread and development of scientific method and the use of computers. Therefore design methodologies must become more logical, more sequential, more transparent and more open to correction. The authors also stress the continued importance of intuition and experience, and see systematic procedures as serving to increase the output and inventiveness of talented designers.

Cross (1989) views prescriptive models of the design process as offering a more algorithmic, systematic procedure to the designer. Cross also notes that many authors emphasise the need for more analytical work to precede the generation of solution concepts to ensure that the design problem is fully understood at an early stage. An example of a systematic design methodology due to Jones (1981) relies upon a basic structure of analysis-synthesis-evaluation. Cross points out that the difference between this and a conventional heuristic descriptive model is the emphasis on performance specifications logically derived from the design problem, in turn generating several alternative design concepts and finally making a rational choice of the best of the alternative designs. A more detailed prescriptive model by Archer (1984) is summarised in Fig. 1.8 and involves dividing the design process into three broad phases: analytical, creative and executive. Archer suggests that the analytical phase requires inductive reasoning whilst the creative phase requires deductive reasoning followed by the execution of the design "...in an objective and descriptive mood. The design process is thus a creative sandwich." More complex models (Pahl & Beitz, 1990; Pugh, 1990) tend to obscure the general structure of the design process by swamping it with fine detail of the necessary tasks and activities. Furthermore Cross recognises several reasons for developing systematic design procedures: The increased complexity of modern design involves new materials and devices, puts greater variety of demands on the designer. Previous experience may well be irrelevant and inadequate. There is a need to develop teamwork so that specialists' contributions are made at the right point in the process. Dividing the problem into sub-problems, a characteristic of prescriptive design methodologies, also helps to allocate work to the team. A systematic approach will reduce risks promoting quicker financial payback in more competitive markets and avoiding catastrophic failure in safety-critical systems. Systematic procedures should improve the efficiency of the design process to reduce lead-times, increasingly through the use of computers which in turn influence more systematic ways of working.

Evbuomwan et al (1996) have reviewed prescriptive models, placing them into two broad categories - those based on the design process and those based upon product attributes. Of other prescriptive models of the design process, the majority, including those by Cross (1989) in Fig. 1.6, Archer (1984) in Fig. 1.8 and Marples (1960) in Fig. 1.9 and base their procedural

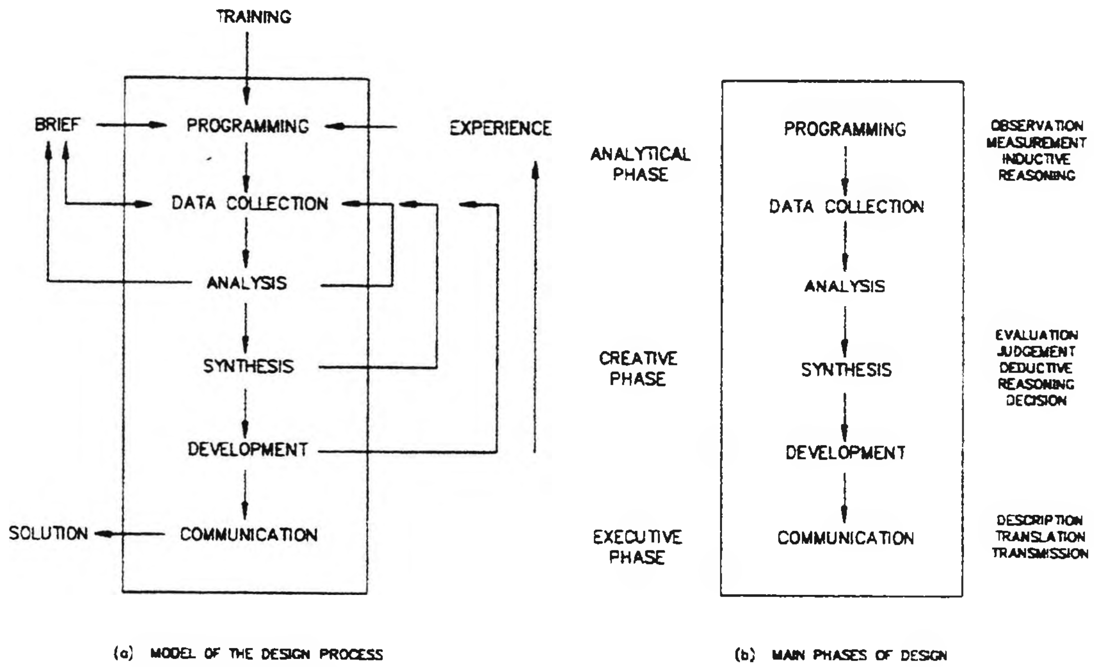


Fig. 1.8 The design model by Archer (1984)

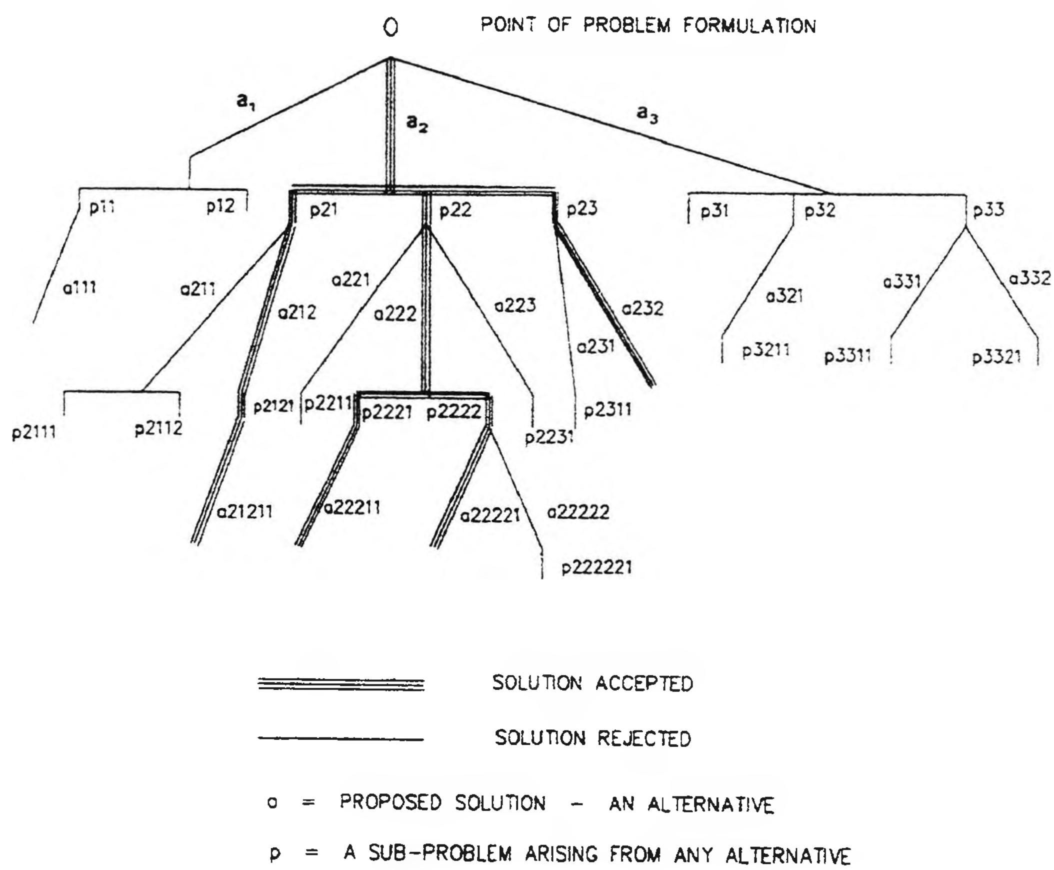


Fig. 1.9 The design model by Marples (1960)

steps on the three activities of analysis, synthesis and evaluation. Some models also incorporate other necessary activities such as optimisation, data collection, selection, decision making, modelling, etc. On the other hand some prescriptive models focus on the different phases of the design process including those by Hubka (1982) in Fig. 1.10, French (1985) in Fig. 1.11, Pugh (1990) in Fig. 1.12 and BS7000 (1990) in Fig. 1.13. These phases may be conceptual design, embodiment design and detail design.

Taguchi's (1986) design model utilises a quality loss function philosophy (Fig. 1.14) to distinguish optimal design solutions on the basis of their robustness to disturbing influences termed 'noise factors'. This attribute of robustness is addressed in three stages - system design, parameter design and tolerance design, which are addressed below. Suh's (1988) axiomatic design model is primarily concerned with design decisions governed by basic principles as applied throughout four phases of a particular design, problem definition, creation of ideas, analysis of proposed solution and checking the final solution against original needs. The core of Suh's axiomatic design is represented by his Axiom #1 which is 'maintain the independence of Functional Requirements' in other words in an optimal product design the design parameters relating to one function can be adjusted without affecting another function. Thus Suh describes design in terms of a process that maps functional requirements (FRs) and design parameters (DPs). Quality Function Deployment (Akao, 1990) also maps functions to parameters but allows a many-to-many mapping. We shall describe this method further below.

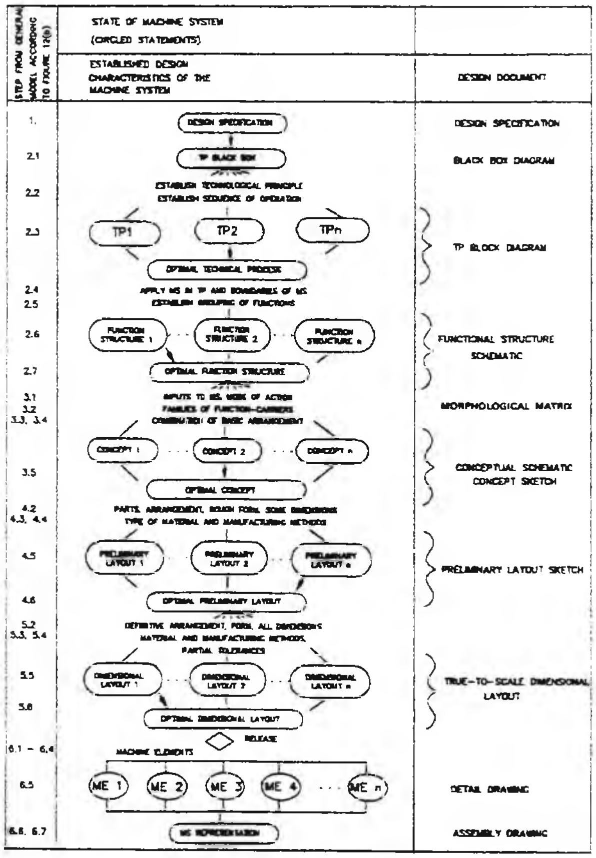


Fig. 1.10 The design model by Hubka (1982)

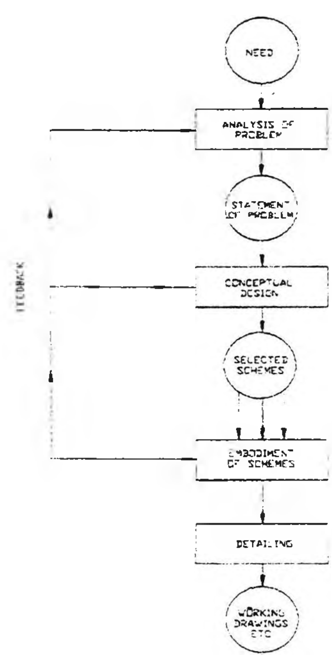


Fig. 1.11 The design model by French (1985)

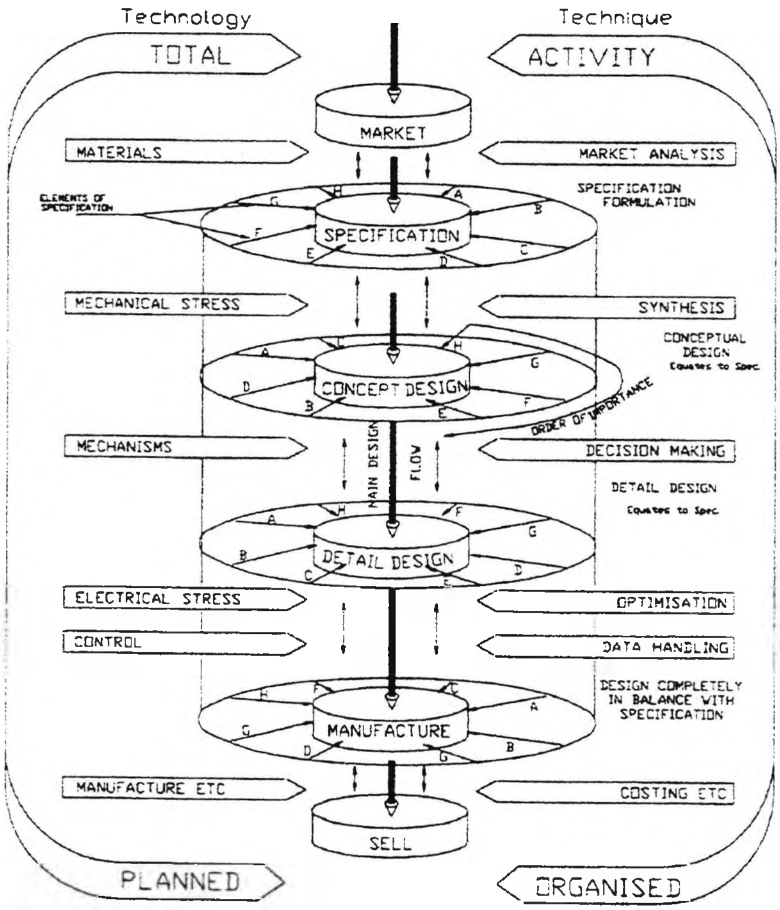


Fig. 1.12 The total design activity model by Pugh (1990)

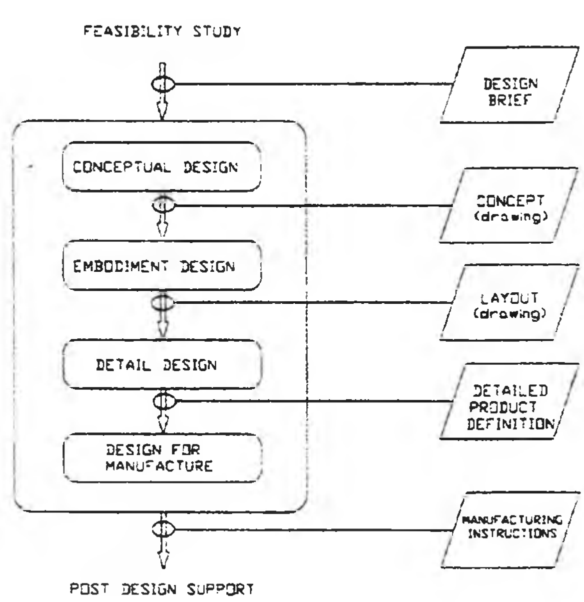


Fig. 1.13 The BS 7000 design model (BS7000, 1990)

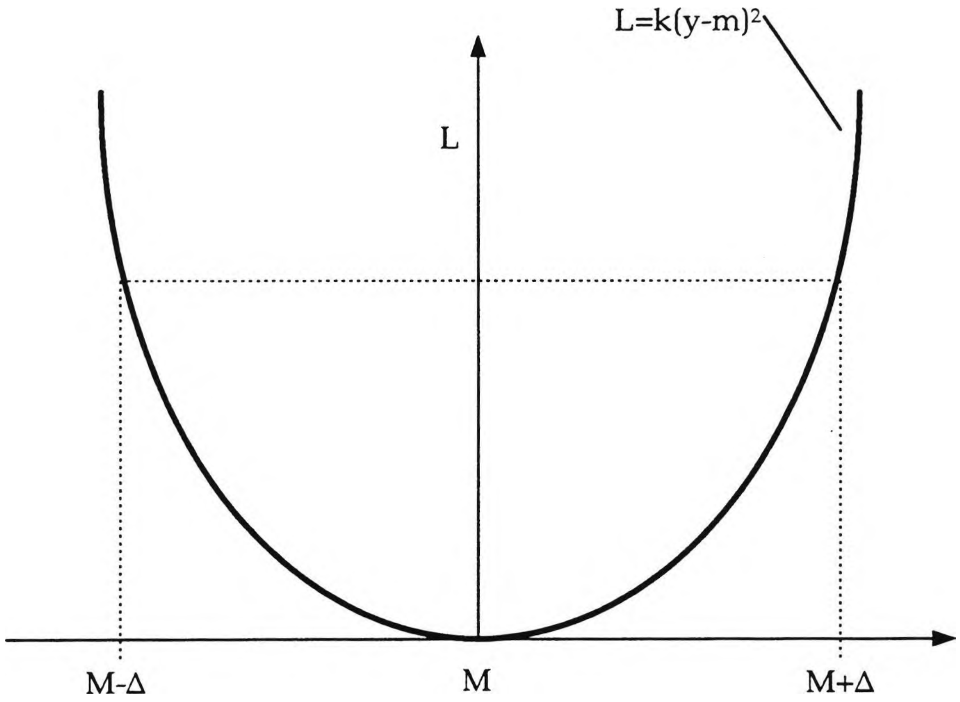


Fig. 1.14 Taguchi's quality loss function (Taguchi, 1986)

1.2 Quality Function Deployment in Product Design

1.2.1 Definition of QFD

Quality Function Deployment (QFD) is an overtly customer-oriented design methodology. The methodology seeks to establish what the customer wants from a product through interaction between customer and designer, and its matrix format will then prioritise the product parameters that contribute to achieving these requirements. The design and manufacturing effort is subsequently deployed according to these priorities.

Quality Function Deployment was conceived in the late 1960's and developed at the shipyards of Mitsibushi in Kobe, Japan during the early 1970's. According to its originator, Akao (1990), QFD is:

> "the converting of the customers' demands into quality characteristics and developing a design quality for the finished product by systematically deploying the relationship between the demands and the characteristics, starting with the quality of each functional component and extending the deployment to the quality of each part and process. The overall quality of the product will be formed through this network of relationships."

According to Shilito (1994) QFD is:

> "an interdisciplinary team process to plan and design new or improved products or services in a way that:
> 1. Focuses on customer requirements.
> 2. Uses competitive environment and marketing potential to prioritise design goals.
> 3. Uses and strengthens interfunctional teamwork.
> 4. Provides flexible easy to-assimilate documentation.
> 5. Translates soft customer requirements into measurable goals, so that the right products and services are introduced to market faster and correctly the first time."

Cohen (1995) describes QFD as:

> "a method for structured product planning and development that enables a development team to specify clearly the customer's wants and needs, and then to evaluate each proposed product or service

capability systematically in terms of its impact on meeting those needs."

Quality Function Deployment can thus be classified at this point as a prescriptive design methodology on the basis that it is driven by the needs of society represented by the customer and it promotes the systematic division of the design problem into sub-problems.

1.2.2 QFD methodology

Quality Function Deployment is commonly viewed as consisting of four phases, attributed to Clausing (1994), shown in Fig. 1.15. Generally, for phases 1 to 3 a *relationship matrix* is used to identify the translation of 'Whats' into 'Hows' by mapping each 'What' onto to each 'How' (Fig. 1.16), typically using one of three symbols to indicate the significance of a relationship wherever it is judged to exist. The meaning associated with 'How' and 'What' is different in each phase of Quality Function Deployment:

(i) Phase 1 or Product Planning, establishes a priority order of *design requirements* ('Hows') from the *customer requirements* ('Whats'). These design requirements are the design team's specification of the design problem. Concept design then takes place prior to Phase 2 as a stand-alone activity open to a range of design methods such as Pugh Concept Selection (Pugh, 1990). However concept design is concerned with generating a best solution judged against the design requirements and their target values.

(ii) Phase 2 or Part Deployment, highlights the target values of the *critical part characteristics* that must be maintained in order to satisfy the priorities from the previous phase. These critical part characteristics are the design parameters judged or shown by the design team to bear a significant relationship with some of the design requirements.

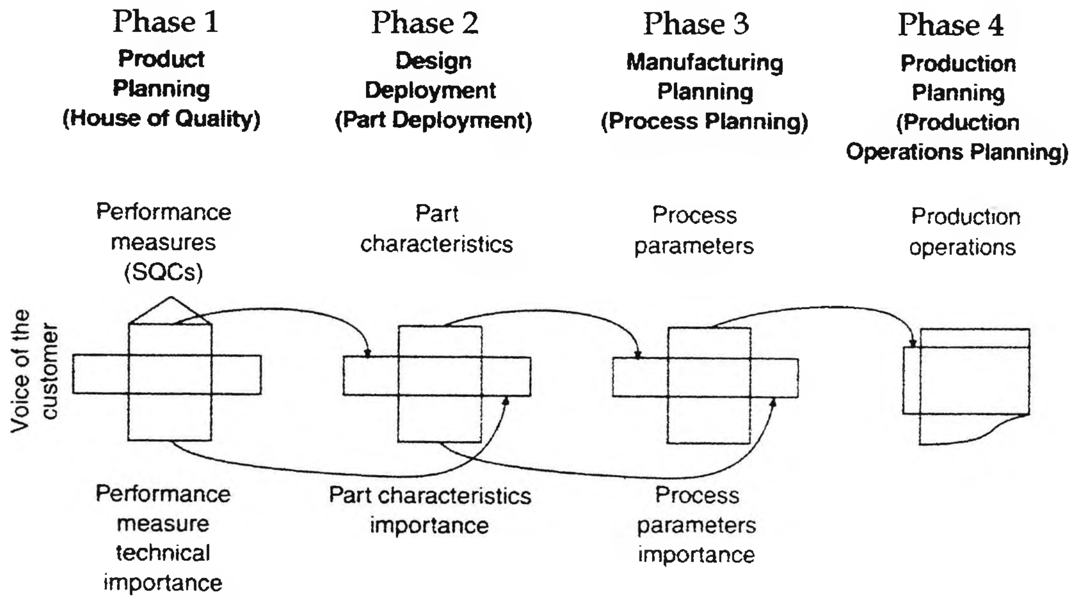


Fig. 1.15 Four-phase QFD model (Cohen, 1995)

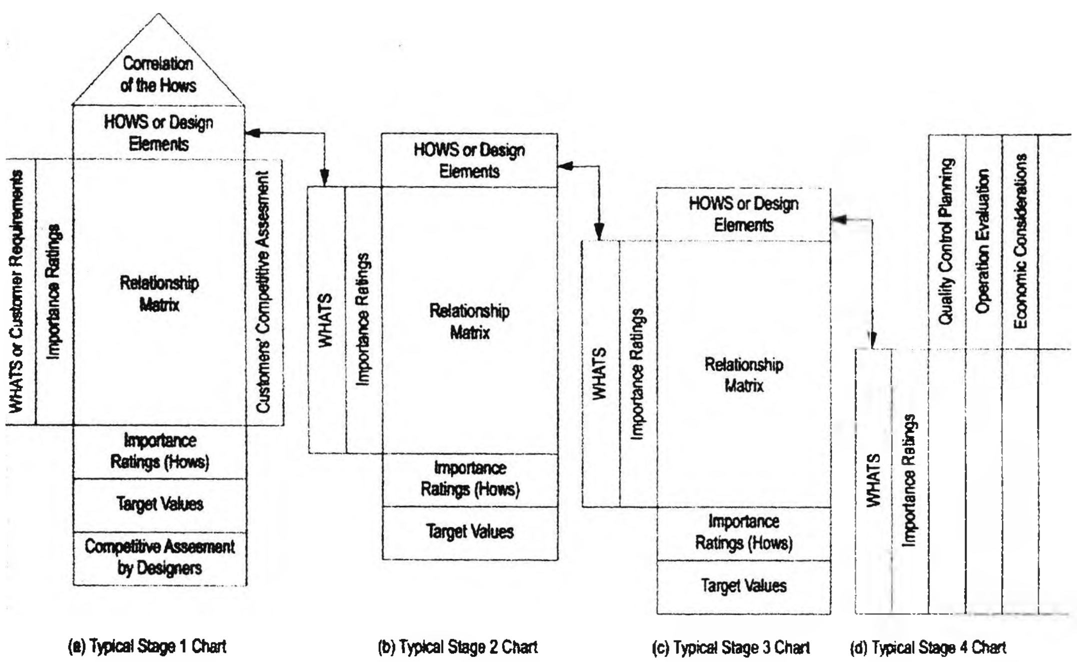


Fig. 1.16 Cascade of QFD charts (Sivaloganathan & Evbuomwan, 1995)

(iii) In phase 3 or Process Planning, the target values of *critical process characteristics* associated with the critical part characteristics are identified in order to inform process control.

(iv) Phase 4 or Production Planning, is concerned with operational issues such as quality procedures, training and maintenance schedules that impinge on Phase 3.

Fig 1.17 shows an example of a phase 1 matrix completed for an automotive car door case study in order to illustrate the basic methodology. The customer requirements are collated as the input to the phase and then the design requirements are brainstormed. The main relationship matrix is then populated with symbols to reflect the relationships between the 'Hows' and 'Whats'. Comparison of customer ratings and engineering competitive assessment for any two or more existing products serves as a check on the success of the translation from customer requirements to design requirements. The triangular correlation matrix at the top, the so-called 'correlation roof', is used to record the interactions identified between the design requirements. These correlations are determined with reference to the direction of the ideal target value (indicated by arrows just beneath the roof) and then corresponding target values can be traded-off. For example, the door close effort (column 1), a smaller-the-better requirement, is shown to have a strong negative correlation with static hold open force (column 3), a larger-the-better requirement. Reducing the former apparently compromises the latter and vice versa. The main output of the phase is the calculation of technical importance values at the bottom of the chart, where the absolute value is calculated by summing column-wise the products of the symbol values and the corresponding customer importance values. For example, for door close effort (column 1) there is one symbol (the strong symbol) of value 9 and multiplied by 7. Thus column 1 sums to 63. The relative score is a percentage value in this case and is used in order to avoid very large scores accumulating as the phases

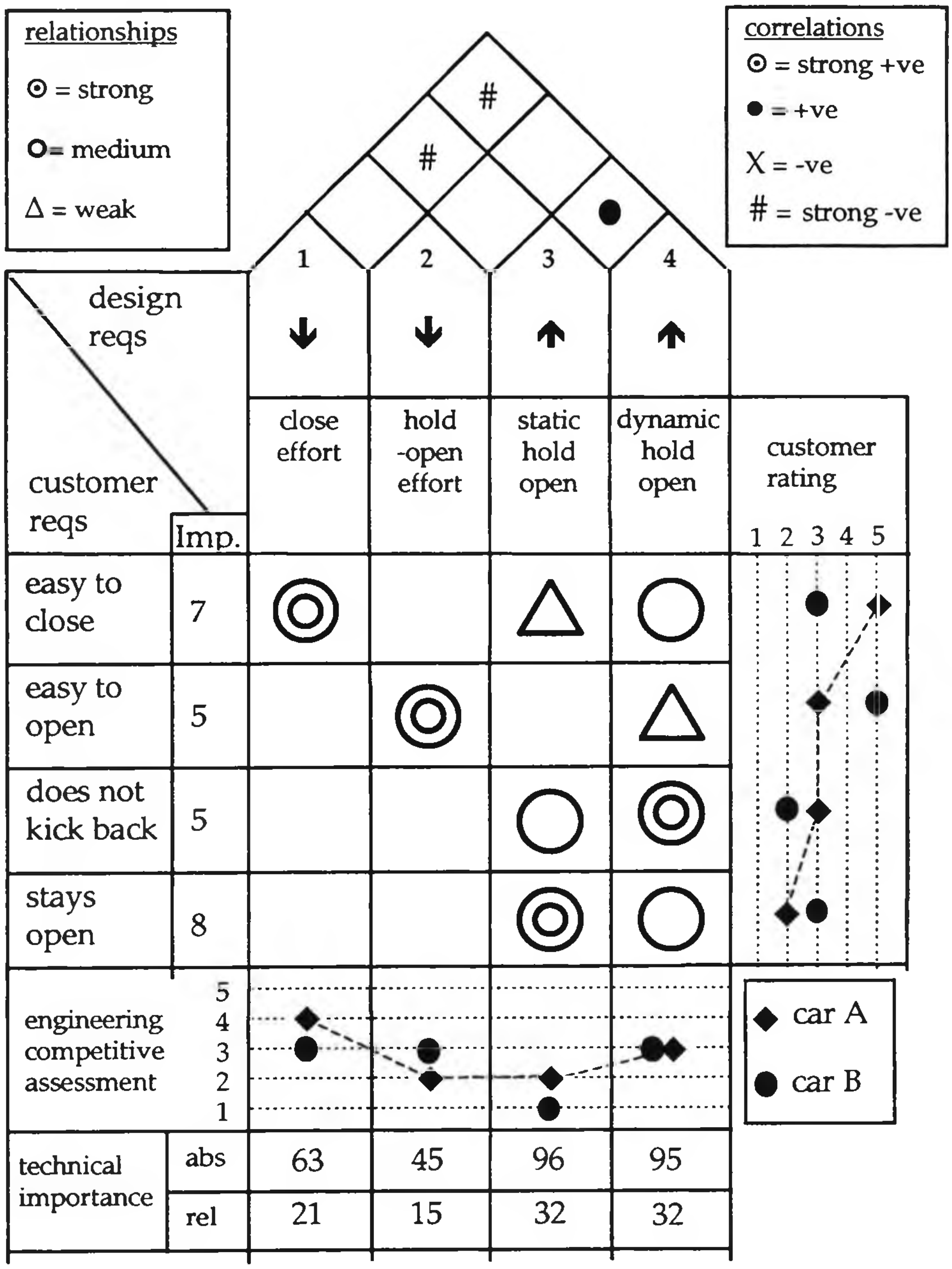


Fig. 1.17 **QFD phase 1 chart**

are progressed. These scores highlight static hold open force (column 3), and dynamic hold open force (column 4) as the main priorities to be addressed in the next phase.

Establishing the relationships between parameters is often considered a matter of 'engineering judgement'. This is certainly the case for completing the phase 2 relationship matrix where the designer needs to understand how the product functions in order to identify which features or properties of the product relate to its physical effects and in turn the design requirements. Furthermore in order to make entries in the correlation roof, the designer must be aware of any significant correlations or interactions between product features. In completing these matrices we see that Quality Function Deployment is capable of concisely recording a large volume of design information.

Sivaloganathan & Evbuomwan (1995) highlight the underlying design model in the four stages of Quality Function Deployment:

(i) Developing the quality plan and quality design.

(ii) Designing the parts and assemblies.

(iii) Designing the manufacturing processes for the fabrication and assembly of parts to form the final product.

(iv) Establishing the production control plans.

1.3 Robust Engineering Design

1.3.1 Definition of RED

There are several terms used in the literature relating to Robust Engineering Design (RED), including 'Parameter Design' (Taguchi, 1986), 'Taguchi Methods' (Bendell et al, 1989), 'Robust Design' (Phadke, 1989), 'Robust Engineering Design' (Jebb & Wynn, 1989) and 'Robust Product Design' (Fowlkes & Creveling, 1995). All these authors present the concept of robustness within a general philosophy of quality improvement concerned with the need to reduce performance variability. Thus Robust Engineering Design and its synonyms are commonly viewed as a central theme of Quality Engineering. Definitions relating to robustness include:

Taguchi (1986) states the purpose of parameter design as:

> "to evaluate the overall variation due to internal and external noises for different levels of the controllable factors, and to find a design that is as immune as possible to noise effects."

Phadke (1989) summarises Robust Design as:

> "Robust Design uses many ideas from statistical experimental design and adds a new dimension to it by explicitly addressing two major concerns faced by all product and process designers: How to reduce economically the variation of a product's function in the customer's environment. How to ensure that decisions found optimum during laboratory experiments will prove to be so in manufacturing and in customer environments."

Fowlkes & Creveling (1995) define Robust Design as:

> "A product or process is said to be robust when it is insensitive to the effects of sources of variability, even though the sources themselves have not been eliminated"

Thus the goal of Robust Engineering Design in product design and development is to minimise output performance variability over the product life cycle. The measured output is referred to as the quality characteristic in order to highlight the importance of the chosen principal characteristic to the customer. Two main groups of parameters influencing the product performance are classified as design factors and noise factors. Design factors are features of the product decided and controlled by the designer. Noise factors are uncontrollable external, unit-to-unit or internal sources of variation (Fowlkes & Creveling, 1995), such as ambient temperature or load (external noise), process drift or non-uniformity in producing product features (unit-to-unit noise), and plastic creep (deterioration noise). Robust Engineering Design aims to identify the general relationship between the output performance and design factors by means of carefully planned design experiments either physical or computational. In effect by employing Robust Engineering Design we are trying to optimise an unknown function, the unknown function being the relationship between the quality characteristic, design factors and noise factors (Fig. 1.18). Selection of the design factors for experimentation has generally relied heavily upon 'engineering judgement' or some prior knowledge or experience, and engineering science and simulation techniques would appear to have been under utilised.

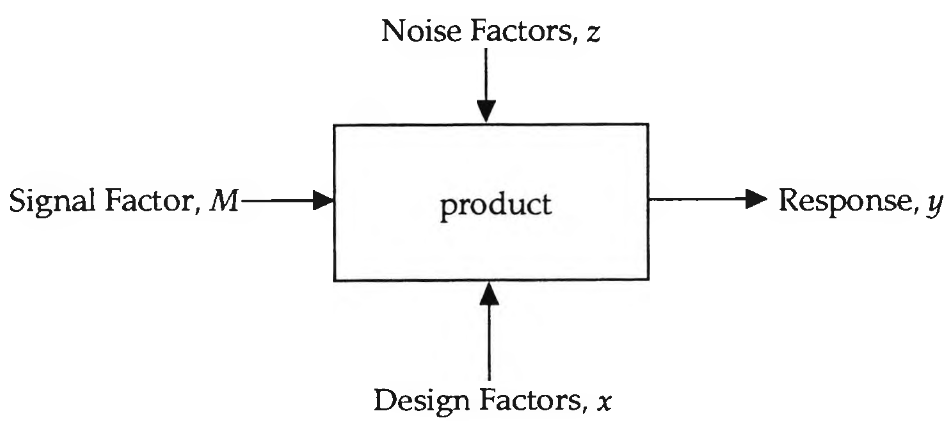


Fig 1.18 P-diagram representation of product parameters

In Robust Engineering Design the design process is considered to have three distinct technical stages and dealing with the effects of noise is different in each one.

1.3.1(a) Concept design stage

At the concept design stage noise is generic and robustness is limited by product configuration and technological development.

1.3.1(b) Parameter design stage

The chosen concept creates a set of parameters from which the design factors that affect product robustness need to be identified and their optimum levels determined. The P-diagram (Fig 1.18) represents all the parameters associated with the product. Thus the response is some function of the signal-, design- and noise factors.

$$y = f\{x, M, z\} = g\{x, M\} + e\{x, M, z\} \tag{1.1}$$

where the component $g = \{x, M\}$ is predictable and desirable and the component $e = \{x, M, z\}$ is unpredictable and undesirable.

1.3.1(c) Tolerance design stage

Robustness can be improved by reducing noise such as by tightening tolerances but this incurs cost and is therefore usually a last resort.

1.3.2 Orthogonal Arrays

The design experiment is a central theme of Robust Engineering Design. Efficient methods of searching the combinations of design factor levels are used usually incorporating Orthogonal Arrays. An Orthogonal Array (OA) is a matrix showing a standard plan for combining design factor levels into experimental trials (groups or treatments) (Fig. 1.19). Each design factor occupies a column and the design factor levels for a particular experiment are represented by a row of digits that signify the level at which each design factor should be set. With most standard Orthogonal Arrays, for any pair of columns all design factor combinations occur an equal number of times. Thus orthogonality means that each design factor has its effects considered in a balanced way against all other

	OA COLUMNS							Results
	1	**2**	**3**	**4**	**5**	**6**	**7**	
Exp 1	1	1	1	1	1	1	1	
Exp 2	1	1	1	2	2	2	2	
Exp 3	1	2	2	1	1	2	2	
Exp 4	1	2	2	2	2	1	1	
Exp 5	2	1	2	1	2	1	2	
Exp 6	2	1	2	2	1	2	1	
Exp 7	2	2	1	1	2	2	1	
Exp 8	2	2	1	2	1	1	2	

Fig. 1.19 Basic L_8 Orthogonal Array (OA) with results column

design factors over the entire range of all design factor levels. In other words when calculating design factor main effects orthogonality is exhibited as a balancing property of the Orthogonal Array where all other design factors take on their levels an equivalent number of times thus cancelling out and isolating the effect of interest. This orthogonality helps the downstream reproducibility of the experimental results with greater precision than from one-factor-at-a-time experiments.

Standard Orthogonal Arrays are selected according to the number of design factors and their levels, and occasionally, specific interactions between design factors can be assigned to a column. In general, the larger Orthogonal Arrays (fractional factorial experiment) offer greater proportional reductions in the number of experiments (Fig 1.20) compared with experimentation on all possible design factor combinations (full factorial experiment).

Standard OA	$\text{Levels}^{\text{factors}}$	N° of Exp trials	Equivalent full factorial trials
L_4	2^3	4	8
L_8	2^7	8	128
L_{12}	2^{11}	12	2,048
L_{16}	2^{15}	16	32,768
L_9	3^4	9	81
L_{18}	$(2^1 + 3^7)$	18	4,374
L_{27}	3^{13}	27	1,594,323

Fig 1.20 **No. of experiments for OA compared with conventional full factorial approach.**

1.3.3 Quality Loss Functions

For **static** Robust Engineering Design there are generally three types of Quality Loss Function (QLF), two of which are considered below.

For a Nominal-is-Best (NB) problem where the quality characteristic has a target value, the related QLF is approximated to follow a quadratic function (Fig 1.21) about the target value of the parameter of interest (e.g. product response or design factor value).

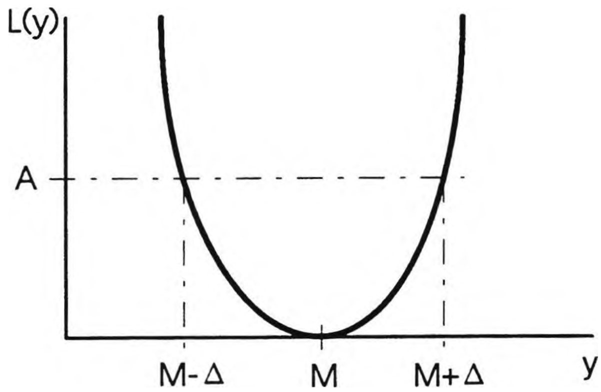


Fig 1.21 Nominal-is-Best Quality Loss Function

If y is the quality characteristic reading and M is the target value, then the quality loss is given by:

$$L(y) = k(y-M)^2 \qquad \textbf{(1.2)}$$

where the quality loss coefficient, k, is a constant.

The Smaller-the-Better (SB) Loss function represents a quality characteristic that is continuous and non-negative, taking any value in the range $(0,\infty)$, with the ideal value being zero (Fig. 1.22).

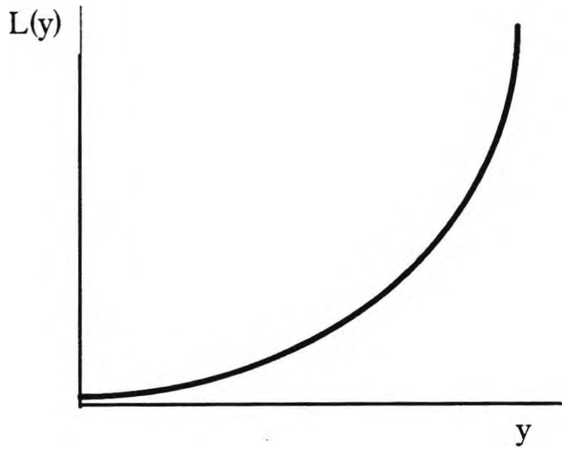


Fig 1.22 Smaller-the-Better Quality Loss Function

There is no target value therefore the QLF simplifies to:

$$L(y) = ky^2 \tag{1.3}$$

The Larger-the-Better (LB) Loss function represents a quality characteristic that is continuous and non-negative, taking any value in the range $(0,\infty)$, with the ideal value being the largest possible (Fig. 1.23).

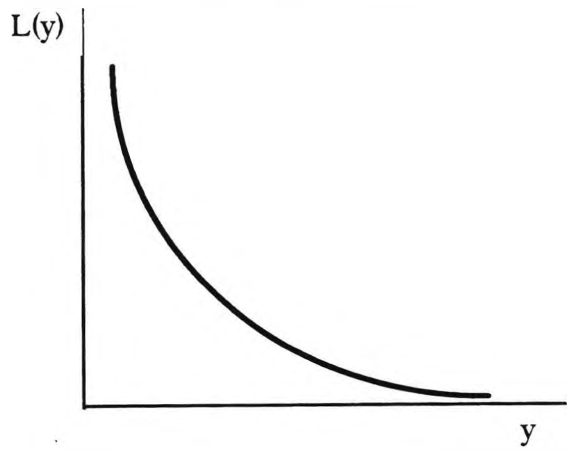


Fig 1.23 Larger-the-Better Quality Loss Function

Again there is no target value therefore the QLF simplifies to:

$$L(y) = k(1/y^2) \tag{1.4}$$

1.3.4 Signal-to-Noise Ratios

The derivation of the Signal-to-Noise Ratio has been addressed by Fowlkes & Creveling, (1995), Phadke (1989) and, in particular, León *et al* (1987). We shall derive Signal-to-Noise Ratios here from the relevant Quality Loss Functions for use in later work.

For a set of quality characteristic readings, $y_1, y_2, \ldots, y_n$, the average quality loss, Q, is:

$$Q = (1/n)\ \{L(y_1)+L(y_2)+\ldots+L(y_n)\} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{1.5}$$

For a NB problem, using Eq. 1.2 and 1.5, the average quality loss becomes:

$$Q = (k/n)\ \{(y_1-M)^2+(y_2-M)^2+\ldots+(y_n-M)^2\}$$

Noting that the mean of y is $\mu = (1/n)\ \Sigma y_i$

and the variance of y is $\sigma^2 = (1/[n-1])\ \Sigma(y_i-\mu)^2$

Then, $Q = k\ \{(\mu-M)^2 + ([n-1]/n)\sigma^2\}$

Which when n is large can be reduced to:

$$Q = k\ \{(\mu-M)^2 + \sigma^2\} \tag{1.6}$$

That is, the quality loss has two components:

(i) $k(\mu-M)^2$ an *accuracy quality loss* proportional to the deviation of the mean from the target.

(ii) $k\sigma^2$ a *precision quality loss* proportional to the mean squared deviation about the mean.

Thus Eq. 1.6 is partly influenced by the deviation from target mean (μ-M) and so a decision based on Q would risk the possibility of not choosing a factor level that minimises sensitivity to noise. However, if Q is adjusted to bring the mean (μ) on target (M) then this first component will disappear and the second will be modified by the adjustment. This represents Taguchi's two stage optimisation philosophy. The adjustment is to increase each reading by M/μ which adjusts Q in Eq. 1.6 to:

$$Q_a = k\,([M/\mu]\,\sigma)^2 = k\,M^2(\sigma^2/\mu^2) \tag{1.7}$$

(quality loss after adjustment)

Since for a given quality characteristic, k and M are constants, attention need only be focused on (μ^2/σ^2). This is the Signal-to-Noise Ratio, as σ^2 is the effect of noise factors and μ^2 is the desirable part of the data, and it can be viewed conceptually as the ratio of $\frac{\text{power of signal}}{\text{power of noise}}$.

Therefore, minimising Q_a, the quality loss after adjustment (or sensitivity to noise), is equivalent to maximising the inverse measure of variability proportional to mean, (μ^2/σ^2), which has a range $(0,\infty)$. It also converts what is in effect a constrained optimisation problem into an unconstrained problem that is much easier to solve. Taking the $\log_{10}$ (or alternatively $\log_e$) improves the additivity of the main effects as in the log domain the range of values is $(-\infty,\infty)$.

Thus, the SNR_{NB} is expressed in decibels by:

$$SNR_{NB}\,(dB) = 10\,\log_{10}(\mu^2/\sigma^2) \tag{1.8}$$

<u>For a SB problem</u>, using Eq. 1.3 and 1.5, the average quality loss becomes:

$Q = (1/n)\,\{L(y_1)+L(y_2)+\ldots+L(y_n)\}$

$Q = (k/n)\,\{y_1^2+y_2^2+\ldots+y_n^2\} = k\,([1/n]\,\Sigma y_i^2)$

Therefore, ignoring the constant k and expressing the quality loss in decibel form:

$$SNR_{SB}\,(dB) = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \tag{1.9}$$

The minus sign follows a 'maximise SNR' convention.

1.3.5 Additive model and prediction

1.3.5(a) Additive model

Recalling Eq. 1.1: $y = f\{x, M, z\} = g\{x, M\} + e\{x, M, z\}$

For static Robust Engineering Design, M is a single value on a zero-point proportional function. Therefore ignore M and the error term for the purposes of this simple illustration.

A simple additive model involving two design factors is assumed to be:

$$y = ax_A + bx_B \qquad \textbf{(1.10)}$$

When the value of x_A is changed it will have an independent and predictable effect on y. Changing x_B might have a more significant and opposite effect but the point here is that we know what contribution to Δy can be expected from Δx_A..

Broadening Eq. 1.10 to include more design factors and reintroducing an error term as in Eq. 1.1 then

$$y = ax_A + bx_B + cx_C + dx_D + error \qquad \textbf{(1.11)}$$

Note that in Robust Engineering Design the x_i may well have discrete levels set by an Orthogonal Array and we can express Eq. 1.11 as:

$$y = \mu + a_i + b_j + c_k + d_l + error \qquad \textbf{(1.12)}$$

Here the a, b, c and d are not the constant coefficients represented above. μ is the overall mean of the data and the deviation from μ caused by:

- setting x_A at level A_i is a_i.
- setting x_B at level B_j is b_j.
- setting x_C at level C_j is c_j.
- setting x_D at level D_j is d_j.

and error = error of the additive approximation + the error in the repeatability of measuring y for a given experiment.

Also, $a_1+a_2+a_3 = b_1+b_2+b_3 = c_1+c_2+c_3 = d_1+d_2+d_3 = 0$ **(1.13)**

because by definition for each design factor the deviation from μ is caused by the three levels.

1.3.5(b) Prediction Equation

In order to develop the additive concept further consider an L9 OA experiment (Fig. 1.24) with 4 three-level design factors (A, B, C, D):

Exp	A	B	C	D	trial means
1	1	1	1	1	y_{t1}
2	1	2	2	2	y_{t2}
3	1	3	3	3	y_{t3}
4	2	1	2	3	y_{t4}
5	2	2	3	1	y_{t5}
6	2	3	1	2	y_{t6}
7	3	1	3	2	y_{t7}
8	3	2	1	3	y_{t8}
9	3	3	2	1	y_{t9}

Fig. 1.24 L9 OA with trial means

The effect of a design factor level is found by averaging the trial means, y_t, at that level, e.g. for level three of design factor x_A:

$$m_{A3} = (1/3)(y_{t7} + y_{t8} + y_{t9}) \qquad \textbf{(1.14)}$$

$$m_{A3} = (1/3)((\mu+a_3+b_1+c_3+d_2+e_7) + (\mu+a_3+b_2+c_1+d_3+e_8) + + (\mu+a_3+b_3+c_2+d_1+e_9))$$

According to Eq. 1.13, ***b,c* & *d*** terms in Eq. 1.14 sum to zero, thus;

$$m_{A3} = (\mu + a_3) + (1/3)(e_7+e_8+e_9) \qquad \textbf{(1.15)}$$

That is m_{A3} is an estimate of $(\mu+a_3)$

or

$$a_3 = m_{A3} - \mu - (1/3)(e_7+e_8+e_9) \qquad \textbf{(1.16)}$$

Here the error term is an average of three terms which can be assumed to have a variance of $(1/3)\sigma_e^2$, where σ_e^2 is the average variance for the error terms $e_1, e_2, \ldots, e_9$. This error variance of the average effect of a particular design factor level, is smaller than that which would be carried through studying one factor at a time.

Generalising the form of Eq. 1.14 and determining the average trial mean for each design factor level then the best level settings can be found. A response table (Fig. 1.25) is often used for this purpose.

design factor	average level 1	average level 2	average level 3	maximum difference	rank
x_A					
x_B					
x_C					
x_D					

Fig. 1.25 Response table for L_9 OA

Combining Eq. 1.12 with Eq. 1.16, and ignoring the error the optimum performance will be predicted by:

$$E(y) = \mu + (m_{A_i}-\mu) + (m_{B_j}-\mu) + (m_{C_k}-\mu) + (m_{D_l}-\mu) \qquad \textbf{(1.17)}$$

1.3.6 Analysis Of Variance

In Robust Engineering Design the term variance is used in the usual sense to describe a statistic that measures the width of a distribution of data about its mean. Analysis of Variance is the most common method employed by engineers in the literature for gaining insight into the role of design factors (Taguchi, 1986; Phadke, 1989; Fowlkes & Creveling, 1995). The *'sums of squares'* approach of the Analysis of Variance method measures variation about the grand mean (the average of all the experiment data) to define the contribution of each design factor. A summary statistic of each experimental trial, such as the Signal-to-Noise Ratio will be represented here by y_t in order to demonstrate the ANOVA method. Therefore, there will be one data point per experiment trial, e.g. a total of 8 (**n**=8) for an L_8 Orthogonal Array:

Total sum of squares, $S_T = \Sigma y_t^2 - CF$ **(1.18)**

where y_t = trial mean, Signal-to-Noise Ratio or other summary statistic and correction factor, $CF = n\,y_m^{\;2}$ (y_m is the grand mean of all data = $(\Sigma y_t)/n)$

Sum of squares due to design factor x_A is $S_A = \Sigma(A_j^{\,2}/n_L) - CF$ **(1.19)**

where A_j = sum of data of factor x_A for level j

n_L = number of data per factor level

Sum of squares due to error, $S_e = S_T - \Sigma S_A$ **(1.20)**

This is the decomposition of error component out of the total.

The total degrees of freedom (dof), f_T = total number of data - 1, which for one data per experiment treatment, is also equal to the dof of the orthogonal array.

Thus dof for a design factor, f_A = number of factor levels - 1.

The dof for error, $f_e = f_T - \Sigma f_A$, which may be zero if all the columns of the Orthogonal Array are occupied by a design factor, which is the recommended Robust Engineering Design practice (Taguchi, 1987), and therefore error has to be estimated by pooling, as discussed below.

Variance is a measure of variability per degree of freedom:

$V_T = S_T/f_T$ **(1.21)**

$V_A = S_A/f_A$ **(1.22)**

$Ve = Se/fe$ **(1.23)**

Note that! comparing with Eq. 1.20, $V_e \neq V_T - \Sigma V_A$.

Two methods are commonly used to obtain an idea of the relative importance of each factor, either the *F-test* or the ***percentage contribution***. In Robust Engineering Design the F-test is used for qualitative comparisons of factor effects (Fowlkes & Creveling, 1995) rather than its more usual statistical role as a probability statement (Box, Hunter & Hunter, 1978). Here we simply take the ratio of the factor variance to error variance:

$$F_A = V_A/V_e \tag{1.24}$$

An F value of less than one suggests that the associated design factor effect is less than the error of the additive model. An F value greater than two means the design factor effect is not small, and F larger than four means the design factor effect is large (Phadke, 1989).

However, in most Robust Engineering Design experiments all the columns of the Orthogonal Array are used to study design factor main effects leaving no degrees of freedom left over for estimating error variance. *Pooling* the weak design factor effects to estimate the error variance is used in many cases (Taguchi, 1987; Phadke, 1989; Fowlkes & Creveling, 1995). The ***pooling-up*** strategy used by Taguchi, pools the sums of squares corresponding to the variances of weaker half of all the design factors, usually taken to be about half the degrees of freedom. The purpose of this is to improve the efficiency of experimentation and it runs the risk of overlooking significant factors (Logothetis & Wynn, 1989). Pooling-up will reveal the most significant design factors and the contributions of the pooled design factors should be ignored when it comes to predicting the optimum performance. This is advisable because if contributions from all factors are included the predicted response is likely to exceed the actual response found in a confirmation experimental trial.

To determine the contribution of a design factor to the total response variability, the sum of squares must be adjusted to remove the error contribution. Considering Eq. 1.22, if V_A is small then x_A is considered to have no significant effect on the response variability, then the variability attributed to error is V_A=V_e. Therefore Eq. 1.23 becomes V_e=S_A/f_A, the error variation component, for a ***'saturated'*** Orthogonal Array (all columns allocated a design factor) which means that $S_A = f_A V_e$. Eq. 1.20 indicates how V_e is then pooled for more than one design factor. Pure sum of squares for x_A becomes:

$$S'_A = S_A - f_A V_e \quad \textbf{(1.25)}$$

The percent contribution of design factor x_A to the total variability is then:

$$pc\ (\%) = S'_A / S_T * 100 \quad \textbf{(1.26)}$$

If the percentage contribution due to error is below 15% it is unlikely that important design factors were omitted from the experiment. If the percentage contribution is over 50% then some important design factors were likely to have been missed from the experiment.

A basic assumption of ANOVA is that error variance is equal for all experiment groups (i.e., each combination of design factors), which may not always be true and therefore there is a small risk that an opportunity to reduce variation could be missed. The pooling-up approach of Taguchi tends to make the ***alpha error***, a design factor will have a larger effect than suggested, as opposed to the alternative pooling-down approach which tends to make the ***beta error***, a design factor will have a smaller effect than suggested. The construction of an estimate for the error variance has attracted criticism (Box & Ramirez, 1986) as a method which can induce extreme bias in a statistical analysis and therefore lead to spurious conclusions.

1.3.7 Probability plots

Researchers from the statistical community (Logothetis & Wynn, 1989; Lochner & Matar, 1990; Grove & Davis, 1992) have recommended the use of probability plots for identifying significant design factors. In particular, the use of half-normal or Daniel plots (Daniel, 1959) is advocated as a significant contribution to objectivity in deciding what is random and what is systematic.

The illustration in Fig. 1.26 (Grove & Davis, 1992) shows the design factor main effects represented as plots of absolute contrast values versus half-normal scores on linear axes for ease of use in computer packages, whereas the classical manual approach uses normal probability graph paper. For n design factors, the absolute contrast value is equivalent to the difference between 2n main effect values for each design factor level, which are then ordered from largest to smallest n values. The half-normal score can then be allocated to each contrast from a standard table (see Grove & Davis, 1992) on the basis of a normal distribution being divided into 2n equal areas over the six-sigma range. Therefore in effect the normal scores represent the number of standard deviations from the mean.

Effects which are actually composed only of random variation will lie on a straight line pointing at the origin. In other words the significant design factors will be conspicuous in lying off the straight line, as for M_o and M_e in Fig. 1.26.

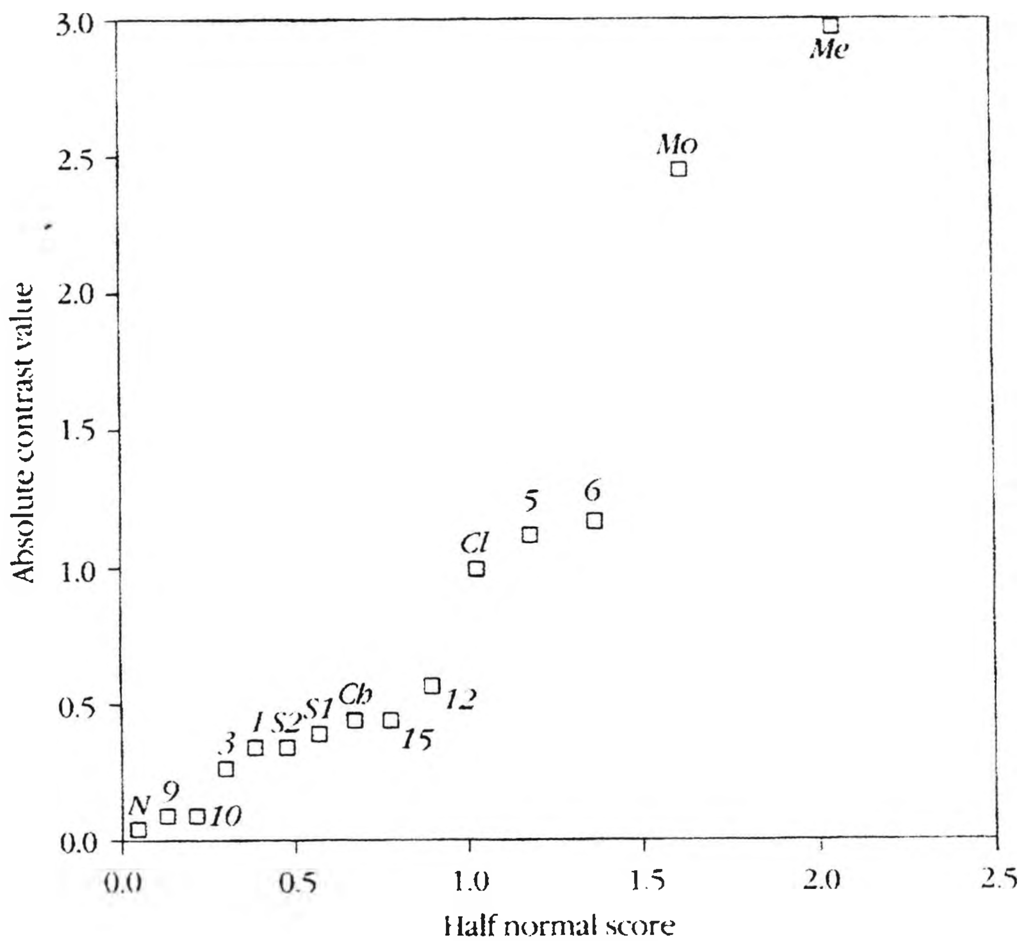


Fig. 1.26 **Daniel plot for glove box lid experiment (Grove & Davis, 1992)**

1.4 Discussion of Design Methodologies

1.4.1 Parameter selection in product design

Like many contributors to systematic design Dieter (1983) does not specifically mention Robust Engineering Design. He does however consider the design of experiments based on a statistical approach and points out the improvements this gives in terms of efficiency of information gathering for optimisation of design factor settings. He also recognises that a statistical basis to experiments gives added credibility to results and notes that conventional design is a deterministic approach which disregards the fact that material properties, component dimensions and applied loads are all statistical in nature. Dieter also claims that factors of safety are used in conventional design but increasingly a probabilistic approach is used to reduce uncertainty and increase reliability.

Pahl & Beitz (1988) build upon the work of Hubka (1982), Koller (1973) Roth et al (1972) and Rodenacker (1970), and view design as the establishment of functions where functions are usually defined by statements consisting of a verb and a noun such as 'transfer force' or 'reduce speed'. Functions are also related to energy, materials and signals. Pahl & Beitz show that Rodenacker, who viewed design as the reverse of physical experiments, was particularly concerned with the identification and elimination of disturbing factors causing quantitative and qualitative fluctuations (Fig. 1.27). However, methods for identifying the influence of disturbing factors are limited to Fault-Tree Analysis of the function structure and elimination of their effects is by virtue of studying and 'negating' the culprit functions.

Pugh (1990) does consider Robust Engineering Design, in the context of his Total Design Methodology but limits his consideration to the loss

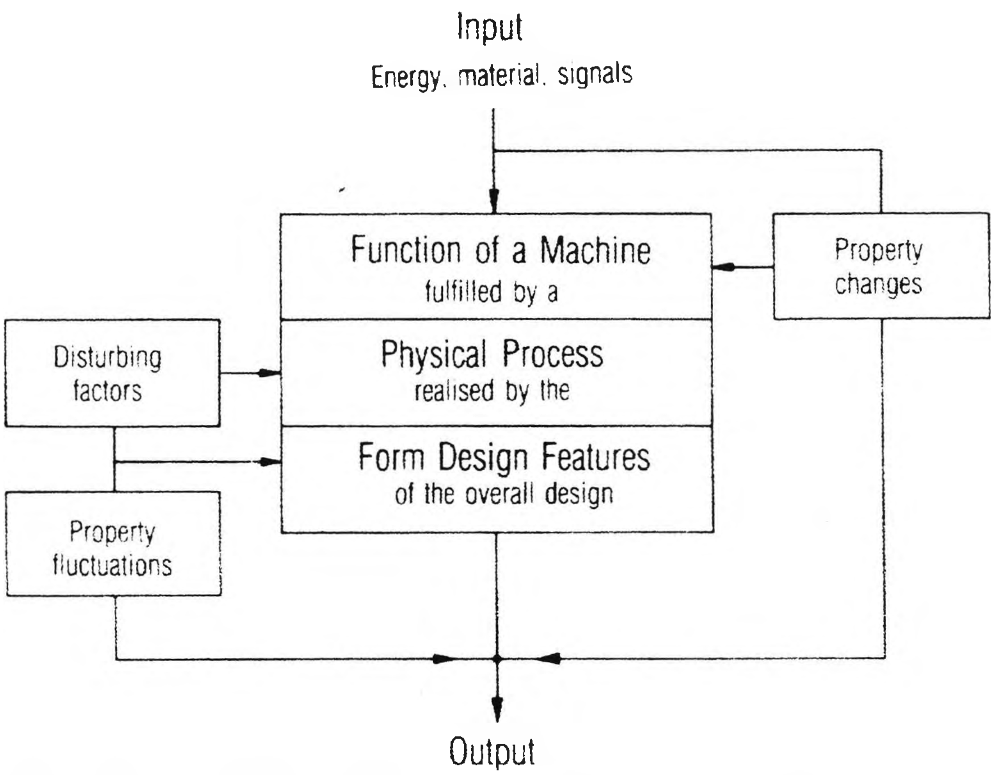


Fig. 1.27 Design steps according to Rodenacker (1970)

function philosophy and exploitation of non-linearity rather than any treatise of how the two methodologies might be integrated.

1.4.1(a) Function decomposition

We have shown that all prescriptive design methods divide the design problem into smaller units. In general a three-stage approach to product development may be postulated:

(i.) Decompose or partition the problem into smaller sub-problems.

(ii.) Solve the sub-problems.

(iii.) Cluster these sub-solutions into an integrated solution.

Cross (1989) highlights how the German standard VDI 2221 (VDI, 1987) model of the design process follows a general systematic procedure of first analysing and understanding the problem as fully as possible, then breaking this into sub-problems, finding suitable sub-solutions and combining these into an overall solution. This relates to Hubka's (1982) view that technical artefacts should be treated as systems which relate to their environment through inputs and outputs. These can be broken down into subsystems, fixing the boundaries through identifying the various sub-functions. This can be termed *Function Decomposition*. The basics ideas here relate well to Robust Engineering Design philosophy as will be explored in subsequent sections. Function Decomposition has been one of the major areas of recent design research activity (e.g. Eppinger et al, 1990; Kusiak et al, 1993) building on the earlier work of Pahl & Beitz (1988).

1.4.1(b) Factor selection

Problems arise from the lack of an agreed definition of the word function which is used to refer to purposes, effects, properties and even costs or constraints. However, the principle of identifying subfunctions clearly has a relevance to the identification of design factors and noise factors for Robust Engineering Design experiments. In terms of factor selection product development would ideally involve the following steps:

(i.) The identification of high-level parameters, such as overall functions, quality characteristics or physical effects.

(ii.) Using physical laws to identify the role of low-level parameters, that is to highlight the significant design factors from the rest.

(iii.) Assigning values to low-level parameters. In other words to estimate appropriate values for design factors in order to achieve optimal performance.

(iv.) Assessing the likely values of the target values assigned to the parameters. Achieving the target value will depend upon production capability and other statistical issues.

In the context of Quality Function Deployment identifying high-level parameters in (i) above is addressed as part of phase 1 and concept design. Furthermore, the multiple mapping of the relationship matrix in Quality Function Deployment highlights that engineering products often involve multiple objectives. Therefore it is of practical importance that approaches to Robust Engineering Design are developed that can deal with more than one objective or quality characteristic.

The 'engineering judgement' exercised in steps (ii) and (iii) above often appears to be based on an insight into the nominal behaviour of the system under investigation gained through experience of similar systems. Whereas for a Robust Engineering Design front-end, effective insight would ideally provide understanding of the influences on system output variability as well as its nominal output but rarely is this the case. In addition using physical laws to identify and then assign values to low-level parameters (design factors) should not just be concerned with the vertical relationships between high-level and low-level parameters. For example it is possible that negative interactions exist between some design factors, where the effect of one design factor on the product performance is dependent upon the value of another design factor. Chemical reactions are a classic example of this effect. Often dealing with interactions will require compromise and trade-off between the target values of the design factors in question (step (iii) above). Consequently, the selection of parameters and the anticipation of relationships between them is an unreliable aspect of contemporary Robust Engineering Design practice. According to Eppinger et al (1990) many authors recommend that decomposition is carried out so as to minimise interactions between sub-problems whereas they feel they are inevitable. Rather than dispute or support either claim at this point it is sufficient to note here that interactions in Robust Engineering Design are also an important issue to be taken into consideration if RED is part of an integrated design methodology. Unexpected interactions discovered later in the design process may require costly design changes to reduce their effects. Interactions can render the predictive power of the Robust Engineering Design method unreliable. Similarly it is therefore important that Quality Function Deployment records interactions for reconsideration at design retrieval, i.e. when performing modifications or redesigning, to prevent changes to design factor target values having an unexpected effect on product robustness.

With regards step (iv) above, production capability effectively sets a confidence interval for the target value, i.e. an expectation that the actual values manufactured will fall within a certain range rather than meet the exact value of the target. The effect of this uncertainty in design factor values on the variability in output should be evaluated.

1.4.2 Benefits to product design of an enhanced QFD/RED methodology

By placing Robust Engineering Design with its objective approach within the Quality Function Deployment methodology, the robustness issue comes into tension with multiple customer requirements and production constraints while searching for optimum solutions. Few researchers have addressed either of these aspects in the context of Robust Engineering Design. The union of the two methods is a key aspect of this research project and serves to keep robustness on the agenda in the embodiment design phase of redesign problems in particular.

As Quality Function Deployment and Robust Engineering Design both require the identification of significant design factors and their relationship with the quality characteristic(s) there is scope to build a more complete design methodology on and around this common ground. For example, positioning Robust Engineering Design within the Quality Function Deployment methodology presents some potential benefits:

(i) Opportunities for improving parameter selection through enhancing engineering judgement with engineering tools incorporated as part of a wider design methodology.

(ii) The relationship between the quality characteristic, design factors and noise factors is more clearly linked with multiple objective optimisation and the influences of production capabilities as a robustness optimisation issue by the four-stage matrix format of Quality Function Deployment.

(iii) Robust Engineering Design is brought further 'upstream' into the design thinking and therefore the concept design is more likely to address the robustness issue and perhaps avoid interactions or at least engage with them through appropriate techniques.

(iv) The correlation matrix, used in Quality Function Deployment, could be developed to interface with Robust Engineering Design by partitioning the design into sub-systems for optimisation purposes.

Partitioning also provides scope for supporting concurrent engineering practice.

As Quality Function Deployment and Robust Engineering Design relate closely to functional decomposition, enhancing these two aspects of quality engineering in terms of parameter selection is timely as the research community is currently very active in developing the subject of function decomposition. A survey of design methodology (Tomiyama, 1997) reviewed the industrial practice and academic research in design and concurrent engineering. This work concluded that too much design research attention is being paid to general and abstract problems resulting in design methodologies that are difficult to apply. The recommendation was that the design community should focus more on actual design problems. A measure of their success could be increased design efficiency.

1.4.3 Hypotheses

Two hypotheses are proposed and developed over the chapters that follow:

1.4.3(a) Hypothesis #1

"Robust Engineering Design can yield efficient results through more pragmatic approaches that involve engineering science and production capability in parameter selection and level setting."

1.4.3(b) Hypothesis #2

"The correlation roof of Quality Function Deployment can be used to inform design procedure and provide a link with Robust Engineering Design".

These have mainly been tested against industrial case studies which bring into focus the complexity of real engineering products and the challenges of co-ordinating product development activities at each level of product, parts and production.

1.4.4 General Objectives

The literature is further reviewed in Chapter 2 with the following general objectives providing a framework for addressing the above hypotheses.

(i.) To capture the development of Quality Function Deployment and identify aspects that require further attention.

(ii.) To review the Robust Engineering Design methodology and identify areas for development which could enhance its practical application to product design.

(iii.) To investigate a method for modelling energy-based systems for use in parameter selection.

(iv.) To review multiple objective optimisation and identify methods suitable for use with Robust Engineering Design.

Chapter 2. Literature Review

2.1 Recent Developments in Quality Function Deployment

2.1.1 Limitations of Quality Function Deployment

Sivaloganathan & Evbuomwan (1995) provide a comprehensive summary and description of Quality Function Deployment highlighting the importance of developing *solution neutral* design requirements for Phase 1, i.e. expressed to keep all possible options open, in order to avoid stifling the creativity of the concept design stage. They also confirm the widely-held view that Quality Function Deployment is best suited to conceptually static products. That is where for new product designs the solution principle remains relatively unchanged on previous designs (variant design). Clausing & Pugh (1991) have addressed the enhancement of QFD for dynamic concepts, i.e. those involving original or adaptive design activity, by adding more design methods post-phase 1 as a front-end to concept design. Sivaloganathan & Evbuomwan cite practical applications of Quality Function Deployment and make the observation that applications and their reported successes are mostly confined to phase 1.

In the relationship matrix one design requirement can address several customer requirements and one customer requirement may spawn several design requirements. As judgement and experience are heavily relied upon and largely reduced to arithmetic, there is a sense in which the outcomes of the Quality Function Deployment methodology can be manipulated by changes to importance values and relationship strengths. Comincini (1994) views this aspect as not entirely a bad thing since the design process can thereby be challenged and also a permanent record of decisions is available.

According to Comincini, design retrieval and concurrent engineering are inherent to the Quality Function Deployment methodology. Retrieval is enabled because most relevant design information is systematically collated in a readily accessible form. Thus for a new design, particularly for a static concept, the design route can be retraced and relevant information incorporated into the new design - significantly reducing the lead time. Concurrency is addressed through the fact that the design is validated against all the constraints simultaneously at each stage of the design process represented by the four phases of Quality Function Deployment.

2.1.2 Design Function Deployment

Sivaloganathan et al (1995) have developed an extension of the Quality Function Deployment methodology called Design Function Deployment (DFD). The underlying design process of DFD is viewed in two dimensions (Fig. 2.1). The principal axis splits the familiar QFD approach into six stages instead of the conventional four:

(i) Establish requirements and specification.

(ii) Establish viable architectures.

(iii) Develop layouts for architectures.

(iv) Establish manufacturing processes.

(v) Generate production plans.

(vi) Select the optimal design.

The second axis (levels) identifies design tools and a design library for databases and information systems.

Wynn, Jebb & Sivaloganathan (1993) illustrate, using the design of a dc motor, the commonality between Design Function Deployment and Robust Engineering Design and the potential of the combined methodologies to investigate the 'solution space', i.e. the possible solutions, and also to account for the downstream long-range noise

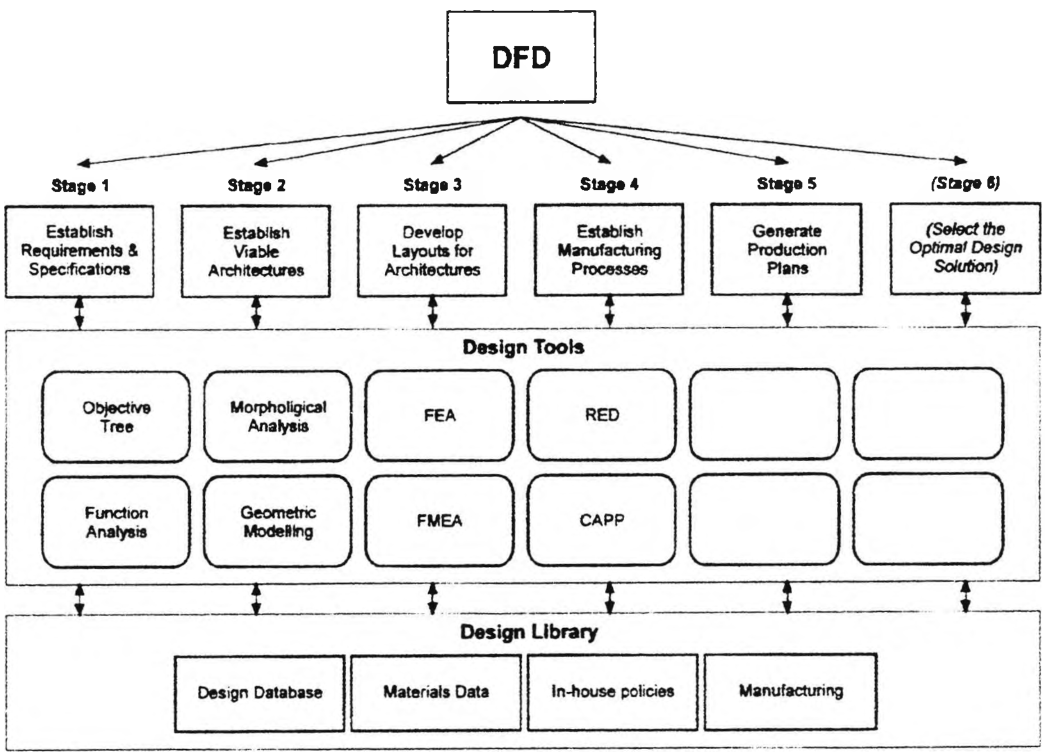


Fig. 2.1 6 stages and 3 levels of DFD (Sivaloganathan & King, 1995)

variables, such as the operating environment or deterioration, affecting the design of the product. Again this is an illustration confined to phase 1 like many other applications.

2.1.3 Correlation Roof

The correlation roof or matrix (Fig. 2.2) is intended to be used for recording interactions where they are judged to exist. For phase 1 each design requirement is compared pair-wise with every other. According to Cohen (1995):

> "the correlation roof is probably the most under exploited part of the House of Quality. Few QFD applications use it fully, yet its potential benefits are great."

The potential benefits of the correlation roof are linked to optimisation. The roof confined to phase 1 by many authors, can be used to record the correlations, i.e. the interrelationships, between design requirements in phase 1, critical part characteristics in phase 2 and critical process characteristics in phase 3. Many design requirements may interact with each other - the roof provides a means of declaring whether these interactions are positive or negative. Subsequently ignoring these correlations and treating the corresponding parameters as independent can be a source of problems if their target values are changed without assessing the corresponding effect for the correlated parameter. An issue that has a direct bearing on Robust Engineering Design. A bi-directional causation has to be assumed because the symbols generally used in the published work offer no causal information. The correlation roof merely notes that an interaction exists. Defining the dependent and independent factors in a relationship is useful information, particularly for redesign, which should be recorded in the roof.

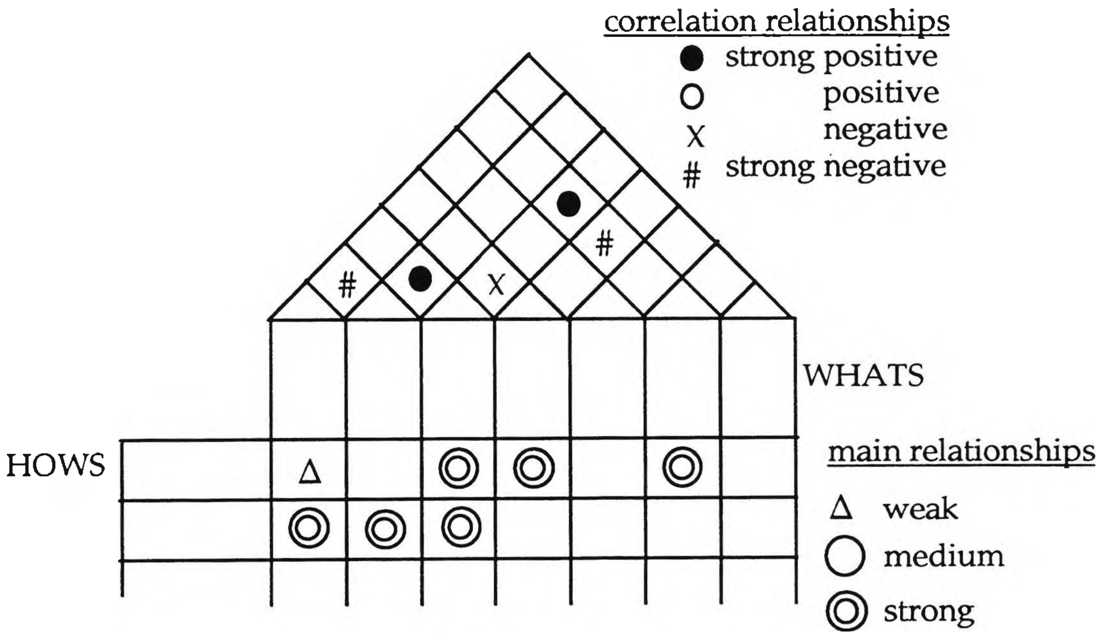


Fig. 2.2 Correlation roof of QFD

2.1.4 Correlation Chains

Comincini (1994) proposed the use of *correlation chains* in place of the correlation roof in order to associate more clearly the correlated parameters ('Hows') with their related outputs ('Whats'). These chains are shown in the main relationship matrix as horizontal boxes that connect the correlated 'Hows' for each 'What' (Fig. 2.3). It is claimed that the correlation chain enables an algorithmic approach to linking the 'Hows' and the 'Whats'. The resulting function is used to rapidly evaluate the impact of design changes by comparing previous and newly formed correlation chains to highlight the elements affected.

The correlation chain method is described by Comincini (1994) in terms of a design modification and shown to be effective when:

(i) Retrieving correlation chains relevant to the subject.

(ii) Identifying all parameters that see their performance parameter stressed by the new conditions.

(iii) Identifying all necessary steps in order to accept and implement the required modification, e.g. changes to specification of bought-in items.

The utility of correlation chains for QFD phase 1 is not clear as Comincini confines the treatment of them to design changes of a pallet for a machining centre where the maximum allowable weight is increased and the affected parameters are investigated (Fig. 2.4). This example is clearly a QFD phase 2 issue where dimensioning will be defined in sufficient detail in order to enable a simulation for the evaluation of the required modifications to be used.

It is apparent that Comincini considers simulation the key outcome of the algorithmic approach associated with correlation chains. The box presentation of the correlation chain is not well-suited to the graphics function of 'manual' QFD i.e. where the chart as originally developed is used as a visual tool by a team of designers. In particular, the capability

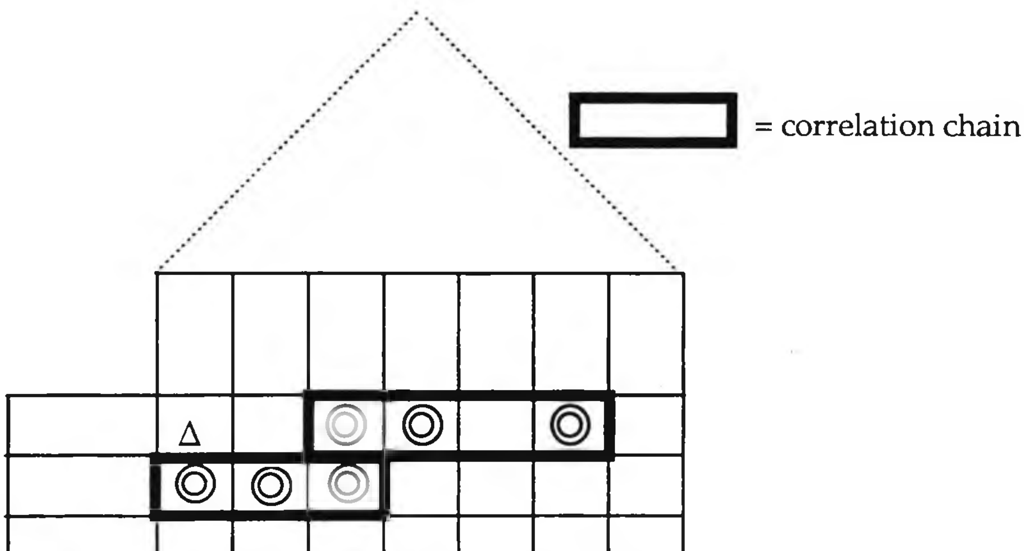


Fig. 2.3 **Correlation chains (Comincini, 1994)**

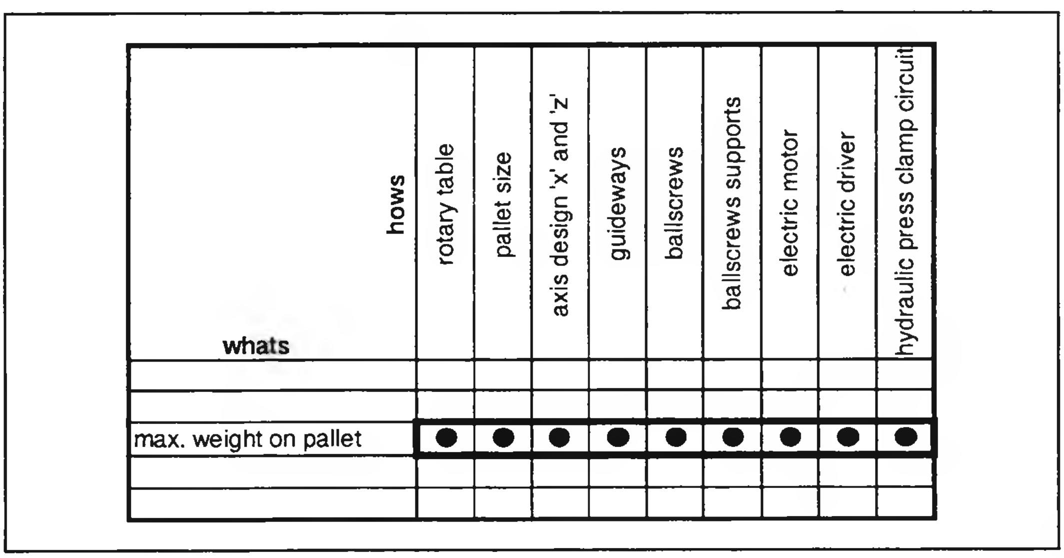


Fig. 2.4 **Correlation chain in DFD application on machining centre pallet design (Comincini, 1994)**

of to visually convey +ve/-ve correlation relationships is lost in replacing the correlation roof by correlation chains.

2.1.5 Summary of Quality Function Deployment issues

From the literature it is evident that the correlation roof is under utilised in practice. It has been suggested that the roof be replaced by correlation chains but this is unproven as they have not been fully demonstrated in all phases of Quality Function Deployment for product development. However, the issue is whether to make a quantitative link between requirements (Whats) and parameters (Hows). Essentially, the existing correlation roof merely serves to note that an interaction exists.

As it has been suggested that the design requirements in phase 1 are ideally solution-neutral this means that identification of interactions is made more difficult and at the same time less important because of the lack of physical meaning at this stage. By physical meaning we mean design requirements expressed in a way that infer particular solution principles. Furthermore, it could be argued that the interactions described in the literature relate more fully to a phase 2 implementation of the correlation roof on top of critical part characteristics. Here the act of deciding target values whilst conforming to interaction relationships parallels that of Robust Engineering Design. Links between Quality Function Deployment and Robust Engineering Design have been suggested but have not been demonstrated beyond phase 1. Thus the phase 2 correlation roof is a potential interface between QFD and RED, where simulation would appear to be well-suited.

2.2 The Development of RED Methodology

2.2.1 Early Developments

2.2.1(a) Design of Experiments and quality engineering

The development of Robust Engineering Design can be considered as the coming together of two themes namely Design of Experiments (DoE) and quality engineering. The former nurtured amidst statistical rigour and the latter concerned with industrial imperatives such as cost and time. Merging the two disciplines has involved some conflict in finding a satisfactory balance but the result is perhaps a clearer view that Robust Engineering Design should be driven further off-line (before production) to give it the greatest influence on improving robustness.

Design of Experiments is widely acknowledged as starting with Fisher (1925) who conducted agricultural experiments by dividing land into individual trials (groups or treatments) and setting the controllable conditions based on 'Latin squares'. Not only did this approach successful randomise uncontrollable conditions but it also enabled more than one factor level at a time to be changed between trials. Fisher also introduced Analysis of Variance (ANOVA) a technique for decomposing the response variation into its various components. By 1934 there is some early evidence that DoE had reached industry with Tippett's (1934) highly fractional factorial experiment in textile manufacturing. In 1946 Plackett & Burman (1946) published a paper on saturated Orthogonal Arrays (OA), in which all columns are assigned a design factor. These were to be used by a Japanese engineer, Taguchi (1987) in the 1950's, who is now recognised as having popularised Robust Engineering Design in the form of *Signal-to-Noise Ratios, two-stage optimisation* and *Dynamic Characteristics.*

The link between quality and statistics was established by Shewart (1925), back in Fisher's time, and he proposed "the application of statistics as an aid in maintaining quality of a manufactured product". This was *'on-line quality'* where the statistics was concerned with economical identification of defectives amongst finished product ready for shipment or use - as it was acceptance sampling by inspection. By 1950 Deming (1992), who had worked with Shewart since 1929, was one of a few encouraging the application of statistics further upstream in the design cycle with

> "cease dependence on inspection to achieve quality. Eliminate the need for mass inspection by building quality into the product in the first place".

This was subsequently interpreted in the West largely in terms of research into statistical process control. Meanwhile in post-war Japan, where high-quality resources were more scarce, the philosophies of the Western quality gurus such as Deming (1992), Juran (1964) and Feigenbaum (1983) captured a more open-minded audience, from the ranks of industrial management.

2.2.1(b) Two-step optimisation strategy

In the 1950's Taguchi (1987) used design of experiments in the development of telecommunications products whilst working for Nippon Telephone and Telegraph Company. His contributions helped to transform the subject into what is now known as Robust Engineering Design. Taguchi established a two-step optimisation strategy where design factors affecting variability are adjusted to their optimal settings first and then adjustment design factors, which affect response mean only, are set to bring the mean response onto target. In particular, Taguchi is credited with introducing the concept of *Signal-to-Noise Ratio* for reliably transforming the experimental data into a condition better suited to analysis and also for referring the data to the quadratic *Quality Loss Function* as an objective measure of quality. These contributions although concepts already in use in other disciplines were novel in terms of their application to design of experiments and quality.

In effect variability as an optimisation issue was brought more clearly into focus by Taguchi (1987) through an emphasis on reducing the effects of variability as opposed to attempting to remove the cause (removing the cause being a practical proposition in the confines of a laboratory but not in a factory or in everyday use). It was this difference of emphasis in the use and development of design of experiments which continued for 20 years or more before widespread acceptance of 'Taguchi Methods' in the West, where design of experiments had been mostly confined to scientific experiments.

It is interesting to note that despite Taguchi receiving the prestigious Deming Award in 1960 for his achievements, his philosophy only reached Western industry in the early 1980s. Several authors such as Clausing (1994), Phadke (1989), Kacker (1985) and Sullivan (1984) championed the use of this approach during the West's 'enlightenment' period between 1980 to 1985. It was as if design of experiments had been rediscovered. ITT, AT&T Bell Laboratories, Ford Motor Company and the Xerox Corporation pioneered their introduction into the United States. In the UK Lucas Industries and Xerox led the way, with Lucas conducting more than 100 projects over the first two years which at the time was considered the best start that any company in the world had yet made (Bendell, 1987). By 1986 the "Taguchi Method" had attracted much attention and controversy from researchers in the field which stimulated considerable research into understanding and improving the underlying statistics Taguchi employed. For example, León *et al* (1987) made the statistical connection between the Signal-to-Noise Ratio and the Quality Loss Function. Emphasis was placed on the dependence of the appropriate performance measure (e.g. Signal-to-Noise Ratio) being dependent on the underlying model representing the product function and the loss function used. Thus they provided an alternative, more general, transformation to the SNR called the Performance Measure Independent of Adjustment (PerMIA). Box (1988) went further and challenged the standing of the

SNR as an appropriate general solution to data transformation. The closely related subject of Response Surface Methods (RSM) to which Box has made major contributions (Box, Hunter & Hunter, 1978) is ignored here.

2.2.1(c) Dynamic characteristic

By about 1989 engineers and statisticians has begun to share the common cause of quality improvement through design at the time by authors such as Jebb & Wynn (1989) and the start of various symposia e.g. 1st European Symposium on Taguchi methods (Bendell, 1988). The Robust Engineering Design literature since appears to have been less occupied with analysis. Coleman & Montgomery (1993) presented a systematic approach to planning experiments discussed at great length in the literature. The method relied on a detailed guidesheet to direct information gathering and planning prior to the experiment. However, this work was a consideration of good pre-experiment preparation not an insight into dealing with the underlying physics or technology for robustness. Other researchers (Kacker, 1993; Otto & Antonsson, 1993a) have considered search issues. Kacker (1993) in addressing balanced noise factor arrays unravels perhaps one of the last unjustified (according to Kacker) facets of Taguchi's approach. However, Taguchi (1987) made another profound contribution which has again been largely overlooked by practitioners over this latter period, that is the *dynamic characteristic* - the quality of performance of a system over its dynamic range rather than just at one static operating point. It is a method closely related to multivariate analysis which avoids much of the mathematical complexity of more statistically rigorous approaches.

The dynamic approach to Robust Engineering Design is concerned with optimising a product's quality characteristic in terms of a range of outputs (Fig 2.5).

i.e. $$y = \beta M \qquad \textbf{(2.1)}$$

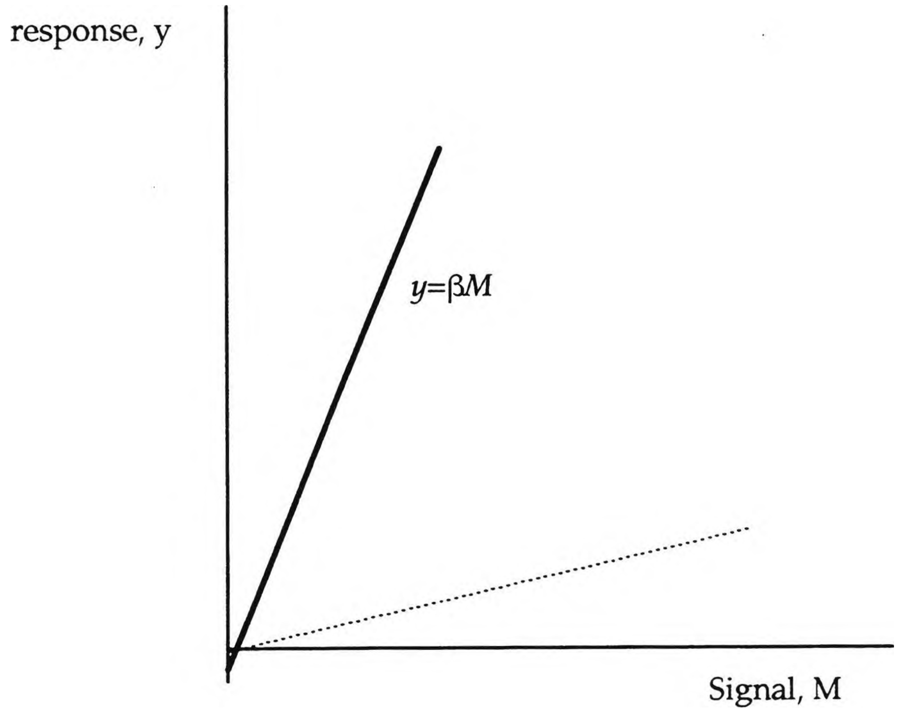


Fig. 2.5 Ideal dynamic relationship between signal and response

where M is the signal and β, is the slope of the linear relationship.

It is a generalisation of the static approach which is concerned with only one output target value. In the dynamic approach several signal values are tried for each experiment trial (Fig. 2.6). The static Nominal-is-Best (NB) approach seeks to find an adjustment factor during the analysis for adjusting the output to the target value, whereas the dynamic approach selects the adjustment factor (the Signal Factor) ***a priori*** ideally based on an energy flow through signal->system->output. The optimisation of a dynamic system involves:

(i) sensitivity - the slope, β, of the line (Fig. 2.5) for a linear relationship.

(ii) variability - about the linear function caused by the noise factors.

(iii) linearity - the form of the relationship, e.g. how close it is to a straight line and whether it passes through the origin.

Linearity is determined through the choice of dynamic Signal-to-Noise Ratio. The dynamic two-stage optimisation becomes, dependent upon the nature of the problem:

(i) Minimising variability and adjusting sensitivity.

or

(ii) Minimising variability and setting the signal factor to target.

Fowlkes & Creveling (1995) define the dynamic Signal-to-Noise Ratio conceptually as:

$$\mathrm{SNR}_{\mathrm{dynamic}} = \frac{\textbf{power of proportionality between } M \textbf{ and } y}{\textbf{power of variability around the proportionality}}$$

and for linear cases is expressed as $SNR_{Dynamic} = 10\log\frac{\beta^2}{MSE}$ **(2.2)**

where MSE, the Mean Square Error, is the average of the square of the residuals from the measured responses to the best fit line.

The recognition that good parameter selection depends upon an energy-based view of the system was clearly established with the advent of the

OA design factors							Results (for each signal)			SNR
A	B	C	D	E	F	G	M1	M2	M3	
1	1	1	1	1	1	1				
1	1	1	2	2	2	2				
1	2	2	1	1	2	2				
1	2	2	2	2	1	1				
2	1	2	1	2	1	2				
2	1	2	2	1	2	1				
2	2	1	1	2	2	1				
2	2	1	2	1	1	2				

Fig. 2.6 **L_8 Orthogonal Array with 3-level signal factor**

dynamic Robust Engineering Design approach. This is equally applicable to static Robust Engineering Design and therefore unless otherwise stated this thesis will continue in the context of static RED. Phadke (1989) has added other criteria regarding the ideal quality characteristic as continuous, monotonic, easy to measure and complete. Thus it would appear that there is significant scope to investigate energy-based simulation techniques as a front-end to Robust Engineering Design for parameter selection.

2.2.2 Noise factor Selection

As noise factors form the basis of the Robust Engineering Design methodology they warrant thorough investigation prior to experimentation. The selection process should aim to include representative noise in the design experiment through:

(i) Selecting likely noise factors by means of noise classifications or other methods of identifying uncontrollable influences on the product.

(ii) Subjecting the product to values or levels of noise that will be experienced by the product in manufacture and use.

2.2.2(a) Standard three noise factor classification

In the context of product and process quality a general Robust Engineering Design literature definition of noise is in terms of all (uncontrollable) causes of variation in the functional characteristics of a product or process (Taguchi, 1987; Phadke, 1989; Lochner & Matar, 1990; Peace, 1993; Fowlkes & Creveling, 1995). It is suggested by Kacker (1993) that this definition of noise originated with Taguchi but other authors have contributed further helpful descriptions. For example, Otto & Antonsson (1993a) confine the term noise factor to only those sources of noise that can be included in an experiment.

Apart from any semantic difference between, say, inner and internal or outer and external, the classification of noise factors still remains largely as Taguchi originally presented it - as three categories: *internal, external* and *unit-to-unit* variations. Definitions generally used in the literature regarding these categories are:

***Internal** noise*:	causes of variation inherent to the system such as wear and deterioration.
***External** noise*:	sources of variation outside the system such as environmental change.
***Unit-to-unit** noise*:	also an internal noise where differences between products are due to material/process variability.

For example Pignatiello (1988), Phadke (1989), Lochner & Matar (1990), Otto & Antonsson (1993b) and Peace (1993) all rely upon noise factor categories of this nature.

The standard Taguchi three-category noise factor classification employed in Robust Engineering Design experiments is difficult to apply to some systems. For example, for processes there are some difficulties in distinguishing between *external* and *unit-to-unit* sources of noise. Here the unit-to-unit variation of the in-coming product to be processed is at risk of being wrongly considered as part of the unit-to-unit variation of the process. Unit-to-unit variation of a process might be more readily recognised as that between several processes of the same design but in the literature the subject of the study is usually only a single process example. However with processes that use different moulds or positions within an oven then this is quite readily categorised as unit-to-unit noise.

2.2.2(b) Other Noise Factor classifications

Kacker who in an earlier paper (Kacker, 1985) relied upon just having the two categories of *internal* and *external* sources of variation, has more recently (Kacker, 1993) subdivided this 'internal' category into four divisions. Two of which appear to address the 'standard' *internal* noise described above, and the other two addressing *unit-to-unit noise* thus providing a total of five categories (our titles in **bold**):

(i) **Deterioration** due to wear and other internal chemical and physical changes.

(ii) Causes of variation inherent in the **measurement** process.

(iii) **External** factors - as described above.

(iv) intra-and inter-experimental unit variations - such as part differences due to differing material **supply** and differing machines or methods.

(v) unavoidable or uncontrolled variations ('**tolerances**') in the levels of experimental factors.

Kacker superimposes a further classification on noise factors which recognises that within the scope of an experiment it is not always possible to identify all the important noise factors due to a lack of time, resources or knowledge of the system. Therefore a surrogate or *pseudo* noise factors is often used which is not the real source of variation but coincides with it, for example '**day**' would be a *pseudo* noise factor representing the *real* noise factor **ambient temperature** and **humidity** that change during the day.

2.2.2(c) Searching Noise Space

Noise space represents the set of all possible values of n- noise factors as a n-dimensional domain (Kacker, 1993) and it can be considered to be divided according to known noise factor and unknown noise factor (identified and unidentified noise factors). In order that a product can be developed to be robust in the noise space it will encounter in manufacture and use, it is preferable that a representative sample of the noise space is simulated during Robust Engineering Design experimentation. Taguchi (1987) makes no reference to noise space, a fact picked up by Logothetis & Wynn (1989) but his earlier use of orthogonal arrays for noise factors, or noise arrays, (Fig. 2.7) is a means of systematically searching noise space.

						noise factor U	1	1	2	2
						noise factor V	1	2	1	2
						noise factor W	1	2	2	1
design factors										
A	B	C	D	E	F	G	Results 1	Results 2	Results 3	Results 4
1	1	1	1	1	1	1				
1	1	1	2	2	2	2				
1	2	2	1	1	2	2				
1	2	2	2	2	1	1				
2	1	2	1	2	1	2				
2	1	2	2	1	2	1				
2	2	1	1	2	2	1				
2	2	1	2	1	1	2				

Fig. 2.7 L_8 Orthogonal Array with L_4 noise array

Kacker (1993) has considered the justification for noise arrays in terms of representative sampling of noise space. Replication is the common safeguard of representative sampling chance to change the noise conditions but it also increases the cost of experimentation and therefore more efficient means are sought. Kacker divides noise space into strata where each stratum is sampled once. However whilst external noise factors, such as ambient temperature, could be considered to have a uniform probability distribution this is not true for the distribution of unit-to-unit noise factors. The underlying principle behind stratification is to achieve a balanced coverage of the full range of each noise factor. However, although Taguchi now advocates the use of compound noise levels (Fig. 2.8) in which the noise factors are grouped according to their effect on the directionality of the response to two levels (low noise and high noise), this is still a constant sampling strategy.

2.2.2(d) Noise space modelling

Modelling noise space variations is considered a separate issue to searching design space by Otto and Antonsson (1993b) as design space points have equal probability of occurrence but noise space points do not. They highlight the fact that Taguchi has used the same factorial approach for both. This is reflected in the standard Signal-to-Noise Ratio which assigns equal noise weighting to each experimental arrangement in summing over the noise space when used in conjunction with a noise array; rather than allowing for the actual probability of experiencing each noise condition particularly for manufacturing variation. Thus Otto & Antonsson model the probabilistic uncertainty of each noise factor with a probability density function and, as each is considered independent of the other, their combined probability is simply the product of each constituent function.

Several authors discuss noise in probabilistic terms, Siddall (1986) identifies some techniques for generating probability density functions

OA design factors							Results	
							CNF1	CNF2
A	B	C	D	E	F	G		
1	1	1	1	1	1	1		
1	1	1	2	2	2	2		
1	2	2	1	1	2	2		
1	2	2	2	2	1	1		
2	1	2	1	2	1	2		
2	1	2	2	1	2	1		
2	2	1	1	2	2	1		
2	2	1	2	1	1	2		

Fig. 2.8 L_8 Orthogonal Array with compounded noise factor levels

from known information such as statistical parameter estimation, mean rank plotting and Jayne's principle based upon maximising entropy. Siddall states:

> "As probability is such a subjective concept when applied to design, the engineer is quite justified in working with probability distributions even when no sample values are available".

Likewise the minimum sensitivity formulation used by Belegundu and Zhang (1989) does not make any assumptions on the distributions of uncertain variables. Wood and Antonsson (1990) followed by Otto and Antonsson (1993b) discuss the simultaneous consideration of ***imprecision*** (uncertainty in choice) with both ***probabilistic*** (stochastic) uncertainty and ***possibilistic*** (uncertainty due to freedom) uncertainty. Imprecision, probabilistic and possibilistic uncertainties being typified by design factors, tolerances and ambient temperature respectively.

The technique expressed by Otto and Antonsson (1993b) shows that when noise factors are of the variational type (unit-to-unit noise), the levels of ***tuning*** parameters can be adjusted to compensate for their effects. Thus tuning parameters can overcome unit-to-unit noise but they are ineffectual against external noise (such as environmental) and internal noise (such as deterioration). The precedence relation between realising the tuning and noise parameter values is important because not all of the tuning parameters are set before all of the probabilistic noise has occurred during manufacture. Of course the use of tuning parameters is counter to the philosophy of Taguchi, and the authors recognise this. But whilst they prefer to recognise the practical convenience of tuning parameters, and stake their claim for introducing a formal method for dealing with them, it is clear from Taguchi (1987) that his philosophy encourages research that focuses on good parameter design instead.

Controlling transmitted variability in the form of unit-to-unit variations is given more specific attention by many authors including Balling et al

(1986), Chase and Greenwood (1988) and Parkinson et al (1990). These variations are assumed to be small in each paper. Balling et al highlight the unlikelihood of all unit-to-unit variations combining to produce the worst case effect. Much has already been stated above concerning the unknown probability density distributions for noise factor but in Chase & Greenwood the problem of tolerance allocation versus tolerance analysis is considered. This recognises that in design the challenge is usually to work back from the target assembly tolerance set by design requirements to the allocation of component tolerances in some rational way, using either worst case or statistical tolerance models (e.g. a cost function). However, here again the assumption of normality is brought into question as the authors suggest that skewness and bias is common in manufactured parts because machines are set up to allow for tool wear (another noise factor). A new model for assembly tolerance accumulation, *Estimated Mean Shift*, is proposed by Chase & Greenwood (1988) which basically includes an estimate of bias giving a more comprehensive definition of a tolerance. Furthermore Chase & Greenwood highlight the need for Robust Engineering Design experiments on processes and machines in order to produce models that will make advanced tolerance analysis available to designers.

Contrary to the discussion above concerning probability density functions of noise factors, Parkinson et al (1990) argue that the normal distribution is acceptable for modelling tolerance variations because the product of distributions will tend towards normality from the Central Limit Theorem. They also advocate the controlling of transmitted variations by trading off tolerances and they use the term *controllable* and *uncontrollable* variables. Again a cost function features in their methodology for balancing the cost of tightening a tolerance with the improved objective.

2.2.3 Design factor Selection

Design factors (or control factors) are according to Phadke (1989) "product parameters that can be specified freely by the designer" which is how design factors are defined by Taguchi (1987), Grove & Davis (1992), Logothetis & Wynn (1989) and many engineering researchers. Other contributors such as Box, Hunter & Hunter (1978) have no definition instead simply referring to 'parameters' - which reflects a view that parameter selection is outside the scope of classical statistical design of experiments. A few authors venture sub-groups for design factors, such as Logothetis & Wynn who identify ***variability control factors*** (also described as *'control'* factors) and ***target control factors*** (also described as *'signal'* factors - which may be confused with the same term used by Taguchi for dynamic characteristics). This classification is equivalent to that used by Taguchi's consultancy organisation, the American Supplier Institute (1993), where a design factor is assigned to one of four classes that result from the permutations of whether it affects/does not affect variability and/or mean respectively. Fowlkes & Creveling (1995) suggest that only one design factor for tuning the mean on target is necessary, it is more important to have several design factors that contribute to the reduction of variability. Phadke highlights that design factors and tolerance factors can both affect variability but what distinguishes them is that design factor levels have no significant effect upon manufacturing cost. Such classifications above serve as a reminder that a primary task of Robust Engineering Design is to identify design factors which affect variability and to exploit these at minimum cost.

For a given design concept, the solution space to be explored by the designer through design experiments is determined by the choice of design factors and their level settings. This planning phase, where design factor selection is a major aspect is of vital importance in Robust Engineering Design according to Coleman & Montgomery (1993) poor planning is the primary reason why statistical design of experiments can fail whereas poor analysis is less often an issue.

Another aspect of design factor selection is in relation to the quality characteristic. The quality characteristic is the output response used to assess the product performance. With reference to additivity (addressed below), Phadke (1989) has developed guidelines for selecting the quality characteristic which are directly related to the ideal input-output energy relationship associated with the system. The guidelines also encourage the use of quality characteristics that are continuous, monotonic and easy to measure or set. Monotonicity relates to a design factor effect that is consistent in one direction. It was Taguchi (1987) that earlier raised the desirability of monotonicity but Phadke more clearly linked it with the basic mechanism of energy transfer of the system and increasingly this approach is supported by more recent literature such as Grove & Davis (1992) and Fowlkes & Creveling (1995).

Logothetis & Wynn (1989), Grove & Davis (1992), and Fowlkes & Creveling (1995) all highlight the selection of design factors that interact with noise factors as vital to successful implementation of Robust Engineering Design. Interestingly then when it comes to design factor selection, guidance is scant in the literature. Logothetis & Wynn observe that brainstorming is the most relied upon method. Phadke stresses the importance of qualitative understanding of how design factors affect a product but does not expand further. Coleman & Montgomery (1993) propose the use of guidesheets which encourage a review of theoretical relationships in listing potential design factors.

Fowlkes & Creveling (1995) endorse engineering analysis for selecting design factors and also put forward an argument for selecting wide design factor levels as having a larger effect than experimental variation and for finding the 'sweet spot'. This supports the advice of Phadke who suggests that sensitivity to noise does not usually change with small changes in design factor settings.

2.2.4 Dealing with interactions

According to Phadke (1989) additivity is a superposition principle applied to the main effects of the design factors which enables a product's performance to be predicted for any combination of design factor levels.

Modifying Eq. 1.9 from Chapter 1 to include an interaction term:

$$y = ax_A + bx_B + c\frac{x_A}{x_B} \tag{2.3}$$

This now means that when changing x_A the contribution to Δy is dependent on x_B and the coefficients a, b and c. In fact the net effect of Δx_A on Δy might be in the opposite direction.

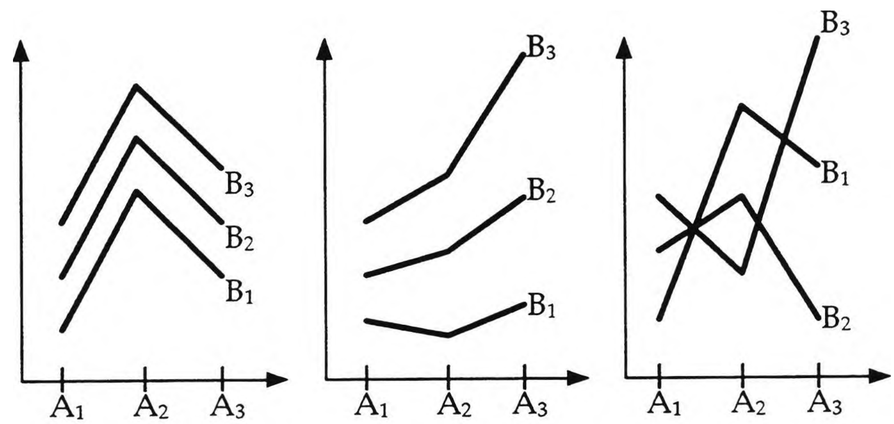
Taguchi (1987) states that finding parameters that exhibit additivity is the most important task for ensuring efficiency in research and development. Additivity is where prediction remains as valid under conditions of customer use as under design experiment conditions.

Interaction between design factor effects is considered to be the opposite of additivity. Phadke (1989) highlights two types (Fig. 2.9):

(i) negative or *antisynergistic* interactions, where the design factors work against each other and thus make prediction unreliable.

(ii) positive or *synergistic* interactions, where the design factors boost each others effect.

Fowlkes & Creveling (1995) go further and suggest that synergistic interactions should be treated as 'superadditivity'. Use of the term interaction in Robust Engineering Design is usually reserved for the antisynergistic type of interaction.



(a) no interaction (b) synergistic (c) antisynergistic

Fig. 2.9 Types of interaction

Phadke also highlights the crucial role the orthogonal array plays in Robust Engineering Design in achieving additivity because unlike one-factor-at-a-time experiments they are capable of detecting the presence of large interactions compared to main effects.

2.2.4(a) Data transformations

Additivity may not apply fully in the metric or scale of the original data, therefore researchers such as Box, Hunter & Hunter (1978), Taguchi (1987) and León et al (1987) have addressed the important role that data transformation can play in improving additivity. Box Hunter & Hunter highlight two classes of interaction:

(i) *Transformable* interactions which can be reduced or eliminated by analysing, for example, the log of the original scale (similar to the Signal-to-Noise Ratio) because they are an artefact of the units or distribution.

(ii) *Non-transformable* interactions such as chemical interactions which cannot be eliminated in this way because they are a physical phenomenon.

For transformable interactions the Signal-to-Noise Ratio is a data transformation that appears to be particularly well suited for use with engineering systems and has already been introduced above in Chapter 1. Alternatively the Box-Cox transformation (outlined in Box, Hunter & Hunter, 1978) is a generalised approach where data is transformed according to:

$$\bar{y}_{gm} = y^{(\lambda)} = \frac{y^{\lambda} - 1}{\lambda (\bar{y}_{gm})^{\lambda - 1}} (for \lambda \neq 0) \quad \textbf{(2.4a)}$$

or

$$\bar{y}_{gm} = \bar{y}_{gm} \ln y (for \lambda = 0) \quad \textbf{(2.4b)}$$

$$\text{where } \bar{y}_{gm} = e^{\frac{1}{n}\Sigma \ln y} = \text{geometric mean} \quad \textbf{(2.4c)}$$

In the Box-Cox approach searching for a suitable transformation uses a method of maximum likelihood by searching for the value of λ for which the error sum of squares is a minimum. However in the literature engineering case studies appear to seldom use this transformation perhaps because its iterative approach is viewed as too time-consuming.

2.2.4(b) Sliding factor levels

Taguchi (1987) sees design factor *sliding levels* as a simple and powerful way of improving additivity by cancelling non-transformable interactions when an obvious interrelationship exists between two or more design factors. Sliding levels are where the actual level values of one design factor depend upon the current level value of the related design factors. According to Taguchi there are two aspects to the sliding level approach:

(i) "To choose levels so that the range which one wishes to learn about will be included and any range known not to be actually useable is not included."

(ii) "Most importantly it has the advantage that it cancels interactions."

According to Hamada & Wu (1995) the sliding levels strategy is not solely Taguchi's but they concede that Taguchi was publishing on sliding levels as early as 1955. Hamada & Wu illustrate that an interaction between design factors can only be eliminated if the relation between them undergoes the correct centering and scaling of factor levels. Introducing these concepts into the relationship between the expected value of the response y and the x_i from Eq. 1.1:

$$E(y) = f_1[(x_A - C_A)/S_B) + f_2((x_B - C_B(x_A))/S_B(x_A))] \tag{2.5}$$

Where the C_i are the centering constants and the S_i are the scaling constants (those for factor B depend on factor A). Here $E(y)$ is a function with the potential for interaction elimination. A shear design (or skewed factorial) is a special case (Hillyer & Roth, 1972) of sliding level where the C_i are linear and the S_i are constant. Thus realising the potential to remove an interaction using this approach will only be achieved if the C_i

and the S_i are chosen correctly. This requires knowledge of the exact relationship between $E(y)$ and the x_i yet because the exact relationship is unknown prior to experimentation then Hamada & Wu question the rationale of interaction elimination as a reason for using design factor sliding levels. They argue that the primary motivation is bad region avoidance.

Hamada & Wu warn that even when interactions are eliminated by proper scaling and centering important information about robustness may be hidden. The terms *symmetrical* and *asymmetrical* interactions are used to describe the relationship between two design factors.

(i) Symmetrical interaction relates to situations where both factors are energy-related and consequently either can be slid with respect to the other.

(ii) Asymmetric design factors pose a problem because these have a definite preference for which one is to be slid, e.g. when one factor is qualitative with discrete levels.

Fowlkes & Creveling (1995) illustrate the use of sliding levels on practical engineering examples such as the development of a simple paper gyrocopter. Their valuable contribution gives a powerful insight of sliding levels through relating wing design factors, length and width. The correct approach is shown to be in assigning the sliding level through understanding the basic physical effects at work. Alternatively assigning length and width independently to the columns of an orthogonal array means that area - the effective function of the wing - is potentially achievable by several combinations of the columns thus confounding the results and yielding poor additivity.

There is little guidance on dealing with interactions beyond that demonstrated by the contributions of the above authors. For avoiding non-transformable interactions and determining the correct relationship between sliding-level design factors is left to rely upon engineering judgement.

2.2.5 Summary of Robust Engineering Design issues

Additivity has been shown to be a most important part of Robust Engineering Design and therefore methods of improving it should be sought. One group of methods would be those that assist in reducing the effects of non-transformable interactions. Sliding levels have been highlighted as effective for dealing with this but selecting the form of the relationship is difficult. Effective insight would be a welcome front-end for Robust Engineering Design and energy-based insight for parameter selection (quality characteristics, design factors & noise factors) in general has strong support from many authors. Energy-based tools would therefore seem to be worth investigating for this purpose.

Noise sampling in Robust Engineering Design is quite basic when the Signal-to-Noise Ratio is employed and yet unit-to-unit noise distribution has received a lot of attention in the more general tolerancing literature. Some of this thinking should find its way into Robust Engineering Design. For example, following up the principle that noise should be equally distributed across design factor levels.

2.3 Bond Graphs for Modelling Energy Systems

2.3.1 Relevance of bond graphs to Robust Engineering Design

Energy transfer has been highlighted as a key consideration of many physical systems when selecting parameters for a Robust Engineering Design experiment. Building an energy-based model of the system might therefore aid the parameter selection process. It is well known that the mathematics behind the dynamic behaviour of physical systems from different energy domains have much in common. Bond graphs are a means of generating rapid mathematical models of multi-energy domain systems which were introduced by Paynter (1961) based on electro-mechanical analogues. Notable contributions have been made by Karnopp (1985b), Rosenberg (1987) and Cellier (1990). The causality assignment associated with bond graphs makes them an interesting proposition for use as a Robust Engineering Design front-end.

2.3.2 Energy and power variables

Dynamic physical systems are concerned with one or more of the following: energy transfer, mass transfer or information (or signal) transfer. Bond graphs are an abstract representation of a system that uses one set of symbols to represent all applicable types of systems in terms of energy transfer (Karnopp, 1990). In particular, they focus on the exchange of power between components (Fig. 2.10).

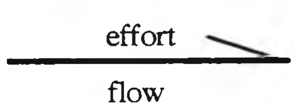


Fig. 2.10 Power bond

An *active bond* or *signal* (Fig. 2.11) indicates a flow of very low power such that it is not considered to affect the power of any device it is connected to. It is used to represent the distribution of information around the system.

Fig. 2.11 Active bond or signal

2.3.2(a) Two power variables

Each line or *bond* with *half arrow* (Fig. 2.10) in a bond graph implies the existence of a pair of signals whose flows are in opposite directions. These signal pairs, or *power variables*, are generally termed *effort (e)* and *flow (f)*. As the system is dynamic they are often functions of time.

Thus: power, $P(t) = e(t)f(t)$ **(2.6)**

The places at which the bonds connect to various elements within the system are termed *ports*. The energy which has passed into or out of a port over time is found from the time integral of power.

Energy, $E(t) = \int_0^t P(t)dt = \int_0^t e(t)f(t)dt$ **(2.7)**

2.3.2(b) Two energy variables

The time integrals of effort and flow are called *momentum p*, and *displacement q*, respectively.

$$p(t) = \int_0^t e(t)dt \qquad \textbf{(2.8)}$$

$$or \quad \frac{dp(t)}{dt} = e(t) \qquad \textbf{(2.9)}$$

$$q(t) = \int_0^t f(t)dt \qquad \textbf{(2.10)}$$

$$\text{or} \quad \frac{dq(t)}{dt} = f(t) \qquad \textbf{(2.11)}$$

Using Eq. 2.9 and Eq. 2.11, then Eq.2.7 can be expressed as:

$$\text{Energy}, E(t) = \int_0^t e(t)dq(t) = \int_0^t f(t)dp(t) \quad \textbf{(2.12)}$$

In engineering systems, effort is often expressed as a function of displacement and flow as a function of momentum such that the equations in Eq. 2.12 become:

$$E_q = \int_{q_0}^{q} e(q)dq \quad \textbf{(2.13)}$$

$$E_p = \int_{p_0}^{p} f(p)dp \quad \textbf{(2.14)}$$

Eq. 2.13 is appropriate to the 'potential' energy stored in a capacitor element and Eq. 2.14 is appropriate to the 'kinetic' energy stored in an inertia element.

2.3.3 Bond graph elements

Only a few basic types of element are required in order to model a variety of energy domains (Rosenberg & Karnopp, 1983; Karnopp, Margolis & Rosenberg, 1990). The elements will have one or more ports and at each port, effort and a flow variables co-exist, one will be controlled but not both simultaneously.

2.3.3(a) Passive 1-port elements

A *1-port* element is one which is connected to the rest of the system through a single port, i.e. a single pair of effort and flow variables exist. In some cases the idealised relationship between *e* and *f* can be complex. Passive 1-ports are termed passive because they contain no *source* of power.

(i.) **1-port resistor, R:** is an element in which a static constitutive function relates *e* and *f*. These generalised resistors usually *dissipate* energy - whenever the product of *e* and *f* is positive.

(ii.) **1-port capacitor, C:** is an element in which e and q are related by a static constitutive function. Whenever the product eq is positive these generalised capacitors *store* energy.

(iii.) **1-port inertia, I:** is another element that generally *stores* energy, whenever the constitutive equation relating p and f is positive.

2.3.3(b) Active 1-port elements

These are usually known as sources because they are used to provide a first approximation of a source of power. In an idealised sense one of the effort or flow co-variables remains an idealised constant or specified function of time, within sensible limits, whilst the other co-variable will certainly vary.

(i.) **Effort source, S_e:** is an element where effort is the idealised function.

(ii.) **Flow source, S_f:** is an element where flow is the idealised function.

2.3.3(c) Basic 2-port elements

Only two basic types of 2-port elements are used. Both conserve power such that $e_1(t)f_1(t) = e_2(t)f_2(t)$ and are therefore idealised versions of the real devices they represent because the efficiency of power transfer is effectively 100% whereas the physical reality would be rather different:

(i.) **2-port transformer, TF:** used for approximating devices that step-up or step-down the power variables according to $e_1 = me_2$ *and* $mf_1 = f_2$, where m is the ***transformation modulus***.

(ii.) **2-port gyrator, GY:** depicts another way of conserving power by essentially interchanging the roles of effort and flow where the constitutive laws are $e_1 = rf_2$ *and* $rf_1 = e_2$ and r is the ***gyrator modulus***.

2.3.3(d) Modulated 2-port elements

There are generalisations of the transformer and gyrator in which power conservation is maintained even when the moduli m or r are not constant - the *modulated transformer*, MTF and the *modulated gyrator*, MGY. The moduli are shown as signals (or active bonds) as no power change is associated with changes in *m* or *r*.

2.3.3(e) 3-port junction elements

3-port junction elements serve to interconnect other elements in the model. Again they are power conserving such that $e_1f_1(t)+e_2f_2(t)+e_3f_3(t)=0$:

(i) **0-junction, flow junction or common effort junction:** where the constitutive laws are $e_1(t)=e_2(t)=e_3(t)$ (i.e. common effort) *and* $f_1(t)+f_2(t)+f_3(t)=0$.

(ii) **1-junction, effort junction or common flow junction:** where the constitutive laws are $f_1(t)=f_2(t)=f_3(t)$ (i.e. common flow) *and* $e_1(t)+e_2(t)+e_3(t)=0$.

2.3.4 Causality

The direction of the half arrowhead on the bond indicates the direction of positive power flow (Rosenberg & Karnopp, 1983). The short bar or *causal stroke* indicates how *e* and *f* are simultaneously determined on a bond, i.e. effort *pushes* towards the causal stroke and flow *flows* away from it (fig. 2.12).

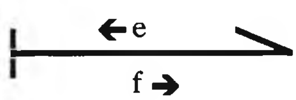


Fig. 2.12 Causal stroke

The study of input-output causality is the unique feature of bond graphs and this helps to show how the underlying mathematics will turn out and hence avoid analytical problems, such as unnecessary differential calculus (Karnopp, Margolis & Rosenberg, 1990). In mathematical modelling the organisation of component constitutive laws into sets of differential equations requires cause-and-effect decisions to be made (Rosenberg & Zhou, 1988).

The basic multiports fall into three categories regarding causality:

(i) Some that are heavily constrained with respect to possible causalities - e.g. effort source S_e, and flow source, S_f.

(ii) Some are relatively indifferent to causality - e.g. Resistors, Transformers and Gyrators.

(iii) Some exhibit their constitutive laws in distinctly different form for different causalities - e.g. Compliances and Inertias.

The different causalities mentioned are related to whether the constitutive equations are in their preferred integral form or the alternative and more difficult to handle derivative form (Rosenberg, 1987). The derivative form gives rise to equations in which derivatives appear on both sides of state-space equations, which means that elements are not dynamically independent and therefore do not contribute state variables. Fig. 2.13 shows some of the basic bond graph elements assigned according to their preferred causality (including both options for R):

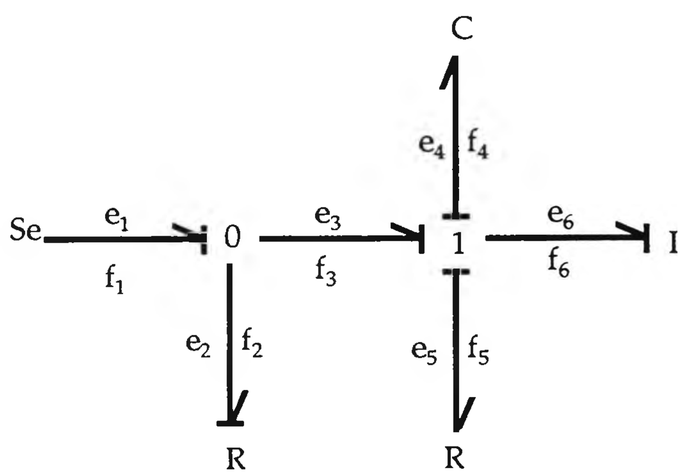


Fig. 2.13 Bond graph with integral causality

2.3.5 Vibratory air pump example

Bond graphs have been used to model a vibratory air pump in different stages of complexity by Martens & Bell (1972). Fig. 2.14 shows a schematic of the pump where an alternating electrical supply drives a magnet attached to a pivoted lever that acts on a rubber bellows pump. Check valves ensure that air flows one way through the pump.

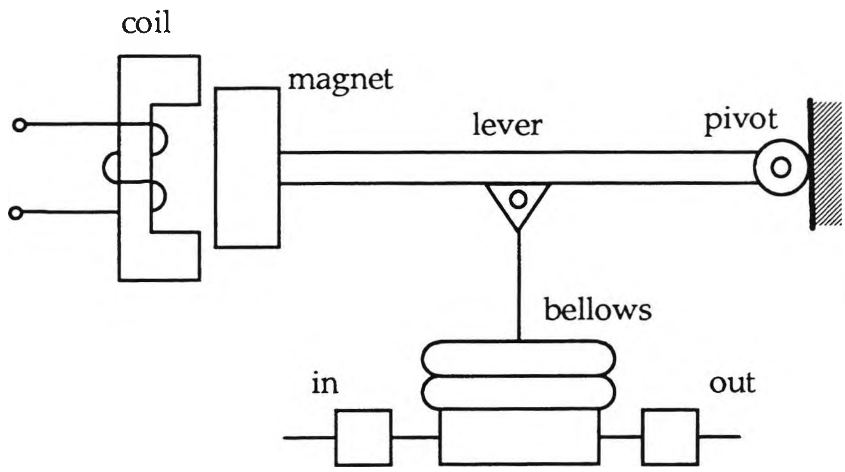


Fig. 2.14 Schematic of air pump

Two bond graphs of differing complexity are reproduced here in Fig. 2.15 and Fig. 2.16 but not all of their associated state-space equations. The bond graphs are used here to relate system input to output through use of the causality assignment that is part of the bond graph methodology.

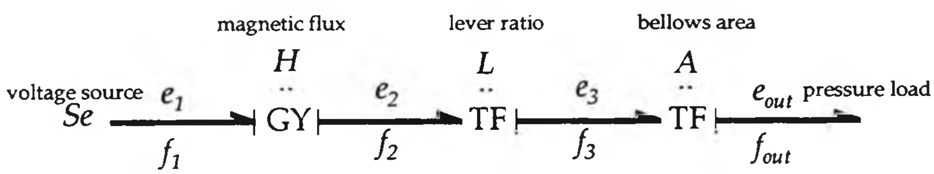


Fig. 2.15 Simple bond graph model of air pump

From Fig. 2.15 the equations for the three 2-port elements written in causal form are:

For the electromagnetic actuator, $f_2 = \frac{1}{H} e_1$ and $f_1 = \frac{1}{H} e_2$

For the lever, $f_3 = Lf_2$ and $e_2 = Le_3$

For the air bellows, $f_{out} = Af_3$ and $e_3 = Ae_{out}$

Combining these equations yields the relations:

$$f_{out} = \frac{AL}{H} e_1 \text{ and } f_1 = \frac{AL}{H} e_{out}$$

In Fig. 2.16, additional parameters are now identified, these are *R, N, M, B, 1/K, C and Ro*.

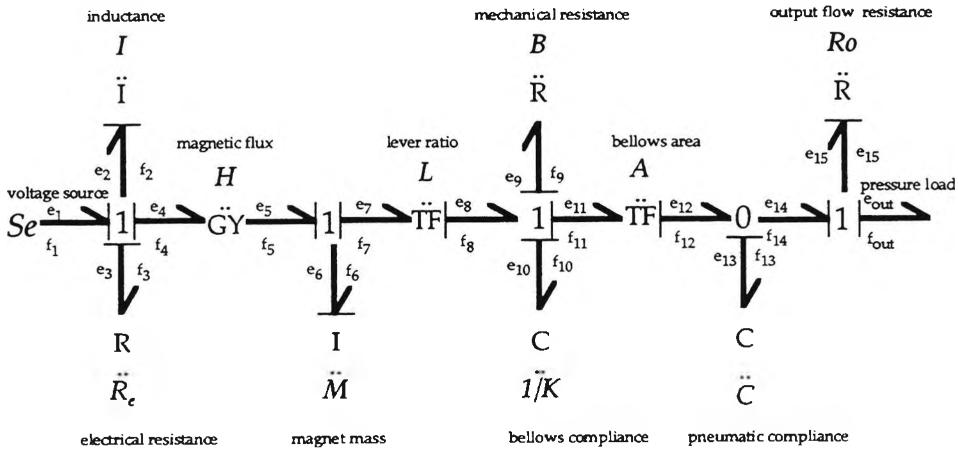


Fig. 2.16 Developed bond graph of air pump

The state space equations become:

<u>The momentum states for each inertia</u>:

$$\frac{dp_2}{dt} = e_1 - e_3 - e_4 = e_1 - R_e f_3 - Hf_5 = e_1 - R_e f_2 - Hf_6$$

$$\text{where} \frac{dp_2}{dt} = I \frac{df_2}{dt}$$

$$\therefore \frac{df_2}{dt} = \frac{1}{I}\left[S_e - R_e f_2 - Hf_6\right]$$

$$\frac{dp_6}{dt}=e_5-e_7=Hf_4-Le_8=Hf_2-L(e_9+e_{10}+e_{11})=Hf_2-L(Bf_9+e_{10}+Ae_{13})$$

$$\frac{dp_6}{dt}=Hf_2-L(BLf_6+e_{10}+Ae_{13})$$

where $\frac{dp_6}{dt}=M\frac{df_6}{dt}$

$$\therefore\frac{df_6}{dt}=\frac{1}{M}\left[Hf_2-L^2Bf_6-Le_{10}-ALe_{13}\right]$$

<u>The displacement states for each capacitance:</u>

$$\frac{dq_{10}}{dt}=f_8=Lf_7=Lf_6$$

where $\frac{dq_{10}}{dt}=\frac{1}{K}\frac{de_{10}}{dt}$

$$\therefore\frac{de_{10}}{dt}=KLf_6$$

$$\frac{dq_{13}}{dt}=f_{12}-f_{14}=Af_{11}-\frac{e_{15}}{R_o}=Af_8-\frac{e_{14}-e_{out}}{R_o}=ALf_7-\frac{e_{14}-e_{out}}{R_o}=ALf_6-\frac{e_{14}-e_{out}}{R_o}$$

where $\frac{dq_{13}}{dt}=C\frac{de_{13}}{dt}$

$$\therefore\frac{de_{13}}{dt}=\frac{1}{C}\left(ALf_6-\frac{1}{R_o}(e_{13}-e_{out})\right)=\frac{1}{C}\left(ALf_6-\frac{1}{R_o}(e_{13}-S_p)\right)$$

Assembling the results in a matrix format we have:

$$\frac{d}{dt}\begin{bmatrix}f_2\\f_6\\e_{10}\\e_{13}\end{bmatrix}=\begin{bmatrix}-\frac{R_e}{I} & -\frac{H}{I} & 0 & 0\\ \frac{H}{M} & -\frac{L^2B}{M} & -\frac{L}{M} & -\frac{AL}{M}\\ 0 & KL & 0 & 0\\ 0 & \frac{AL}{C} & 0 & -\frac{1}{CR_o}\end{bmatrix}\begin{bmatrix}f_2\\f_6\\e_{10}\\e_{13}\end{bmatrix}+\begin{bmatrix}\frac{1}{I} & 0\\ 0 & 0\\ 0 & 0\\ 0 & \frac{1}{CR_o}\end{bmatrix}\begin{bmatrix}S_e\\S_p\end{bmatrix}$$

Finally,

$$f_{out}=\frac{e_{15}}{R_o}=\frac{e_{14}-e_{out}}{R_o}=\frac{e_{13}-S_p}{R_o}$$

Thus explicit state equations are obtained with integral causality. For example, for the pneumatic compliance R_o, A and L are related to C. In particular from the form of the equation we might expect R_o and C to be correlated. This appears to be confirmed in the matrix representation where the coefficients on the leading diagonal of the main matrix are time constants.

2.3.6 Summary of bond graph issues

Bond graphs offer a means of simulating the behaviour of energy-based systems which will be applicable to a wide range of engineering products, particularly those involving several energy domains. Familiarisation with bond graph models brings with it a rapid insight into causal relationships operating within the system under investigation. Another important property of bond graphs is that the topology of the physical system is maintained because of the unique way in which the efforts and flows are not separated graphically. Simulation packages based upon bond graphs enable models of the proposed system to be rapidly built and evaluated. The literature offers no case studies on the application of bond graphs to Robust Engineering Design.

2.4 Multiple Objective Optimisation

2.4.1 Optimisation in design methods

Optimisation is generally defined as making a system or process as good as possible in some defined sense subject to restrictions or constraints that are imposed (McGraw-Hill Encyclopaedia of Science & Technology, 1997; Tabucanon, 1988).

Dieter (1983) points out that optimisation is inherent to the design process and recalls Siddall's (1986) review of the development of optimal design methods, which addresses optimisation by evolution; by intuition; by trial-and-error; and by numerical algorithm. Evolution improves on existing designs where the best survive. Intuition is the art of knowing what to do without knowing why it is done. Trial-and-error modelling goes about improving on an initial estimate which is not considered true optimisation. Numerical algorithms are concerned with mathematical strategies of searching for an optimum.

No standard techniques are offered as it is seen to depend upon the nature of the problem. Mathematical approaches to optimisation are increasingly applied to engineering design for which there can be considered a general framework (McGraw-Hill, 1997) including:

(i.) Forming a system model that represents all of the important features of the problem.

(ii.) Establishing and treating constraints as they restrict the values that can be assumed by the system.

(iii.) Determining feasible solutions that simultaneously satisfy all constraints.

(iv.) Assigning performance measures which is a key step as success critically depends upon selection of meaningful measures.

Quality Function Deployment addresses (ii) and (iii) to the extent that design solutions are judged against the constraints through the relationship and correlation matrices. Robust Engineering Design addresses (i), (iii) and (iv) by virtue of the additive model, searching design space with the orthogonal array and using the Signal-to-Noise Ratio as the means of judging superior performance. However, multiple objectives (iv) has not been addressed by Robust Engineering Design and the Quality Function Deployment correlation roof has already been shown to be underexploited.

Evbuomwan et al (1996) note the vast array of methods available at the conceptual stage of design in order to systematically deal with the range of possible attributes and objectives that can be assembled for even a simple product brief. The terms attributes, objectives and criteria are invariably used to describe decision problems where there is more than one performance measure of interest. There are no universal definitions but *multiple criteria* seems to have emerged as accepted nomenclature (Tabucanon, 1988)) for describing all models and techniques dealing with *multiple objectives* and *multiple attributes*. Multiple attributes often deal with relatively small numbers of discrete alternatives - i.e. problems of choice. Multiple objectives are more often used with reference to large number of potential solutions involving variables - i.e. problems of design where mathematical techniques are needed, which is our concern herein. Conflict is a defining feature of all multiple criteria problems where there has to be at least two conflicting criteria and at least two alternative solutions. Thus for multiple objectives as we increase the satisfaction of one objective this characteristically results in decreasing satisfaction with the other objective and trade-off is inevitably involved.

The methods employed and described in the literature for practical engineering design problems generally employ either a modified single objective function or a unifying objective function. For example, Dieter (1983) details Johnson's (1980) Method of Optimum Design (MOD) as especially suited to non-linear problems. MOD deals with multiple objectives by choosing a main objective and making the others into constraints. Whereas the approach presented by Woodson (1966) allocates a relative weighting value to each objective and combines them in a utility function for optimisation. There are certain cases with the former approach where there is no feasible region of design space remaining after constraints are introduced, furthermore approaches of the latter type are considered more elegant as they enable a sensitivity analysis to be performed (Dieter, 1983; Tabucanon, 1988). In particular *utility functions* have been applied.

2.4.2 Utility functions for multiple objectives

Utility theory was originally developed by von Neumann & Morgenstern (1947) with later developments from Fishburn (1970) and a standard reference text by Keeney & Raiffa (1976), and recent contributions from Thurston (1997a; 1997b). Derringer and Suich (1980) built on the work of Harrington (1965) to provide a ***desirability function*** for optimising polymer formulations to meet a set of property specifications through experimental design. This method transforms each response, Y_i, into a desirability variable, d_i (Eq. 2.15). and then combines them using the geometric mean (Eq. 2.16). As d_i's are continuous functions of the Y_i's and also D is a continuous function of the d_i's then D is therefore a continuous function of Y_i's and a multivariate problem is condensed into a univariate one.

$$d_i = h(y_i) \qquad (0 \leq d_i \leq 1) \tag{2.15}$$

$$D = (d_1 * d_2 * \ldots * d_k)^{1/k} \tag{2.16}$$

The desirability function and other similar utility functions enable the objective function to be plotted as a function of one or more of the independent variables (design factors) and thus determine sensitivity to small changes in the design factor.

2.4.3 Summary of multiple objectives issues

Multiple objectives are inevitable in engineering design but the Robust Engineering Design literature has largely overlooked this issue. Utility functions appear to be well-suited to linking with Robust Engineering Design but this presents a stochastic-to-deterministic hurdle to be overcome. Also the nature of the function used requires justification. Suggested approaches are only briefly made in the literature but without sufficient example.

Design experiments are concerned with a particular concept option selection and its design factors whilst more general creative activity is suspended. Here the experimenter is faced with fewer criteria to satisfy and yet interestingly the majority of design experiments in the Robust Engineering Design literature focus on a single primary criterion. Taguchi (1987) only makes a passing reference to the possibility of more than one target characteristic. Phadke (1989) goes a little further proposing that joint consideration of two quality characteristics will inevitably involve trade-offs between conflicts and proffers the Loss Function to deal with this. However, no example is cited. Fowlkes & Creveling (1995) recommend limiting design factors affecting mean to one in order to help to avoid cooptimisation issues.

2.5 Summary of the Literature Review

2.5.1 Discussion

Quality Function Deployment and Robust Engineering Design have been introduced over the past 30 years and shown to be very successful methodologies bringing improvements to the effectiveness (and efficiency) of the design process. They can be viewed as design systems in their own right but we have begun to consider the ways in which they might be combined as a more effective systematic design method for addressing robustness than conventional design methodologies which do not. Drawing together the areas of the literature reviewed in this chapter there are two main themes for development, function decomposition and multiple objective optimisation, which will be seen to be closely related to each other to the extent that there are specific issues relevant to both.

2.5.1(a) Function decomposition

Function decomposition has been a major theme of recent design research, we have shown that it is also an inherent product of the translation process of Quality Function Deployment and also relevant to Robust Engineering Design in terms of parameter selection and performance prediction. Therefore the meaning of 'function' needs to be clarified with respect to these customer-centred and robustness-centred aspects of a quality engineering design methodology. Quality Function Deployment presents a picture of function decomposition as very much a 'multi-start' issue in that there is not just one design requirement but many to be broken down. However, Quality Function Deployment leaves something of a gap between each phase which other methods currently have to fill. Between phase 1 and phase 2 there is the vital activity of product concept design and embodiment in which enhanced Quality Function Deployment approaches employ design methods such as Pugh Concept Selection. Phase 1 outputs design requirements and Phase 2 continues with the critical part characteristics which means that the bulk of function decomposition has already occurred in this gap and which has a critical bearing on subsequent phases. Therefore there is scope for exploring these interfaces with concept design in order to keep quality clearly on the agenda. Robust Engineering Design would appear well-suited to playing a role here as it is concerned with correctly breaking the problem down in order to reduce performance variability to a minimum. Improving the means of parameter selection in Robust Engineering Design has been widely supported and the general energy-based approaches advocated in the literature point towards more engineering science such as bond graph modelling at the front-end of RED. Interactions or the potential for interactions will occur and the method by which they should be handled has to be developed in order to achieve the vital property of additivity for subsequent prediction purposes (see second major theme). In Robust Engineering Design experiments we need to accurately determine likely interactions before the experiment begins and employ techniques such as sliding levels to negate their effects on the experimental results. Another interaction issue is the QFD correlation roof which could be more effectively utilised by using the information contained in it more fully as an aspect of function decomposition.

2.5.1(b) Multiple objectives

Multiple objectives are inevitable in design problems. As we have already noted in the above context, this is reflected in Quality Function Deployment by the mapping of the collection of 'Hows' onto the 'Whats' as a record of the way in which the emerging design is addressing the cascade of objectives translated from phase to phase. Ideally it would be a one-to-one mapping to avoid conflict but the correlation roof serves to highlight that engineering design of complex products invariably presents a trade-off of conflicting requirements. The correlation chain goes some way to modelling the links between each requirement and the means of achieving it which is a strong hint of the connection between Quality Function Deployment and Robust Engineering Design. However Robust

Engineering Design literature has largely overlooked the multiple objective issue. Furthermore, as production variability is both a QFD Phase 3 issue and a RED noise consideration its influence on the multiple objective decision-making process would appear to be worthy of investigation. Thus multiple objective optimisation is a complementary issue to function decomposition in that we desire to assess the impact of nominal values (and variability) of the lower-level parameters that have emerged from the decomposition on the higher-level requirements. A two-way flow of information that ideally can be viewed more simultaneously through developing this combined QFD/RED design methodology.

The two themes above offer some opportunities to enhance the efficiency of concurrent engineering design.

The hypotheses below appeared in the introductory chapter.

2.5.2 Hypotheses in relation to the literature

2.5.2(a) Hypothesis #1

"Robust Engineering Design can yield efficient results through more pragmatic approaches that involve engineering science and production capability in parameter selection and level setting."

The themes of decomposition and multiple objectives relate well to this hypothesis. In brief we wish to use engineering science to make the initial parameter selection followed by Robust Engineering Design experiments to modify level settings in light of production capability influences on variability and with regard to another pragmatic issue of multiple objectives.

2.5.2(b) Hypothesis #2

"The correlation roof of Quality Function Deployment can be used to inform design procedure and provide a link with Robust Engineering Design".

Again drawing on both of the themes above by firstly using the correlation roof as part of the function decomposition process with the intent of plugging this output into the front-end of Robust Engineering Design using engineering science. Secondly by developing the roof as a means of recording conflict and trade-off information gathered from Robust Engineering Design as an important aid to any subsequent redesign.

2.5.3 Project objectives

(i) To demonstrate the decomposition of the correlation roof into design procedures and the link between Robust Engineering Design and correlation chains.

(ii) To consider the use of energy-based methods in selecting parameters and determining sliding levels for Robust Engineering Design experimentation, focusing on bond graphs and dimensional analysis.

(iii) To gather practical guidance on selecting design factor levels and noise factor levels for product Robust Engineering Design experiments conducted in a production environment.

(iv) To utilise different noise factor level weightings and model them against design factors in order to better reflect noise behaviour in reality.

(v) To show how quality loss functions can be established for multiple objective optimisation in practical Robust Engineering Design using competitive benchmarking and capability mapping for optimisation of total loss.

Chapter 3. Proposed Philosophy

3.1 Replace the Current QFD Correlation Matrix

3.1.1 The use of a square matrix to accommodate asymmetrical relationships

In attempting to complete the correlation roof of the House of Quality (Fig. 2.2 in Chapter 2) it is often difficult in practice to identify all the relationships without defining dependent and independent factors first. These causal relationships are clarified by using a square matrix with the same design requirements assigned to rows as corresponding columns. This will mean that the matrix is not symmetrical (Fig. 3.1). From this asymmetry of causal relationships it will be possible to determine an order for addressing each factor or requirement. This reduces the total solution space dramatically for two aspects of the design problem:

(i) The *procedural domain* which includes all design requirements, some of which cannot be measured or target values set, which are recorded at a general level in QFD phase 1.

(ii) The *physical domain* which can now be quantified. Once the independent factors are set the others must follow from physical laws.

3.1.2 Determining design procedure in phase 1

3.1.2(a) Method

In Chapter 2 it was highlighted that the correlation chain concept (Comincini, 1994) has been applied to algorithmically linking the 'Whats' and the 'Hows' at QFD phase 2 level in the context of information retrieval for design modifications. Here it is proposed that whilst some parameters are linked strongly via equations, not all correlations are quantitative in phase 1. However correlation chains can still be developed from the 'Hows' of QFD phase 1, i.e. the design requirements, in order to establish a design procedure. It has already been noted that in Quality Function Deployment the correlation roof is viewed as under utilised - the roof being considered to be too difficult to complete fully in some cases. The elements of the correlation chains explored here are not to be confined to the raw design requirements of QFD phase 1 but also include design functions, parameters or modules further developed as part of the concept generation design activity prior to conducting QFD phase 2 (Part Deployment). The suggested approach is as follows:

(i.) List the important design functions, parameters or modules ('design requirements' for brevity) preferably in a solution-neutral form ('embodiment-neutral' for redesign problems).

(ii.) For each of the design requirements identify on which of the other design requirements it has a direct and substantial influence.

(iii.) Collate these interdependencies as a network of correlation chains.

(iv.) Develop the network into a hierarchy with the most independent design requirements at the top.

(v.) Design will thus proceed from the top of the hierarchy.

We are therefore performing a decomposition of the overall design problem which should help to partition the design activity into a set of tasks or procedures that are grouped according to their interdependence.

An automotive body example will illustrate the steps:

(i.) List important design requirements

For example, from QFD phase 1 consider the following are our key design requirements.

A - air drag

B - crash resistance

C - passenger space

D - engine space

E - wheel space

F - luggage space

G - appearance

(ii.) Identify direct and substantial influences

Identify the dependencies between design requirements and use the modified correlation roof to record them.

		Y	Y		Y	G
Y					F	
				E		
Y	Y		D			
Y		C		Y		
	B					
A						
A air drag	B crash resistance	C passenger space	D engine space	E wheel space	F luggage space	G appearance

Fig. 3.1 Direct and substantial influences

In Fig. 3.1 each column identifies the design requirements that are directly influenced by the design issue assigned to the column. For example, air drag considerations (e.g. target value, positions of air intakes) are shown here to directly influence the passenger space, engine space and luggage space decisions. Similarly, wheel space is shown to directly influence passenger space (but not vice versa according to the designers) and so on.

(iii.) Form network of correlation chains (Fig. 3.2)

(iv.) Develop hierarchy of correlation chains (Fig. 3.3)

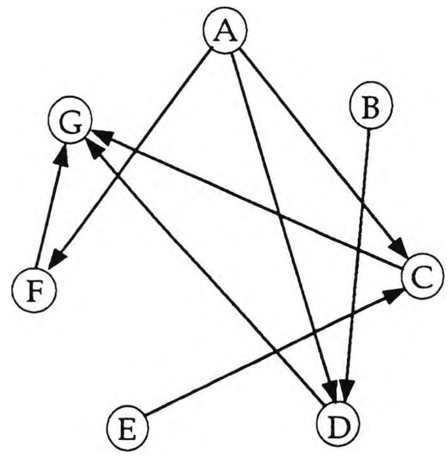


Fig. 3.2 Network of correlation chains

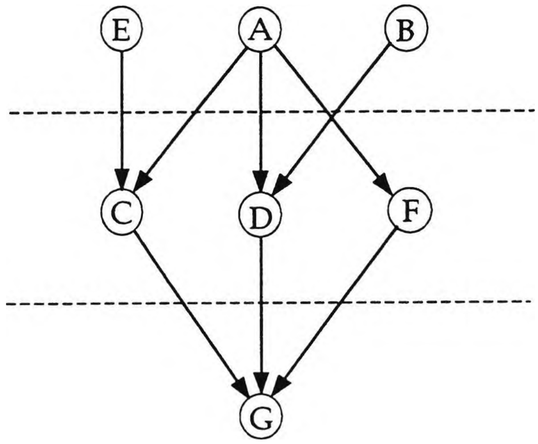


Fig. 3.3 Hierarchy of correlation chains

(v.) Design procedure

For this simple example the correlation chains established can be readily assembled into a hierarchy as shown in Fig 3.2 and Fig 3.3. The hierarchy suggests that the design be tackled in three stages:

- Addressing air drag, crash resistance and wheel space requirements.
- Determining space requirements for passengers, engine and luggage.
- Establishing the appearance of the body.

It is important to note that design solutions are heavily dependent on design procedure and therefore, in this approach, on the influences identified in the correlation roof. Thus in phase 1 it is important to be clear about the nature of the influences identified. In the above example, the body appearance will be explored with a clear idea of space requirements which in turn have been influenced by requirements such as crash resistance.

3.1.2(b) Application to Solar Car

An experienced solar car design team were asked to complete steps (i) & (ii) above after they had already produced and run a vehicle for the World Solar Car Challenge in Australia (Duke, 1996).

(i.) List important design requirements

A - air drag: Viewed as the most important factor by the team as it accounts for considerable energy consumption and limits the top speed potential of the car.

B - chassis vibration: Excess vibration will damage the solar panels.

C - vehicle weight: Reducing weight is important in reducing power consumption and the dynamic loads on wheels and suspension.

D - rolling resistance: Must be low for minimum energy consumption.

E - power system efficiency: Vital to energy efficiency as it affects the management of energy between storage and discharge.

F - maintenance/repair: It is obviously important that maintenance and repairs can be conducted quickly during a race.

G - driver comfort: Travelling over 3000 miles makes this an important issue. It also relates to the design of the suspension.

H - wheel/tyre design: Number, size and construction of the wheels.

I - chassis shape: Is the basic layout and shape of the vehicle.

J - motor/drive configuration: Ideally of the in-hub type and has to be chosen with regard to energy management considerations.

K - batteries: A large number of batteries are required to provide adequate energy storage.

L - solar array: Converts sunlight into electricity, therefore requires maximum exposure. Solar cells are expensive items which are vulnerable to damage.

M - suspension: Determines the ride characteristics of the car.

N - electrics: must be reliable and safe.

O - cockpit visibility: good visibility important for safety reasons.

(ii.) Identify direct and substantial influences

The design team then addressed each combination of design requirement and indicated direct and substantial influences by placing a Y in the column of the influencing requirement (Fig 3.4).

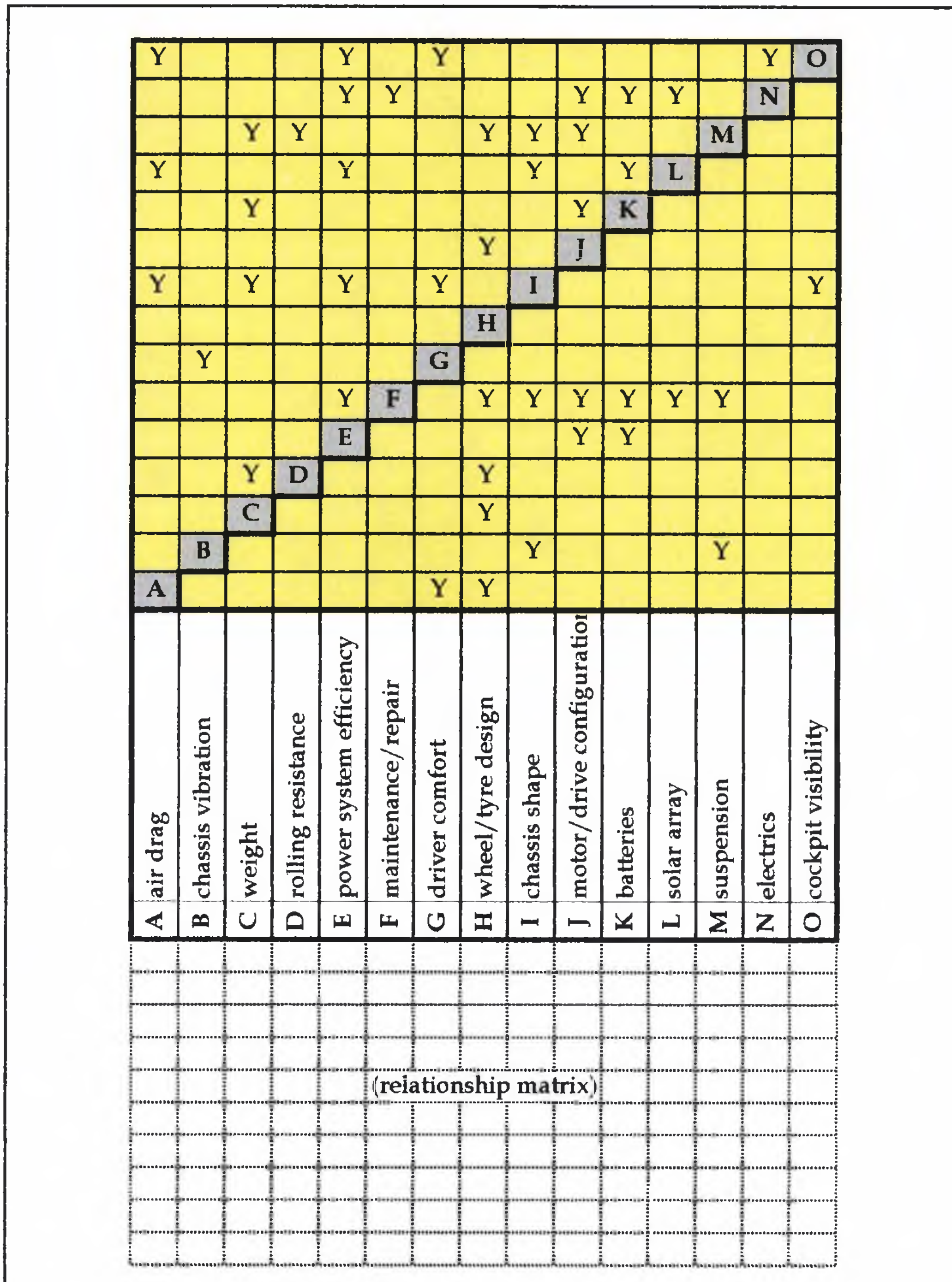


Fig. 3.4 Assessing influences in the correlation chain

(iii.) Network of correlation chains

The relationships identified in Fig. 3.4 are not symmetrical which enables a raw network of links (correlation chains) to be established (Fig. 3.5) which can be rationalised through removing the causal redundancy between some nodes. For example, the direct link between H and D (marked with a X in Fig. 3.5) can be deleted as the indirect links H-C-D (marked with a ✓ in Fig. 3.5) maintain the causal connection between H and D. Fig. 3.6 shows the result of this rationalisation process. The chain line shows that a large proportion of the network is locked in a closed loop.

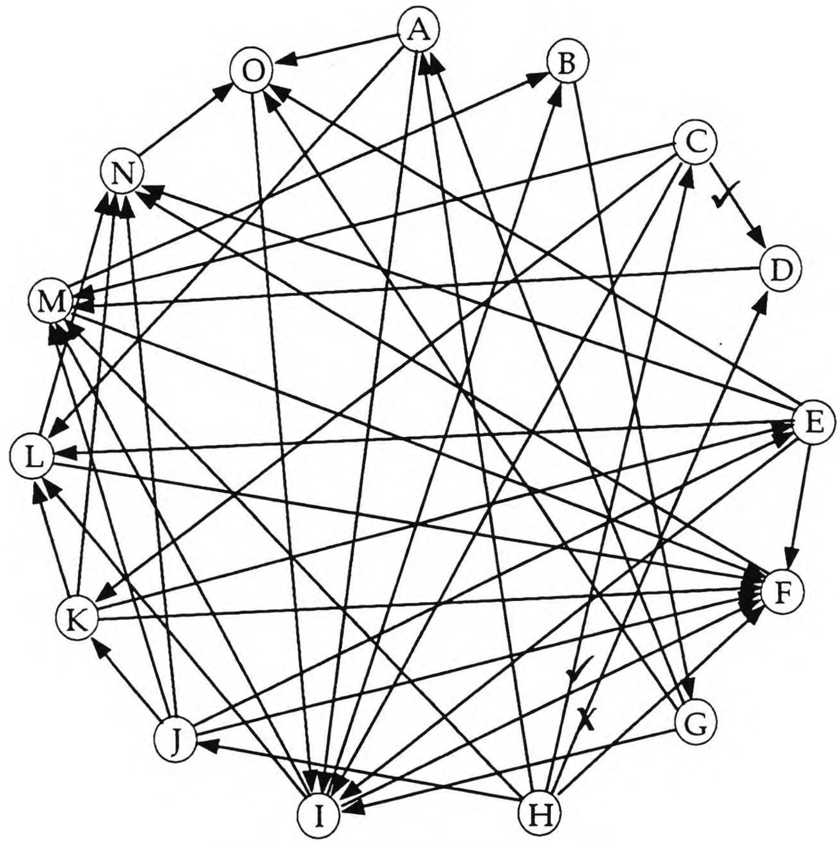


Fig. 3.5 **Raw network of correlation chains**

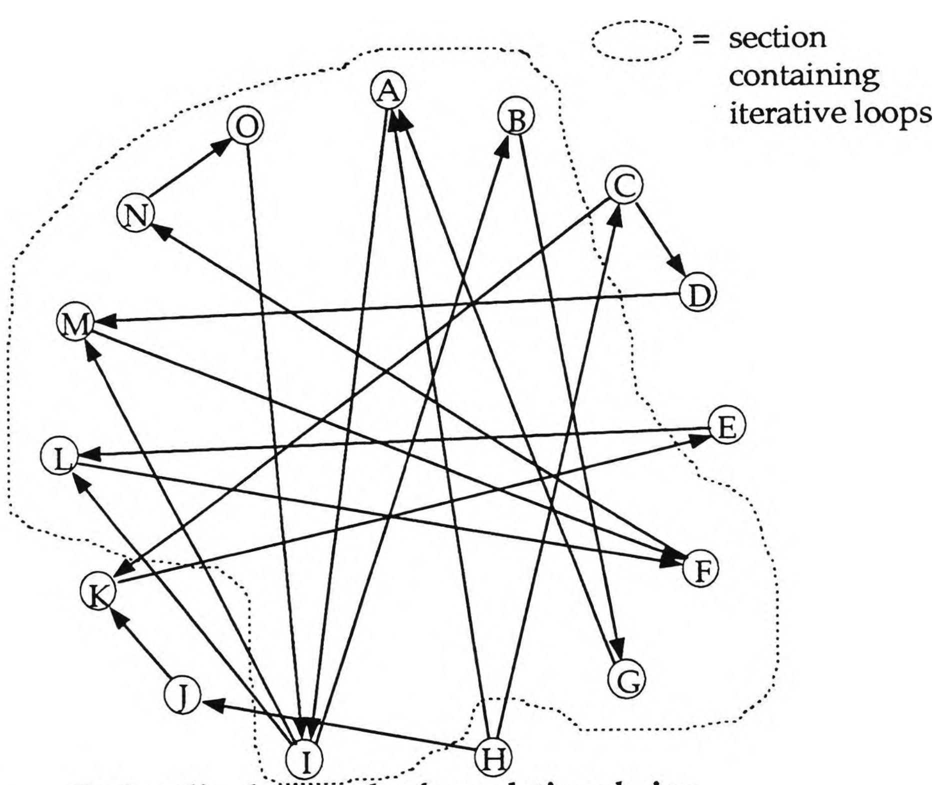


Fig. 3.6 **Rationalised network of correlation chains**

(iv.) Network hierarchy of correlation chains

Further consideration of Fig. 3.6 shows that node H is the most independent node and therefore can be placed at the top of the hierarchy. Dealing first with the nodes outside of the closed loop, section A, quickly generates further strata (*'design stages'*). The remainder of the nodes, in section B, which form the closed loops are not quite so straightforward to allocate to stages. The links with the nodes in section A, aided by technical associativity of related issues such as driver comfort and cockpit visibility, help to establish appropriate positions, as shown in Fig. 3.7

(v.) Design procedure

The resultant design procedure in this case is a ten-stage process, with one, two or three design requirements addressed at each stage. Stages 1 through to 4 should be tackled with a view to each of them containing aspects of the design embodiment that can materialise before moving on to the stage that follows. Stages 5 through to 10 having loops which are now viewed in a time context, can be considered to be iterative loops that will be cycled through until at least the most important issue (not indicated by stage) is satisfied.

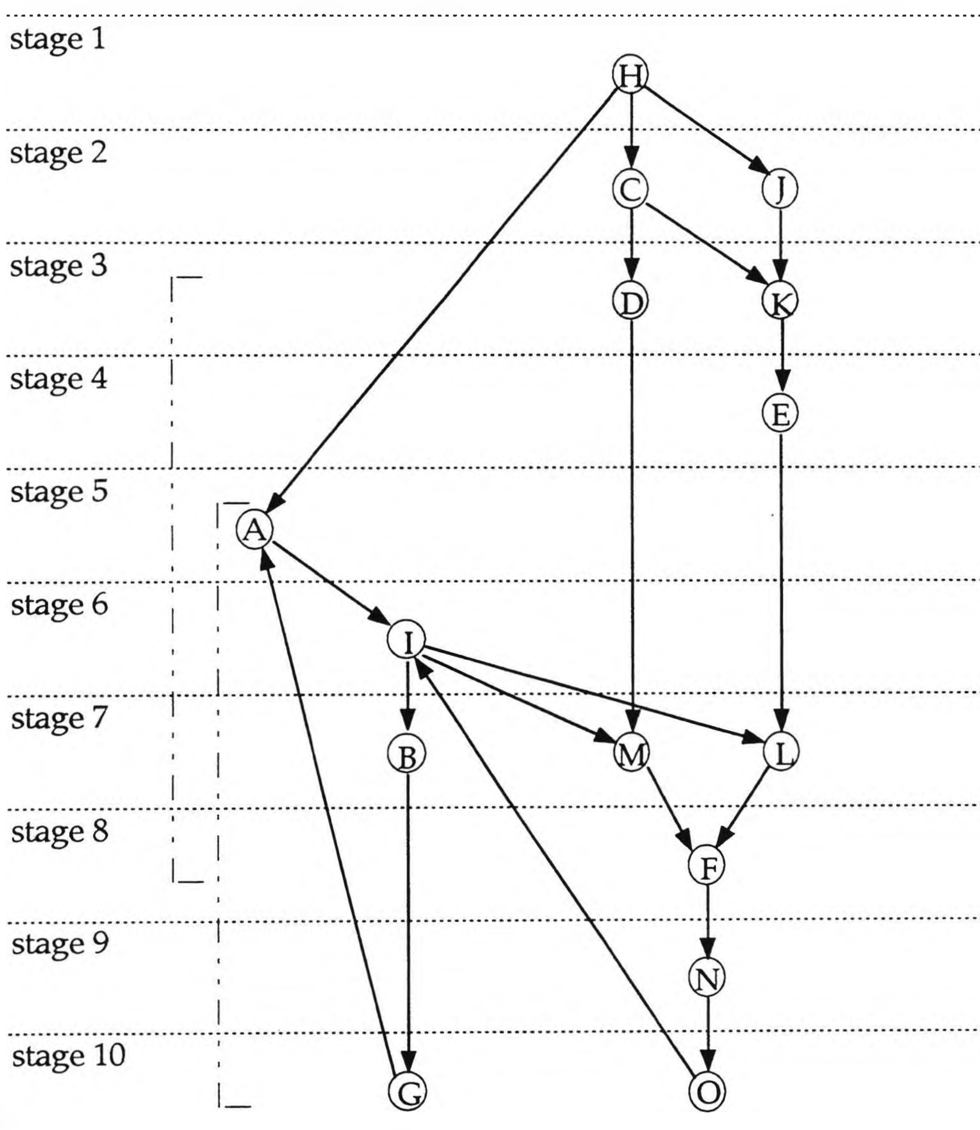
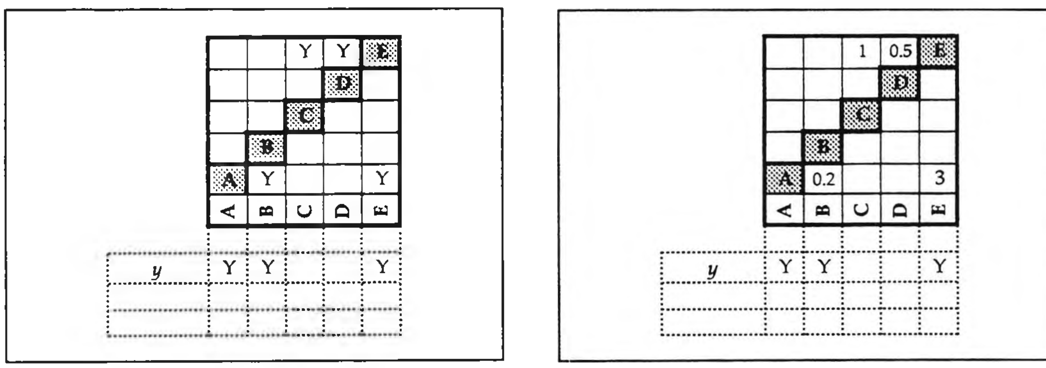


Fig. 3.7 **Final correlation chain network hierarchy**

3.1.3 Enhancing design retrieval in phase 2

The conventional correlation roof, which is symmetrical, implies (unknown) partial derivatives where for example $\frac{\partial A}{\partial B}$ and $\frac{\partial B}{\partial A}$ are given equal weighting. Whereas causal relationships can be recorded in the new correlation roof by virtue of its asymmetry.



(a) basic causal relationships **(b) added coefficients**

Fig. 3.8 **Phase 2 correlation roof**

For example in Fig. 3.8(a) the basic relationship matrix implies that *y=f(A,B,E)*, however a column-wise scrutiny of the completed correlation roof suggests an elaboration of the form:

$$y = \vartheta(A,B,E)\phi\left(\frac{\partial A}{\partial B},\frac{\partial E}{\partial C},\frac{\partial E}{\partial D},\frac{\partial A}{\partial E}\right)$$

The matrix can be further exploited by inserting values to record the strength of these relationships as shown in Fig. 3.8(b).

3.2 Wider Parameter Selection Based on Energy

3.2.1 Bond graphs as a front-end to RED for factor selection

3.2.1(a) Graphical insight

Modern engineering systems often involve several different physical domains that interact both in energy and information terms. Since equations do not normally express energy structure directly this cannot be observed but engineers are often interested in developing this 'feel' for energy flow in certain systems. One advantage of the bond graph representation is that the system topology is maintained and thus an idea of the causal relationships between parameters is conveyed which offers some guidance on parameter selection. Such an insight into system behaviour is important when planning Robust Engineering Design experiments on energy-related products, in order that appropriate design factors and noise factors are included. For appreciating the role of energy-based parameters in Robust Engineering Design the use of bond graphs is proposed. It will be demonstrated that a bond graph model can assist the designer in selecting parameters for inclusion in a Robust Engineering Design experiment by exploiting the causal insight provided.

It has been shown in Chapter 2 that bond graphs offer a unified approach to modelling that represents a system with one set of abstract symbols based upon the dynamic exchange of power between components, that can serve several energy domains (useful for dealing with mechatronic systems). Another property of this generalised modelling tool is that any design factors represented are all at the same 'level' of complexity or detail within the system. The clear link between the bond graph graphical representation and the computational causality was clearly demonstrated in the air pump example. It is commonly accepted (e.g. Martens & Bell, 1972; Rosenberg, 1987; Cellier 1990) that with sufficient practice identification of potential significant system parameters can be gained just from the bond graph graphical representation. This has not been demonstrated for Robust Engineering Design and so the following procedure is put forward here.

(i.) Draw the bond graph of the system ensuring integral causality (follow sequential causality assignment procedure Rosenberg & Karnopp, 1983).

(ii.) Obtain a feel for the significant design factor through visualising or sketching the state-space equations and assigning estimated values, including a sensitivity analysis on these values.

(iii.) Select each inertia and capacitance from amongst the chosen design and trace the causal links to find any interacting design factors.

For example,

Step (i) - recalling the air pump example from Chapter 2 (Fig. 2.16 reproduced below).

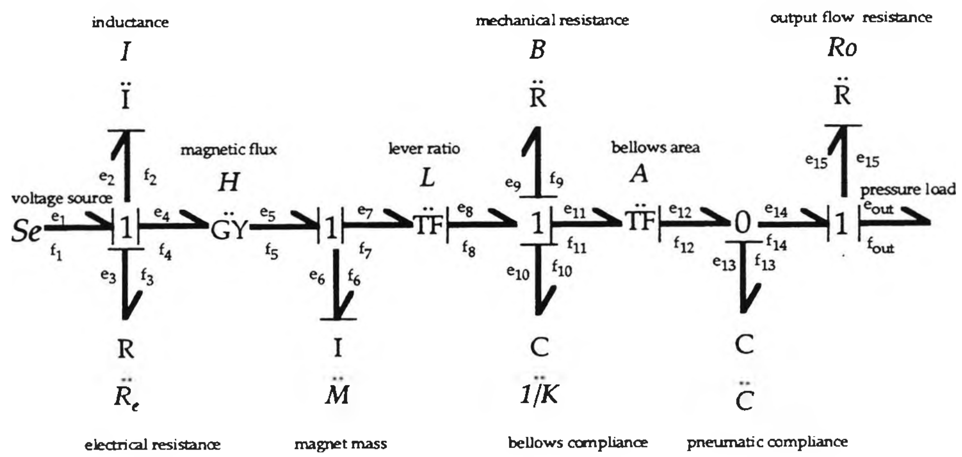


Fig. 3.9 Bond graph of air pump (Fig. 2.16 reproduced)

Step (ii) would be equivalent to visualising and assigning values to the matrices presented in Chapter 2. Here we use the values used in the original paper by Martens & Bell (1972).

$$\frac{d}{dt}\begin{bmatrix} f_2 \\ f_6 \\ e_{10} \\ e_{13} \end{bmatrix} = \begin{bmatrix} -\frac{R_e}{I} & -\frac{H}{I} & 0 & 0 \\ \frac{H}{M} & -\frac{L^2B}{M} & -\frac{L}{M} & -\frac{AL}{M} \\ 0 & KL & 0 & 0 \\ 0 & \frac{AL}{C} & 0 & -\frac{1}{CR_o} \end{bmatrix} \begin{bmatrix} f_2 \\ f_6 \\ e_{10} \\ e_{13} \end{bmatrix} + \begin{bmatrix} \frac{1}{I} & o \\ o & o \\ o & o \\ o & \frac{1}{CR_e} \end{bmatrix} \begin{bmatrix} S_e \\ S_p \end{bmatrix}$$

$$\frac{d}{dt}\begin{bmatrix} f_2 \\ f_6 \\ e_{10} \\ e_{13} \end{bmatrix} = \begin{bmatrix} -577 & -3.34 & 0 & 0 \\ 1190 & 0 & -902 & -0.09 \\ 0 & 116 & 0 & 0 \\ 0 & 54000 & 0 & -1700 \end{bmatrix} \begin{bmatrix} f_2 \\ f_6 \\ e_{10} \\ e_{13} \end{bmatrix} + \begin{bmatrix} 24.35 & o \\ o & o \\ o & o \\ o & 1700 \end{bmatrix} \begin{bmatrix} S_e \\ S_p \end{bmatrix}$$

Assuming that each value can vary by say 1% then R_e, H, K and C are suggested by observation (one from of each row of the main matrix).

Step (iii) - selecting the pneumatic compliance, C, which according to the causality assignment determines the effort at the effort junction, then tracing the effort causality onto the final flow junction (and ignoring the effort going back up the system for brevity) we see that it leads on to the R_o element - implying an interaction between R_o and C. (This pair also occur on the leading diagonal of the above matrix.)

3.2.1(b) Simulation

The availability of bond graph simulation software (e.g. 20-sim, Twente University, Holland) enables the designer to concentrate on representative modelling of the physical system whilst the underlying mathematical model is generated automatically. For the early stages of design it is advantageous to reduce the simulation effort compared with conventional approaches.

Conventional simulation based on mathematical modelling:

(i.) Identify parameters to be modelled by analysing an idealised conceptual representation of the system.

(ii.) Partition the system into manageable sub-systems - represented as block diagrams.

(iii.) Write equations for each 'block'.

(iv.) Sort equations according to block diagram.

(v.) Run simulation (decide parameter values and initial conditions).

Simulation based on bond graph method:

(i.) Identify parameters to be modelled by analysing an idealised conceptual representation of the system.

(ii.) Draw the bond graph.

(iii.) Generate equations automatically from bond graph.

(iv.) Run simulation (decide parameter values and initial conditions). Orthogonal Arrays should be used here to arrange parameter values in the simulation and obtain the usual benefits of the many-factors-at-a-time approach.

3.2.2 Bond graphs for estimating QFD phase 2 critical part characteristics and correlations

3.2.2(a) For initial estimates

Bond graph models can be linked to Quality Function Deployment as shown schematically in Fig. 3.10. Having selected the concept design (following QFD phase 1) and carried out the embodiment of it, the designer will then build a bond graph model of the system that will provide the following:

(i.) An initial estimate of the energy-based critical part characteristics (CPC) to be identified in QFD phase 2 by virtue of observing the effect of parameter values on system performance. These CPC will be a subset of the parameters modelled in the bond graph.

(ii.) Highlight some of the correlations between parameters that can be incorporated into the QFD phase 2 correlation roof through identification of causal relationships. Input variables, output

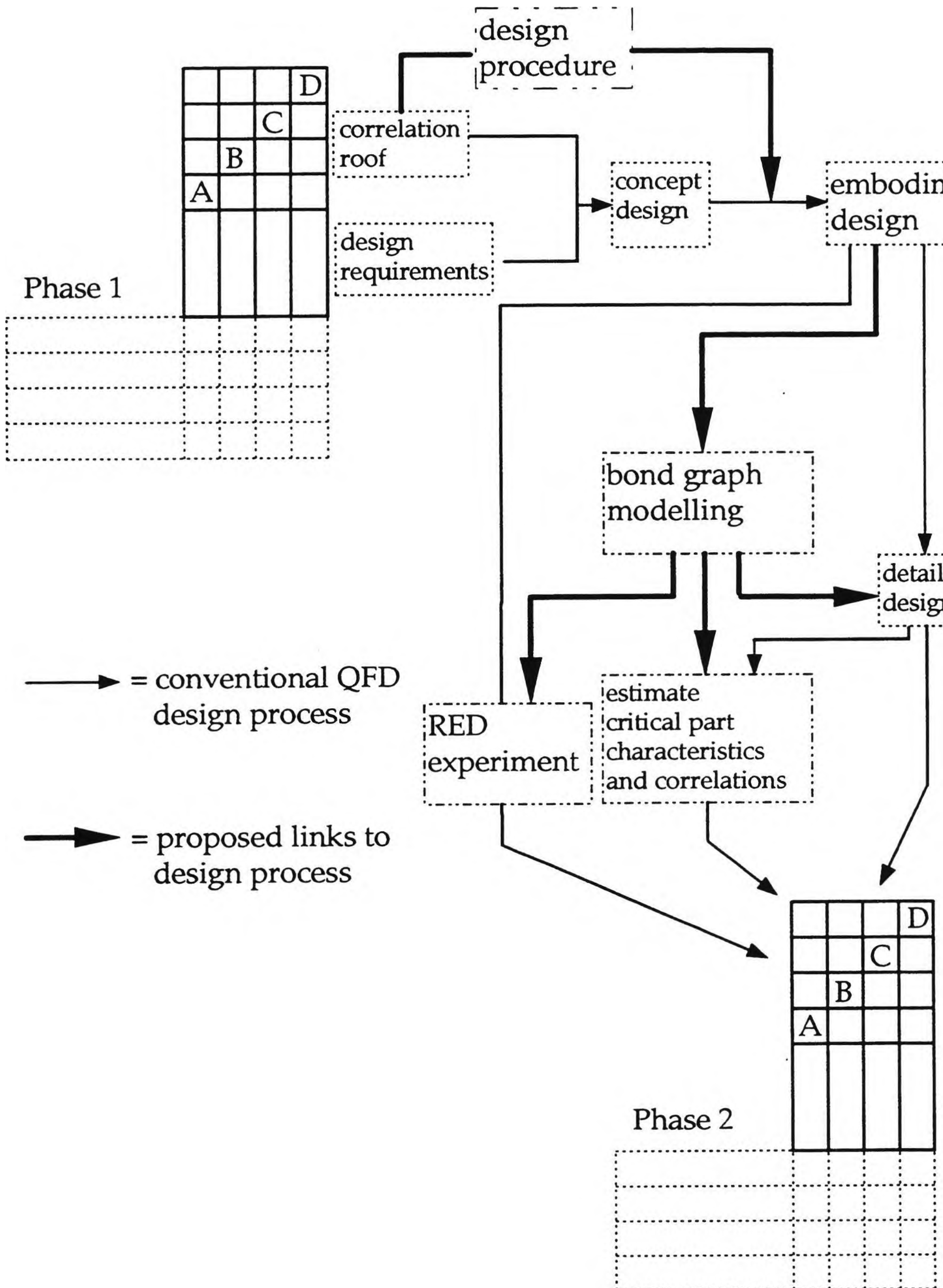


Fig. 3.10 Proposed link between bond graphs and QFD

variables and state variables are identified during the process of creating the bond graph model.

The bond graph model will be further developed following actual physical experimentation but in the meantime the insight gained above will enable design activity to continue.

There is also an opportunity here to bring Robust Engineering Design philosophy into the Quality Function Deployment method through readdressing the concept design in order to minimise the number of design factors that influence any one physical effect. Thus by iterating through the simulation and concept embodiment the designer should be able to assess whether any of these proposed concepts are likely to achieve additivity and in effect explore how interactions might be overcome.

3.2.2(b) For design retrieval

Comincini (1994) considered the desired outcome of his correlation chain approach to be simulation of the algorithmic relationships between design parameters in order to evaluate the impact of design changes. No further detail was provided on the simulation techniques to be employed or how the simulation would be linked with Quality Function Deployment.

It is proposed that, where appropriate, bond graph models can be linked with Quality Function Deployment phase 2 for design retrieval and modifications, where parameter values are defined in sufficient detail for simulation. This will not only provide a rapid means of evaluating design modifications but will also enhance a concurrent approach to re-design where the system designed involves several energy domains. This linking of Quality Function Deployment and bond graphs could also be considered as an enhancement to mechatronic design.

3.2.3 Energy-based noise factor categories

3.2.3(a) Definition

It is proposed that there has been some imbalance in the noise factor selection activity of Robust Engineering Design which is a consequence of the noise factor categories employed in selection. A wider and more representative coverage of noise space in experiments is sought through augmenting selection categories and encouraging appropriate noise factor modelling as a front end. From the literature it has already been shown that noise modelling has centred on *unit-to-unit* variation. A noise factor category should help the experimenter to view the system in a way which helps to identify all the significant noise factors acting on the system under investigation.

It is reasonable to assume that as the output of many engineering systems is energy-related that many noise factors might also be energy-related in order to have an effect upon the response of the system (Taguchi, 1987; Phadke, 1989). Thus, *direct-*, *indirect-* and *no*-energy linked noise factors are also introduced here for general consideration.

direct-energy: noise factors that are directly and clearly a manifestation of energy variations acting on, or being acted upon by, the system. For example, gravity, load, torque, force and current.

indirect-energy: noise factors with an indirect influence on the energy transformation or modifying the flow of energy. For example, inertia, strength, deflection, eccentricity and surface roughness.

no-energy: noise factors with no clear link with energy. Therefore should be a minor category for energy systems and more significant for systems concerned with method, information and error.

This provides further incentive to investigate energy-based modelling in order to enhance qualitative insight for informing noise factor selection.

However, in practice many noise factors are not actually as uncontrollable as the accepted definition might imply. For reasons of convenience or economy, that will be familiar to the practitioner, such noise factors are allowed to vary. Classifying noise factors into ***controllable disturbances*** and ***uncontrollable disturbances*** has not been proposed in the literature but is included here to identify those that could be tackled through design.

controllable: noise factors that for reasons of convenience or economy are allowed to reach a level of influence on the system.

uncontrollable: noise factors which are to be considered by the experimenter as beyond their sphere of influence or a *fait accompli*.

3.2.3(b) Noise factor survey

Case studies available in the literature offer an insight into the types of noise factor that combine to form noise space in typical Robust Engineering Design experiments. The sixty two noise factors considered here (Table 3.1) have been obtained from twenty two European case studies spanning 1988 to 1990 (Bendell, 1988; Bendell, Disney & Pridmore, 1989; Greenhall, 1990). Thus whilst not being exhaustive or a study of the most recent cases, it is representative of the period of growth in the industrial use of Robust Engineering Design in the West.

system		noise factor description (bold = based on a control factor)	Taguchi, 1987	Kacker, 1993	Kacker, 1985	influence	energy	bond graph	misc
			i = internal e = external u = unit-to-unit	d = deterioration m = measurement e = external s = supply t = tolerance	r = real NF p = pseudo NF	c = controllable u = uncontrollable	d = direct energy i = indirect energy n = no energy	e = effort f = flow i = inductance r = resistance c = capacitance	m = method l = load
process	1	gravity	e	e	r	u	d	e	
process	2	kiln temp dist	u	s	r	c	d	e	m
process	3	ambient temp	e	e	r	u	d	e	
product	4	gain var	u	t	r	c	i		
product	5	yield strength var	u	t	r	c	i		
	6	mag particle size	u	t	r	c	n		
	7	furnace-furnace var	u	s	p	u	d	e	m
process	8	adhesive app method	u	s	p	c	n		m
	9	m/c setting	u	s	p	c	n		m
	10	position in oven	u	s	p	c	d	e	m
process	11	operator	e	e	p	c	n		m
	12	measurement occassion	u	m	p	c	n		m
	13	position in furnace	u	s	p	c	d	e	m
process	14	mould number	u	s	p	c	n		m
	15	unit-to-unit var	u	s	p	u	n		
	16	raw material batch	e	s	p	u	n		
	17	day	e	e	p	u	n		
process	18	production method	u	s	p	c	n		m
	19	cleaning method	u	s	p	c	n		m
	20	power supply	e	e	r	u	d	e	
product	21	alternator load	e	e	r	u	d	i	L
	22	carbon build-up	i	d	r	u	n		
	23	malfunction	i	d	r	u	n		
	24	air quality	e	e	r	u	n		
product	25	wheel/shaft imbalance	i	t	r	c	i		
	26	eccentricity	i	t	r	c	i		
	27	bearing clearance	i	t	r	c	i		
	28	road conditions	e	e	p	u	i		L
	29	tyre out-of-round	i	t	r	c	i		
product	30	s/w load	e	e	r	u	d	i	
	31	cpu housekeeping	i	t	r	c	n		
	32	no of instructions	i	t	r	c	n		
	33	signal protocol	e	e	r	u	n		L
	34	priorities	i	t	r	c	n		
product	35	card bend	e	e	r	u	n		
	36	head offset	u	t	r	c	n		
	37	card wear	e	e	r	u	n		
	38	motor gear eccentricity	i	t	r	c	i		
	39	encoder fit	u	t	r	c	n		
	40	power supply	e	e	r	u	d	e	
	41	torque var	u	t	r	c	d	e	
	42	gain var	u	t	r	c	i		
	43	head current	i	t	r	c	d	f	
	44	wiring loom force	u	t	r	c	d	e	
	45	dust	e	e	r	u	n		
	46	nut tightness	u	t	r	c	d	r	
process	47	conditioning time	e	e	r	c	n		
	48	conditioning temp	e	e	r	c	d	e	
	49	conditioning rel humidity	e	e	r	u	n		
	50	relative humidity	e	e	r	u	n		
process	51	time trend	e	t	r	u	n		
	52	device type	u	s	p	c	n		
	53	board on panel	e	s	r	c	n		
	54	photoresist thick. var	i	t	r	c	i		
	55	oxide thick. var	i	t	r	c	i		
	56	overetch time	u	t	r	c	i		
	57	pin location	u	s	r	c	n		
	58	capillary deterioration	i	d	r	u	n		
	59	user loading	e	e	r	u	d	i	L
	60	salt grain size var	e	t	r	c	n		
	61	resin aspect	e	t	r	c	n		
	62	cooling water temp	e	e	r	u	d	e	
		control factor based=19%	i=23% e=37% u=40%	d=5% m=2% e=32% s=23% t=38%	r=76% p=24%	c=61% u=39%	d=27% i=19% n=54%	e=19% f=2% i=5% r=2% c=0%	m=18% L=6%

Table 3.1 Noise Factor classifications

Only 29% of the case studies are based upon product design yet they account for 45% of the noise factors identified. Comparing all the classifications shown in Table 3.1 simultaneously reveals some further observations:

- *Internal* noise factors only represent 23% of the total but are all *real* noise factors.
- *External* noise factors account for 47% of the total.
- 76% of the noise factors identified are judged to be a *real* source of variation.
- A large proportion (46%) of noise factors can be linked to energy.
- 19% of noise factors relate directly to *effort* forms of energy.
- 38% of the noise factors are *tolerance*-related.
- *Toleranced internal* noise factors represent 18% of the total and are all *controllable*.
- The majority (61%) of noise factors can in fact be considered to be *controllable*.
- *Load* variation only accounts for 6% of noise factors.

3.2.3(c) Discussion of noise factor classifications

It is important to remember that all the noise factors considered in Table 3.1 were probably originally identified through the use of the standard three category classification. Therefore identifying the membership of alternative categories retrospectively can be problematical. However, from Table 3.1, noise factor number 60 serves to illustrate the difficulty of categorising some process noise factors with the generally accepted three-category classification.

(i) The noise factor raw material grain size is not a process parameter thus it is *external* to the system.

(ii) This noise factor is based upon a control factor and thus by this definition is controlled *within* the process.

(iii) Unit-to-unit variation in raw material grain size is a source of *unit-to-unit variation* in the output of the process.

Thus for some process noise factors the standard classification is open to differences of interpretation. By considering noise factors numbers 35 and 37 in Table 3.1, the dependence of the appropriate category on context for product noise factor can also be observed. Here because of their association with *deterioration*, these noise factors are at risk of being categorised as *internal* noise unless it is recognised that they are external to the system which takes precedence. However, successful categorisation of process noise factors might not be a simple case of using the *external* label for all in-coming product-related variations as the product may have a preparation or pre-processing that forms part of the process.

Kacker's *external* category largely coincides with that of the standard classification except for a few noise factors which are more appropriately identified as *tolerance* noise. Which highlights that tolerance/unit-to-unit variation is a common source of variation. It would be naive to assume that tolerances are chosen on purely technical grounds and not due to any internal politics between design and manufacturing factions.

As the majority of noise factors used in the case studies are *controllable* (61%), they can feasibly be adjusted to reduce variability albeit at some cost. In many cases it will be through tolerance design that this reduction is achieved. Indeed a reason for this propensity for such *controllable* noise factors to be considered, might be that the old habit of combating variability by removing or reducing any causes of variation still prevails amongst these cases. Couple to this the fact that 76% of noise factors are *real* and this brings into question whether the identified noise space is being adequately sampled in each case study as limitations of time, resource and experience should encourage the use of *pseudo* noise factors.

Internal noise is underrepresented in these studies and this could be explained to some extent by the scarcity of noise factors associated with wear, corrosion, erosion, ageing, creep, build-up, leakage, malfunction and other forms of deterioration being considered. Tolerance factors are considered the most likely source of *internal* noise in these case studies. Also, *internal* noise factors beyond the realms of system understanding is too difficult to identify. Any that are identified via a thorough understanding are thus more readily expressed as *real* noise factors. This gives an impression that experimental practice sticks to familiar ground when selecting *internal* noise factors. Or similarly a sense of a system understanding being a prerequisite for identifying *internal* noise factors. Either way, in terms of product robustness this must represent an important part of the noise space that is not being sampled.

Considering *measurement* as a noise factor category is of debatable validity, as in many cases the error or 'noise' contributed by measurement will not exist in the noise space of the actual product - only in the experimentation.

Load factors are relatively few (6%) yet most products and processes are dynamic systems. None of the cases utilise dynamic quality characteristics which might otherwise use some loads as signal factors instead of as noise factor. These dynamic loads cause significant variations in performance. With good understanding of a system, load can be recognised in terms of a static quality characteristic such as load-bearing capacity, or alternatively in terms of say, the effect load fluctuation has as on a more direct noise factor. An example of this latter phenomenon appears when alternator load is assumed to be wholly about its mechanical energy effects, such as torque fluctuation, on an engine. Whilst this lack of consideration for its electrical energy effects, such as on coil supply voltage, ignores any noise effects on ignition- and hence combustion-quality (and ultimately torque, specific fuel consumption, smoke and hydrocarbons emissions etc.). Keeping alternator load as a noise factor probably includes both of these mechanical and electrical effects in the experiment. As load is unlikely to appear as a dynamic characteristic, it should be included as a noise factor more often as it plays such an important role in deterioration (see Carter, 1986).

It is interesting that approximately half (46%) of the noise factors can be identified as *energy*-related. However, on the basis that most systems should be considered to transmit or modify energy as their basic function, it could be expected that greater insight might reveal energy playing a leading role as noise in more cases. A simple example would be 'position in oven' which is obviously related to temperature distribution and hence heat energy transfer. A less obvious example might be the way an inappropriate bearing clearance would serve to divert energy into producing heat rather than conveying it on to perform useful work. Perhaps another indicator of the familiarity each investigator has with their particular system, is the fact that all the *energy*-related noise factors can also be categorised as *real* and *controllable*. The bond graph classification was included in Table 3.1 to further categorise energy-related noise factors.

3.3 Techniques for Pragmatic Factor Level Selection

3.3.1 Linking Robust Engineering Design with dimensional analysis

The parameters used in Robust Engineering Design experiments often exhibit variety in relation to the physical dimensions used to describe them. These physical dimensions when expressed in standard SI metric units will be seen to be based upon a few base or *primary dimensions*, such as mass, length and time (Fig. 3.11). The principle of *dimensional homogeneity* means that any equation used to describe a physical system or phenomenon must be consistent with respect to the component base units. This is the basis of *dimensional analysis* which has been applied in various fields of science and engineering (Massey, 1971; Douglas & Matthews, 1996). Dimensional analysis offers insight both into factor selection and the selection of factor levels.

Firstly, let us establish a theoretical link between dimensional analysis and Robust Engineering Design.

3.3.1(a) Simplified power-law dimensional model building

From Eq. 1.1 consider the relationship to be a power law for univariate input and output, which becomes:

$$y = cx^{\alpha} \tag{3.1}$$

where c and α are constants. In simple terms we have

$$\frac{dy}{y} = \alpha \frac{dx}{x} \tag{3.2}$$

where dx and dy represent small changes in x and y respectively.

Now assume that x is a random variable with mean x_0 and standard deviation σ_x, and similarly for y. Let $\frac{dy}{dx}$ be the derivative at x_0 then the Taylor expansion gives the linear approximation

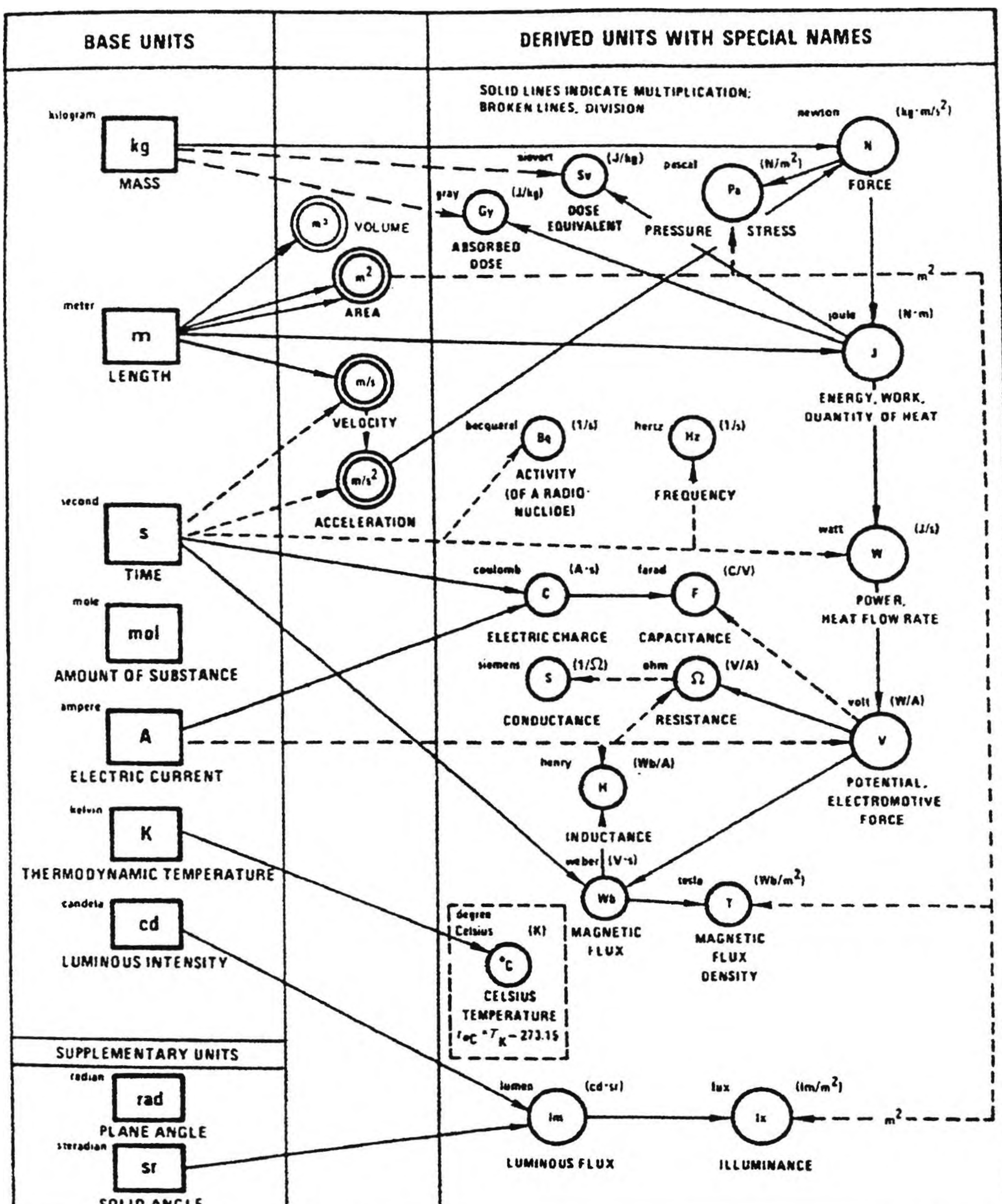


Fig. 3.11 Relationship between SI metric units (Campbel, 1993)

$$y = cx_0 + \frac{dy}{dx}(x - x_0) \tag{3.3}$$

for which the mean and standard deviation are given by

$$y_0 = cx_0 \tag{3.4}$$

$$\sigma_y^2 = \left(\frac{dy}{dx}\right)^2 \sigma_x^2 \tag{3.5}$$

Now returning to Eq. 3.2 and setting $x=x_0$ and $y=y_0$ we have after squaring and rearranging

$$\left(\frac{dy}{dx}\right)^2 = \alpha^2 \left(\frac{y_0}{x_0}\right)^2 \tag{3.6}$$

Thus eliminating $\frac{dy}{dx}$ from Eq. 3.5 using Eq. 3.6 $\sigma_y^2 = \alpha^2 \left(\frac{y_0}{x_0}\right)^2 \sigma_x^2$ or

$$\frac{\sigma_y^2}{y_0^2} = \alpha^2 \frac{\sigma_x^2}{x_0^2} \tag{3.7}$$

the quantities $\frac{\sigma_y^2}{y_0^2}$ and $\frac{\sigma_x^2}{x_0^2}$ can be compared with Eq. 1.8 in Chapter 1 and interpreted as the Signal-to-Noise Ratio.

Furthermore Eq. 3.1 can be written as $\pi = yx^{-\alpha} = c$ (3.8)

where π = c is a first attempt at a dimensional model building.

3.3.1(b) Restrictions on the model and scale invariance

From Eq. 3.2 we may write

$$\frac{dy}{y} - \alpha \frac{dx}{x} = 0 \tag{3.9}$$

Then if the vector $\phi^T = \left(\frac{dx}{x}, \frac{dy}{y}\right)$ (3.10)

and

$a^T = (-\alpha, 1)$ (3.11)

then Eq. 3.9 can be written

$$\phi^{T}a = 0 \tag{3.12}$$

The generalisation of this says that the more restrictions of the form $\pi = c$ that we place on the model the more restriction we place on the degrees of freedom for the Signal-to-Noise Ratio.

The central idea behind dimensional analysis is that of scale invariance with respect to the scale group of transformations, where the scale is taken to apply to the canonical quantities, $q_1, \ldots, q_m$ typically with principal dimensions mass, length and time (M,L,T) although the theory is quite general. The scale transformations are written

$$q_j \to \lambda_j q_j \tag{3.13}$$

The model parameters, $p_i, \ldots, p_n$ (which include design factors, noise factors and response, y, can be viewed as depending upon the q_j in terms of power laws as follows

$$p_i = \prod_{j=1}^{m} q_j^{\alpha_{ij}} \tag{3.14}$$

then the scale transformation Eq. 3.13 induces transformations on the p_i

$$p_i \to \prod_{j=1}^{m} \lambda_j^{\alpha_{ij}} p_i \tag{3.15}$$

It is convenient to write $\lambda_j = 1+\varepsilon_j$ where the ε_j are small and the transformations are locally linear.

$$p_i \to p_i\left(1 + \sum_{j=1}^{m} \alpha_{ij}\varepsilon_j\right)$$

Now let A be the matrix of indices, $A = \{\alpha_{ij}\}_{i=1,j=1}^{n,m}$ (3.16)

We seek dimensionless quantities π_k which are powers of the p_i and are invariant under the scale group Eq. 3.13.

Let $\pi_k = \prod_{i=1}^{n} p_i^{\beta_{ki}}$ $\quad (k = 1, \ldots, s)$ (3.17)

Then the β_{ki} are given by the Buckingham π-theorem (Massey, 1971). Thus

let $B = \{\beta_{ki}\}_{k=1,j=1}^{s,n}$ **(3.18)**

Then a necessary and sufficient condition for invariance is $AB=0$, that is the vectors of β_{ki} for the π_k lie precisely in the null space of the matrix of α_{ij}.

But since $AB=0$ we must have from Eq. 3.11, Eq. 3.12 & Eq. 3.16 that ϕ lies in the row space of A or there is a vector θ such that

$\phi = A^T\theta$ **(3.19)**

We can interpret θ directly as $\theta = (\theta_1, \ldots, \theta_n) = \left(\frac{dq_1}{q_1}, \ldots, \frac{dq_n}{q_n}\right)$ **(3.20)**

or as some intrinsic deviation. The covariance matrices of θ and ϕ are related by

$\sum_\theta = A^T \sum_\phi A$ **(3.21)**

which can be considered as a generalised Signal-to-Noise Ratio.

To summarise we now have a connection between dimensional analysis and Robust Engineering Design which suggests that if we define models in terms of invariants then we impose restrictions on the (local) Signal-to-Noise Ratio. Moreover the space of the Signal-to-Noise Ratio is parameterised by the same parameters, A, which define the model parameters, p_i, in terms of the principal dimensions, q_j, on which the scale group operates.

3.3.2 Dimensional analysis to establish design factor sliding levels

It has been highlighted earlier that in the Robust Engineering Design literature, sliding factor levels are considered by Taguchi (1987) as the most powerful way of dealing with non-transformable interactions. Fowlkes & Creveling (1995) have shed light on the use of engineering science as key to establishing the relative factor level values.

In Chapter 2 it was shown that according to Hamada and Wu (1995) the equation relating centering and scaling of design factors to each other, (Eq. 2.5) would have to be satisfied but to choose sliding factors properly the expected output, *E(y)*, needs to be known and it isn't. It is proposed that dimensional analysis provides some insight into *E(y)* and it can be used as a technique for establishing relative sliding factor levels in Robust Engineering Design experiments on appropriate systems.

Developing a qualitative model, that draws on dimensional analysis, as a front-end to a Robust Engineering Design experiment will have the following objectives:

(i) Bring out underlying physical relationships in an experimentally useable form.

(ii) Suggest reduction through elimination or grouping of factors.

From Buckingham's π Theorem (Massey, 1971) it will be observed that there will be *n-m dimensionless groups* ($\pi_1, \pi_2 \ldots \pi_{n-m}$) in the equation relating *n* parameters containing *m* primary dimensions.

$$\pi_1 = \phi\,(\pi_2, \pi_3 \ldots \pi_{n-m})$$

where π_1 contains the dependent output parameter, y.

If *A, B* and *C* are design factors in a Robust Engineering Design experiment and following a dimensional analysis include the groups:

$\pi_1 = y/(AB)$ and $\pi_2 = (A/C)$

Then *A* and *B* can be considered from the relationship identified by π_1 to be *non-transformable* interactions because they are a product of the underlying physics (or primary dimensions) rather than the choice of parameter metric (units) and it also seems reasonable to assume they will be *symmetric* factors i.e. either one can be slid against the other.

Returning to the central idea behind dimensional analysis of *scale invariance*, whereby the experiment is conducted under conditions of *geometric similarity* and *dynamic similarity*. Geometrical similarity is achieved when the ratio of corresponding lengths in two systems is constant - i.e. one is the scale model of the other. The two systems are dynamically similar when the forces acting in one system have the same ratio to each other as the corresponding forces in the other system. Therefore the ratio π_2 = *(A/C)* must also be maintained within any experiment trial.

To make the basic connection between an orthogonal array and dimensional analysis consider a simple positive displacement pump acting on an incompressible fluid (density, ϱ) comprising a piston of diameter, D with stroke S at speed ω. Clearly mass flow, y is some function of ϱ, D, S and ω :

$$y = \Phi(D^a, S^b, \omega^c, \varrho^d)$$

i.e. five parameters where the primary dimension are:

$$y = \left[\frac{M}{T}\right] \quad D = [L]^a \quad S = [L]^b \quad \omega = \left[\frac{1}{T}\right]^c \quad \varrho = \left[\frac{M}{L^3}\right]^d$$

Thus n-m = 2 π groups expected.

Equating powers of M, L and T,

M: $1 = d$

L: $0 = a + b - 3d$

T: $-1 = -c$

$\therefore c = 1,\ d = 1,$ and $a = 3 - b$

The π groups are:

$$\pi_1 = \left[\frac{y}{\omega D^3 \sigma}\right] \quad \pi_2 = \left[\frac{S}{D}\right]^b$$

For a given fluid density, factors ω and D determine the denominator of π_1. It is important to note here that D is a generalised dimension thus the

D^3 is a characteristic volume which we will quickly recognise to actually be D^2S on the physical artefact.

In order to see how the design factor ratios (π_1) should be assigned to an Orthogonal Array, recall the contribution of Fowlkes & Creveling (1995) on sliding levels where the wing design factors, area and width, were slid one against the other. Area was used because resistive area is a fundamental property of the design. Width was assigned to a column and length determined by ***area/width*** assigned as ***length = area/width*** to another column. In the case of a wing, optimum wing area at one stratum of design space has to be determined to balance resistive area against mass (weight). At another stratum, and also simultaneously due to the Orthogonal Array, the optimum levels for length and width have to be determined in respect of increasing length causing increasing deflection and as a consequence reducing effective area. Thus three design factors are inextricably linked through a joint property and the best combination must be found with respect to this.

Returning to the pump, it is now clear that ω, D, and S are linked such that they cannot be assigned independently to the Orthogonal Array and avoid their interactions upsetting the additivity of the effects. Here for the pump, π_1 is highlighting (ignoring density) that swept volume (recognised to be D^2S for our concept solution) along with speed, ω, are fundamental to the intent of achieving y. Thus the assignment of columns (consider an L_4) should primarily be concerned with sliding ω against *swept volume (D^2S)*. This is the main point of the argument i.e. sliding ω against *swept volume*. In following the logic of the argument through, then S will have to be slid against D^2, as in Table 3.2.

L_4	ω	D	S
Exp 1	$\omega = const1/D^2S$	1	$s = const3/D^2$
Exp 2	$\omega = const1/D^2S$	2	$s = const4/D^2$
Exp 3	$\omega = const2/D^2S$	1	$s = const4/D^2$
Exp 4	$\omega = const2/D^2S$	2	$s = const3/D^2$

Table 3.2 L4 OA with sliding levels for ω and *s*.

Thus the experiment is transformed into one that searches design space orthogonally in the dimensions of ***diameter***, ***swept volume*** and ***rate of swept volume***. Physical Robust Engineering Design experiments will reveal their optimal levels from a signal-to-noise perspective and then suitable ω and s levels can be unfolded.

The changes in design factor levels organised by the Orthogonal Array are equivalent to scale changes between the factors. As two or more of the design factors interact (e.g. factors ω and D in π_1 above) the additivity will be improved over that which would be encountered by assigning these factors independently to the Orthogonal Array.

3.3.3 Dealing with the production constraints on design factor levels

The factor level settings arranged by Orthogonal Arrays for physical experiments are inferred to be nominal values corresponding to level 1, level 2 etc. In reality the values of the parameters may vary about these intended nominal levels. Such variation is considered as a source of noise (unit-to-unit noise).

For design factor level settings determined in a production environment it would be preferable for economic reasons or convenience if they could be obtained from within or close to the specification limits. That is by carefully selecting individual items from the distribution of the production capability, it is feasible to group actual values around two or more levels. Fig. 3.12 shows the idealised production distribution of a parameter to be used as a design factor in a Robust Engineering Design experiment. The design factor levels selected from within these $\pm$ 3σ ('six sigma') limits are also shown and are also idealised as normally distributed.

Taguchi (1987), Phadke (1989) and others have postulated non-linear relationships between these design factor level distributions and the system output (shown in Fig. 3.13). The design factor levels are shown close together to represent levels taken from production as considered here, therefore differences in output response will be small, both in terms of mean and variability.

The role of noise factors in Robust Engineering Design experiments is clearly important. The prevailing wisdom is that each experiment must undergo a similar experience of noise space. Orthogonal Arrays have been used to arrange noise conditions for each experiment but current practice tends to favour the compound noise approach where noise factor effects are grouped into either best and worst, or two extremes of noise conditions. Each experiment is then exposed to both groups of noise. For external noise factors this should not pose a problem as each experiment has equal chance of experiencing the same noise conditions but for internal noise, and unit-to-unit noise in particular, it is not so straightforward. In practice for assembled products small numbers of unit-to-unit noise factors selected from a production run are unlikely to be normally distributed even when normality is held in the production run. A main reason for this is that even though tolerances are independent of each other, non-selective processing and assembly means that any one product has a random combination of parameter values from each

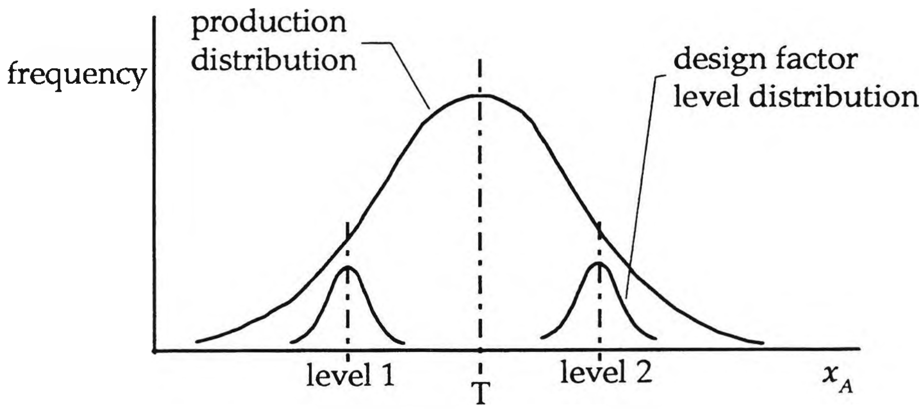


Fig. 3.12 **Idealised production distribution of parameter value with "sub-six sigma" design factor levels (means of level 1 and level 2).**

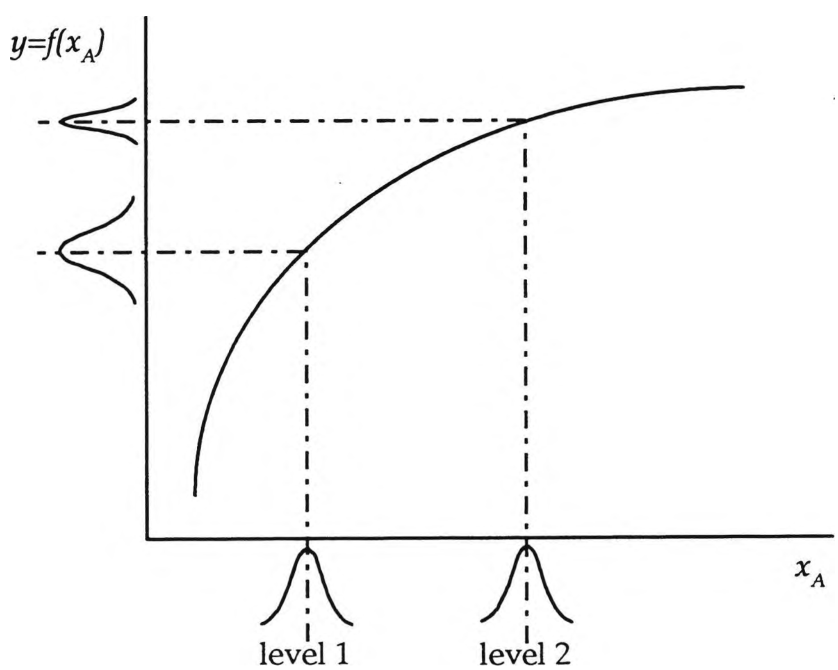


Fig. 3.13 **Localised optimisation around the "sub-six sigma" design factor levels**

associated distribution. The net result is that products used for the design experiment inevitably have some unit-to-unit noise factor values that are either unequal and/or skewed about the design factor level (local mean). This is illustrated in Fig. 3.14. In this case noise conditions can no longer be considered to be orthogonal across the whole design experiment, in other words each experiment run will experience different noise space conditions by virtue of the unit-to-unit noise being stronger for some experiment runs more than others. In subsequent analysis the implied effect of the associated factor levels will be distorted and therefore require adjustment. A means of dealing with this in physical experiments based on production is desirable and is provided below.

Here it is proposed that Robust Engineering Design methodology can be enhanced for conducting meaningful experimentation through the use of design factor levels obtained by selective grouping of items taken from a production distribution. These levels will generally be separated by less margin than experiments not relying on production items.

For an engineering system with weak interactions between main effects the additive model will hold. Then for say an L_8 Orthogonal Array the mean effect of level 1 of design factor, x_A, in column 1 is found from:

$$m_{A1} = \frac{1}{4}(y_1 + y_2 + y_3 + y_4) \tag{3.22}$$

The y_i are the means or measures of dispersion for each experiment trial and are collated in a response table. Typically the Signal-to-Noise Ratio will be used to measure dispersion.

From Eq. 2.17, calculation of the Signal-to-Noise Ratio for a smaller-is-better (SB) characteristic from the experiment data will be:

$$\mathrm{SNR}_{\mathrm{SB}} = -10 * \log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \tag{3.23}$$

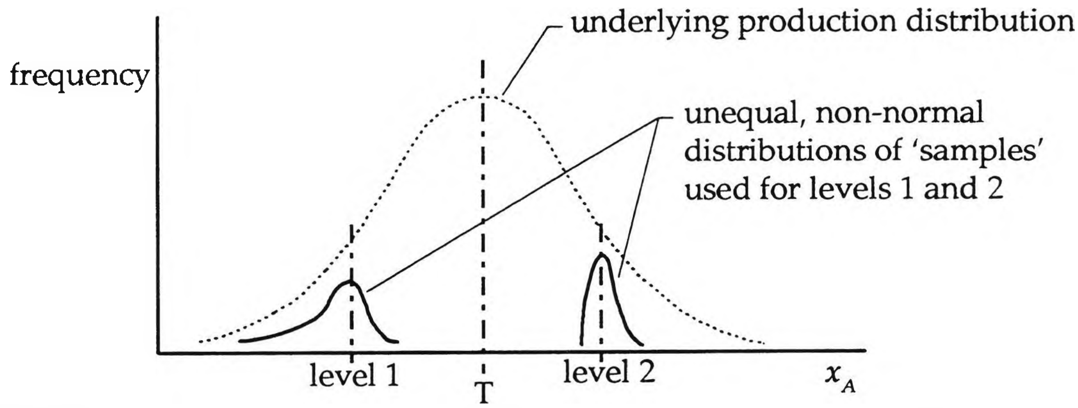


Fig. 3.14 **Possible distributions of tolerance noise about nominal design factor levels**

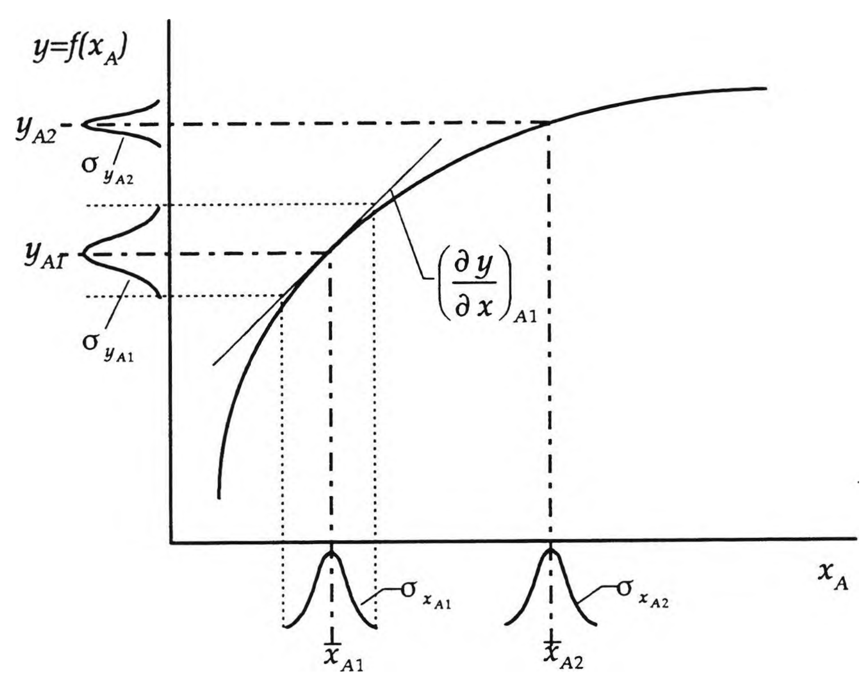


Fig. 3.15 **Behaviour of σ_y, σ_x and $\partial y/\partial x$ local to level 1 of Factor A**

The sum of squares of the y_i can be estimated using the mean and standard deviation of the responses associated with level 1 of the design factor, x_A, which is based on an idea proposed by Taguchi (1987) used for simulating noise factor levels (Phadke, 1989).

Estimate of SNR_{SB} for design factor, x_A level 1 (in place of Eq. 3.23):

$$= -10 * \log_{10}\left(\frac{1}{3}\sum \left(\overline{y}_{A1}{}^2, \left(\overline{y}_{A1} + \sqrt{\tfrac{3}{2}} * \sigma_{yA1}\right)^2, \left(\overline{y}_{A1} - \sqrt{\tfrac{3}{2}} * \sigma_{yA1}\right)^2\right)\right) \qquad \textbf{(3.24)}$$

In the local area around the factor level of interest we can use the relationship $\left(\frac{\partial y}{\partial x}\right)_{A1} = \frac{\sigma_{yA1}}{\sigma_{xA1}}$ to make an adjustment to σ_{yA1} with reference to σ_{xA2} (Fig. 3.15), according to:

$$\sigma_{yA1adj} = \sigma_{yA1} * \frac{\sigma_{xA2}}{\sigma_{xA1}} \qquad \textbf{(3.25)}$$

Therefore the adjusted value of σ_{yA1adj} can be used to estimate an adjusted Signal-to-Noise Ratio using Eq. 3.24 as follows:

(i) Estimate SNR using $\overline{y}_{A1}$, $\sigma_{y_{A1}}$, $\overline{y}_{A2}$, $\sigma_{y_{A2}}$ from data in Eq. 3.24.

(ii) Determine $\sigma_{x_{A1}}$, $\sigma_{x_{A2}}$ and compare with specification and then

adjustment factor = $\frac{\sigma_{x_{A\,closest}}}{\sigma_{x_{A\,other}}}$

(iii) Multiply $\sigma_{y_{A1}}$, by the adjustment factor.

(iv) Adjust the SNR using new $\sigma_{y_{adj}}$ in Eq. 3.24.

(v) Calculate differences between SNR level 1 and level 2 for original and adjusted values.

Estimate	**SNR_{LB} level 1**	**SNR_{LB} level 2**	**difference**
original	-11.934	-12.887	0.953
adjusted	**-12.106**	-12.887	**0.781**

Table 3.3 SNR_{LB} values estimated from σ_{yA1} and σ_{xA1}.

(vi) Using 0.781/0.953 = 0.82 adjust the difference between the values of the actual experimental results as follows:

Experiment	**SNR_{LB} level 1**	**SNR_{LB} level 2**	**difference**
original	-11.902	-12.713	0.811
adjusted	**-12.048**	-12.713	**0.665**

Table 3.4 Experiment SNR_{LB} values with adjustment.

The difference between actual Signal-to-Noise Ratio values calculated from the experimental data is therefore modified in light of the difference in noise factor distributions experienced at the two levels of design factor, x_A. The immediate consequence of this suggested change in the effect of the factor is that its contribution relative to other factors has changed and thus must be brought into perspective.

3.3.4 Weighted noise levels

Further to section 2.2.2 we can assign different weightings to noise factor levels using standard orthogonal contrasts (Montgomery, 1991) as a type of noise array (Fig. 2.7 in Chapter 2) in order to promote representative noise space sampling. Then these weightings can be applied to the associated data in the analysis for producing the regression models (e.g. using MiniTab).

3.4 Multiple Objective Optimisation in RED

Weighted utility function approaches were highlighted in Chapter 2 as being suitable for optimising an engineering system against multiple objectives. Recalling Eq 2.15 and Eq. 2.16 it was shown how a multivariate problem could be reduced to a univariate one by use of the desirability function (Derringer & Suich, 1980). The Quality Loss Function is demonstrated here as a superior utility function for multiple objective optimisation in Robust Engineering Design.

3.4.1 Exploiting design factor - noise factor interactions through fitted models

A common approach to Robust Engineering Design is to absorb information obtained about the noise into the sample standard deviations s_i computed over the noise factors, within each configuration of the design factor or noise factor. This avoids modelling the effect of noise directly with consequential simplicity of analysis. A sophistication is to present a separate response surface for the noise, see for example Nelder and Lee (1991), taking advantage of modern methods of variance estimation.

Here the inclusion of the noise factor in the model is preferred for a number of reasons:

(i) **Scientific understanding**. Despite the fact that by definition the noise factors are not controllable there may be important scientific significance attached to them. For example the increasing importance in design attached to the effect of and on the environment demands better understanding.

(ii) **Design**. Identifying *which* noise factor affects *which* design factor may have important design implications. It will be shown below that noise factor-design factor interactions are the key to Robust Engineering Design and it is therefore important to target these interactions accurately. This is discussed in the next subsection.

(iii) **Quality Loss Function.** Incorporating noise into the trial standard deviations encourages modelling of the Quality Loss Function, for example Signal-to-Noise Ratio. An alternative is to consider the Quality Loss Function as a function of the response directly. This is presented below.

Consider the situation of a single response, Y, which is simply modelled against design factors, x_D, and noise factors x_N, to produce a fitted model (shown in Eq. 3.26) which is an elaboration on Eq. 1.1 from Chapter 1:

$$Y = \theta_0 + \sum_{i=1}^{k} \theta_i x_{D_i} + \sum_{j=1}^{l} \phi_j x_{N_j} + \sum_i \sum_j \psi_{ij} x_{D_i} x_{N_j} \qquad (3.26)$$

Where the ψ_{ij} are the interaction parameters. Assume that the x_{D_i} are fixed and the x_{N_j} are uncorrelated with mean m_j and standard deviation s_{N_j} ($j = 1,\ldots l$). We can compute the mean and variance of Y under the noise distribution:

$$E_N(Y) = \theta_0 + \sum_{i=1}^{k} \theta_i x_{D_i} + \sum_{j=1}^{l} \phi_j \mu_{N_i} + \sum_i \sum_j \psi_{ij} x_{D_i} \mu_{N_i} \qquad (3.27)$$

$$Var_N(Y) = \sum_{j=1}^{l} \sigma_{N_j}^2 (\phi_j + \sum_{i=1}^{k} \psi_{ij} x_{D_i})^2 \qquad (3.28)$$

The variance (or standard deviation) can be reduced by direct minimisation subject to design constraints on the x_{D_i}. If $E_N(Y)$ must be kept on target then it is convenient to use an x_{D_i} for which $\psi_{ij} = 0$, so that the variance is not affected. Even in the case that $E_N(Y)$ or $Var_N(Y)$ are unknown we can try to reduce the sensitivity to a noise factor. Which could be interpreted as the partial derivative:

$$\frac{\partial Y}{\partial x_{N,j}} = \phi_j + \sum_{i=1}^{k} \psi_{ij} x_{D_i} \qquad (3.29)$$

the same term that appears in $Var_N(Y)$.

3.4.2 Competitive benchmarking for defining the quality loss function

The abundance of design experiments concerned with a single quality characteristic is partly explained by accepted experimental technique. The approach of Phadke (1989) promotes a single portmanteau quality characteristic as the aggregate metric of optimisation, ideally based upon the energy transformation function of the system under investigation. However, apart from experimental technique it is suggested here that the lack of an accepted method for dealing with multiple quality criteria in engineering design experimentation is an additional contributory factor of comparable significance.

The desirability function reviewed in Chapter 2 (Eq. 2.15) operates on mean values of the original response metric as commonly used not variability, which could explain why its use appears to have been confined to a few applications and not used for Robust Engineering Design problems. The approach below, as with the desirability function, seeks to attain the best balance among the objectives in preference to the optimisation of one response with constraints on the remainder as obtained using methods such as linear programming. The Quality Loss Function is employed as the utility for condensing a multivariate problem into a univariate one. By using *'competitive benchmarking'* to define this utility, and through observing the effects of individual design factors and noise factors on the overall loss, a more powerful argument in favour of the best configuration for robustness is provided for decision making.

For two Quality Loss Functions, the societal loss associated with each quality characteristic is shown in Fig. 3.16. Each Quality Characteristic is considered to follow the Smaller-the-Better relationship where:

$$\textit{Loss due to } QC1,\ L_{QC1} = k_{QC1} y_{QC1}^{\ 2} \qquad \textbf{(3.30)}$$

$$\textit{Loss due to } QC2,\ L_{QC2} = k_{QC2} y_{QC2}^{\ 2} \qquad \textbf{(3.31)}$$

The 'Smaller-the-Better' Quality Loss Function, (Eq. 1.3 in Chapter 1), suggested by Taguchi attempts to represent a relationship between non-conformance of a 'zero-is-best' quality characteristic and the costs attributable to not obtaining it. In practice it is difficult to verify the validity of this function for a given response but it does act as an incentive for continual improvement and can also provide a rational basis for making trade-offs between conflicting requirements. For example, establishing the absolute values of the constants k_{QC1} and k_{QC2} in practice will be virtually impossible due to the difficulty of determining actual costs of reworking product produced away from the zero ideal value. However, relative values of the constants can be derived by setting arbitrary losses (*£L*) against benchmark products in each category. Thus in Fig. 3.16 the performance of product A on L_{QC1} will set the constant k_{QC1} and likewise product B on L_{QC2} will set k_{QC2}. This 'common currency' of Loss can then be used to compute the relative total loss, any similar product will cause society and therefore facilitate identification of a best configuration for minimum overall loss:

Relative Total Loss, $L=L_{QC1}+L_{QC2}$ **(3.32)**

3.4.3 Optimising the quality loss through capability mapping

The loss functions can be model-based in accordance with Eq. 1.1 in Chapter 1 and using the argument above incorporated into the form

Relative Total Loss, $L = k_{QC1}Y_{QC1}^2 + k_{QC2}Y_{QC2}^2$ **(3.33)**

From this the behaviour of L over a range of noise factor values x_{N_j} (or Noise Space) can be investigated to find the optimum design factors x_{D_i}, obtained from design experiments, a further simplification is to confine the investigation to the investigation of the discrete levels of x_{D_i}.

In actual manufacture the x_{D_i} level settings will be met with a certain accuracy due to the capability of the manufacturing process. Knowing this capability in advance enables a tolerance analysis or *capability mapping*

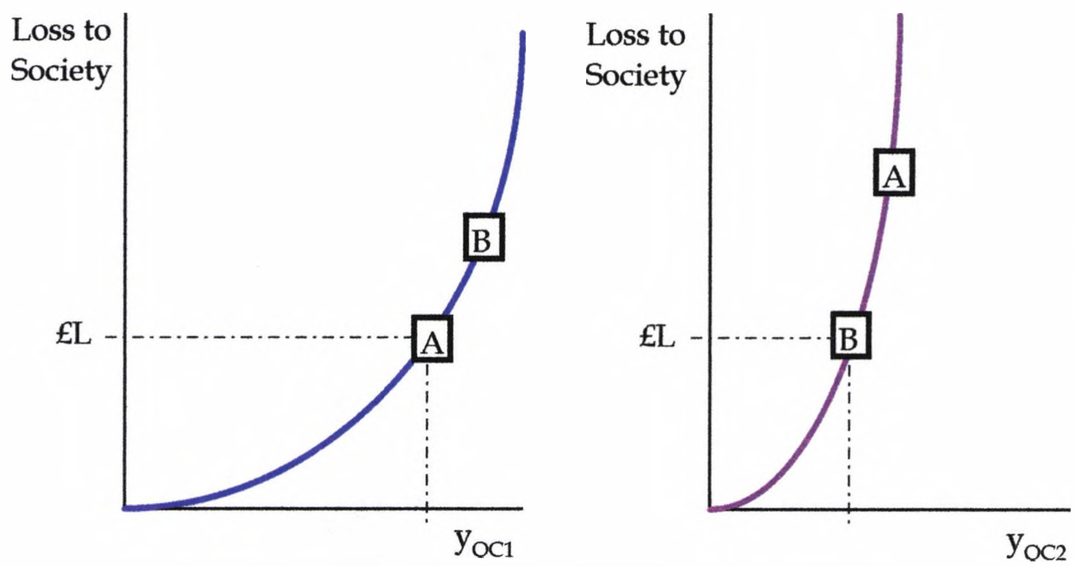


Fig. 3.16 Loss functions for two Smaller-the-Better quality characteristics determined using best product performance

to be performed in terms of the Relative Total Loss. Plotting the Relative Total Loss against the $x_{D,i}$ a non-linear relationship can be expected from Eq. 3.26. This is indicated in Fig. 3.17.

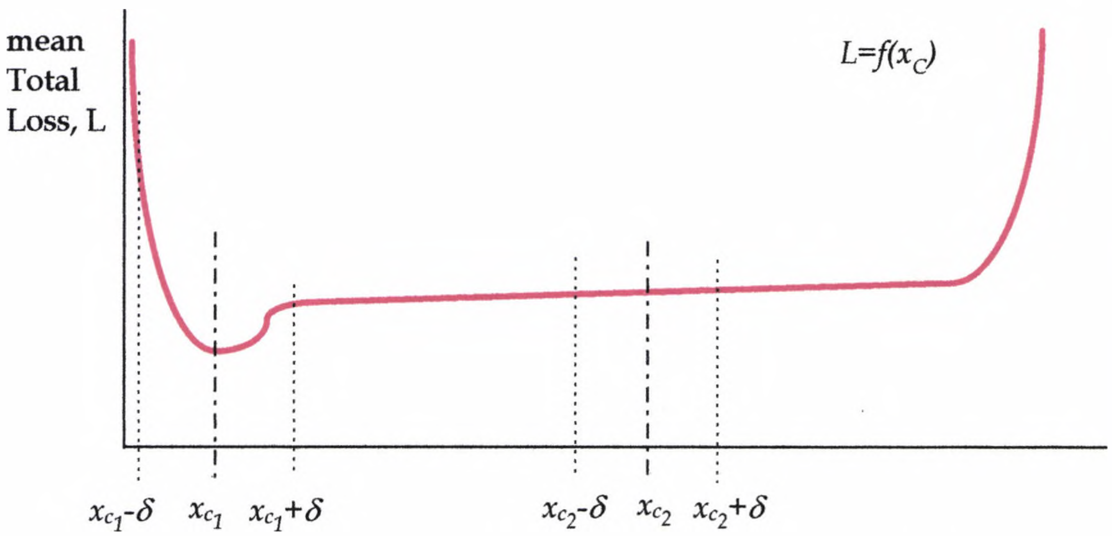


Fig 3.17 **Total loss versus design factor setting with *capability mapping***

3.5 Conclusions of Proposed Philosophy

The hypotheses and specific project objectives are presented again below but now with the addition of key aspects of the philosophy developed in this chapter.

3.5.1 Hypotheses restated

3.5.1(a) Hypothesis #1

"Robust Engineering Design can yield efficient results through more pragmatic approaches that involve engineering science and production capability in parameter selection and level setting."

3.5.1(b) Hypothesis #2

"The correlation roof of Quality Function Deployment can be used to inform design procedure and provide a link with Robust Engineering Design".

3.5.2 Project objectives expanded in light of proposed philosophy

(i) *To demonstrate the decomposition of the correlation roof into design procedures and the link between Robust Engineering Design and correlation chains.*

- The correlation roof has been underexploited in Quality Function Deployment.
- Correlation chains could be developed to generate design procedures.
- The resulting design procedure will assist in the planning of Robust Engineering Design experiments through assisting the identification of design partitions and highlighting the order in which results should be obtained.

(ii) *To consider the use of energy-based methods in selecting parameters and determining sliding levels for Robust Engineering Design experimentation, focusing on bond graphs and dimensional analysis.*

- Bond graphs could provide an effective means of identifying factors for experimentation.
- The use of bond graph models could also provide a practical link between Quality Function Deployment and Robust Engineering Design. These models would not only inform experimentation but the updated model would provide simulations for rapid assessment of any proposed design modifications.
- Dimensional analysis could help to improve the additivity of experimental results through identifying parameter relationships in the assignment of sliding factors to orthogonal arrays.
- The use of the standard three categories should be augmented by the use of other categories, for internal noise in particular, in order to focus on *deterioration, environment, tolerance* and *load*. In addition a set of categories for an *energy-based* classification should be investigated.

(iii) *To gather practical guidance on selecting design factor levels and noise factor levels for product Robust Engineering Design experiments conducted in a production environment.*

- Setting design factor levels based upon production capability is economically attractive and convenient even when balanced against the accompanying limited search of design space.
- The effect of any difference in the distributions of the noise factor levels on design factor main effects will be taken into account in the subsequent analysis.

(iv) To utilise different noise factor level weightings and model them against design factors in order to better reflect noise behaviour in reality.

- Noise space should not be sampled with an equal probability approach as for the approach to searching design space. This is a criticism of the Taguchi approach. Sampling noise space involves using levels for the noise factors that reflect the nature of the noise distribution. For many sources of noise a valid probability density is unidentified.

(v) To show how quality loss functions can be established for multiple objective optimisation in practical Robust Engineering Design using competitive benchmarking and capability mapping for optimisation of total loss.

- A method for dealing with multiple quality objectives in Robust Engineering Design has not been clearly presented in the literature.
- Design factor - noise factor interaction modelling should be investigated for use in multiple objective optimisation.
- Competitive benchmarking offers a means of addressing loss functions that avoids the need to obtain actual product financial information which is usually too difficult to obtain.
- Capability mapping could link tolerance variability with total loss for selection of the overall optimum.

3.5.3 Project objectives to be realised through case studies

The key aspects of the philosophy summarised above will be addressed by the subsequent case studies contained in the chapters as indicated in the matrix below.

Themes of specific project objectives	**Chapter 4** Mixing System	**Chapter 5** Loudspeaker	**Chapter 6** Hedgetrimmer	**Chapter 7** Fuel Injector
(i) correlation roof: QFD Phase 1: (design procedure)	✓	–	✓	–
QFD Phase 2: (design retrieval)	–	✓	✓	–
(ii) energy-based: bond graphs:	–	✓	✓	–
dimensional analysis:	✓	✓	–	–
(iii) Selecting factor levels in production	–	–	–	✓
(iv) noise factor weightings	–	–	–	✓
(v) multiple objective optimisation	–	–	–	✓

Chapter 4. Mixing System Case Study

4.1 Introduction

4.1.1 Overview and purpose of case study

Prototype products are commonly made from resin materials with similar characteristics to the plastics that will be used in the proposed production item. The two-part resins used have a wide range of viscosities (400 to 2000 centipoise) and are mixed in volumetric ratios of 1:1, 2:1, 4:1 or 10:1. Thorough mixing is therefore essential for consistent properties. The author is currently supervising a Teaching Company Scheme project which has the aim of developing vacuum casting equipment for the production of prototypes using two-part resin materials. The conceptual design for this equipment is already decided in comprising of two systems - the resin Mixing System for producing batches of thoroughly mixed resin and the Vacuum Chamber for degassing the mould. In effect this is a re-design problem because the basic positive displacement configuration of the mixing system has already been decided.

The aim of this case study was to apply the proposed Quality Function Deployment phase 1 correlation roof to the resin Mixing System and follow through the embodiment design to physical Robust Engineering Design experiments with an emphasis on dimensional analysis for selecting sliding levels for design factors. The experimental results show that nozzle diameter is a significant design factor and also that interaction effects between the two design factors was avoided through the use of appropriate sliding levels.

4.2 Partitioning the Design Problem in QFD Phase 1

4.2.1 Identification of design requirements

The design requirements identified for the resin Mixing System are:

A - **visibility of resin components:** it is desired that the two resin component materials are visible in order for the operator to monitor their quantity and condition.

B - **filling:** the process of charging the positive displacement chambers with the correct volumetric ratios of resin components.

C - **dispensing:** the process of delivering the two materials at the correct relative rates.

D - **mixing:** thoroughly blending the resin components into a homogenous mixture.

E - **sealing:** ensuring that the resin components or the resultant mixture do not leak from or within the system.

F - **chemical resistance:** the materials used in the system should be resistant to attack from the chemicals used.

G - **scratch resistance:** the materials used should be scratch resistant in order generally to prevent resin sticking and in some areas to remain transparent.

H - **cleaning:** the system should be easy to clean.

I - **maintenance:** the system needs to be maintainable by the customer.

J - **assembly/disassembly:** in order to accommodate the range of volumetric ratios and also to reflect the production facilities of the manufacturer it is important that the system is designed for ease of repeated assembly/disassembly.

K - **mix ratio alteration:** the ratios used are discrete values including 1:1, 2:1, 3:1, 4:1 and 10:1.

L - **valving:** as the system is positive displacement, valves are a likely feature of its operation.

4.2.2 Completion of correlation roof

In this case the designer was asked to complete the correlation roof shown in Fig. 4.1 by identifying the direct influence one design function has on another (column-wise) in terms of deciding their embodiment detail.

4.2.3 Formation of correlation chains

Fig. 4.2 shows the resulting correlation chain hierarchy in which it is indicated that for efficient design activity the filling and dispensing embodiment details should be decided before valving, sealing and other issues are tackled. However, deciding the means of ratio alteration will be addressed later. Another important embodiment issue relates to the material selection for chemical resistance and its relationship with the design of valving and cleaning features. Finally, there is a high degree of interdependence at the lowest level between the mix ratio, cleaning, maintenance and assembly embodiment design.

The correlation chain shown should not be considered as a single-pass embodiment design issue, as it is likely there will be several iterations through the chains before a satisfactory design is completed.

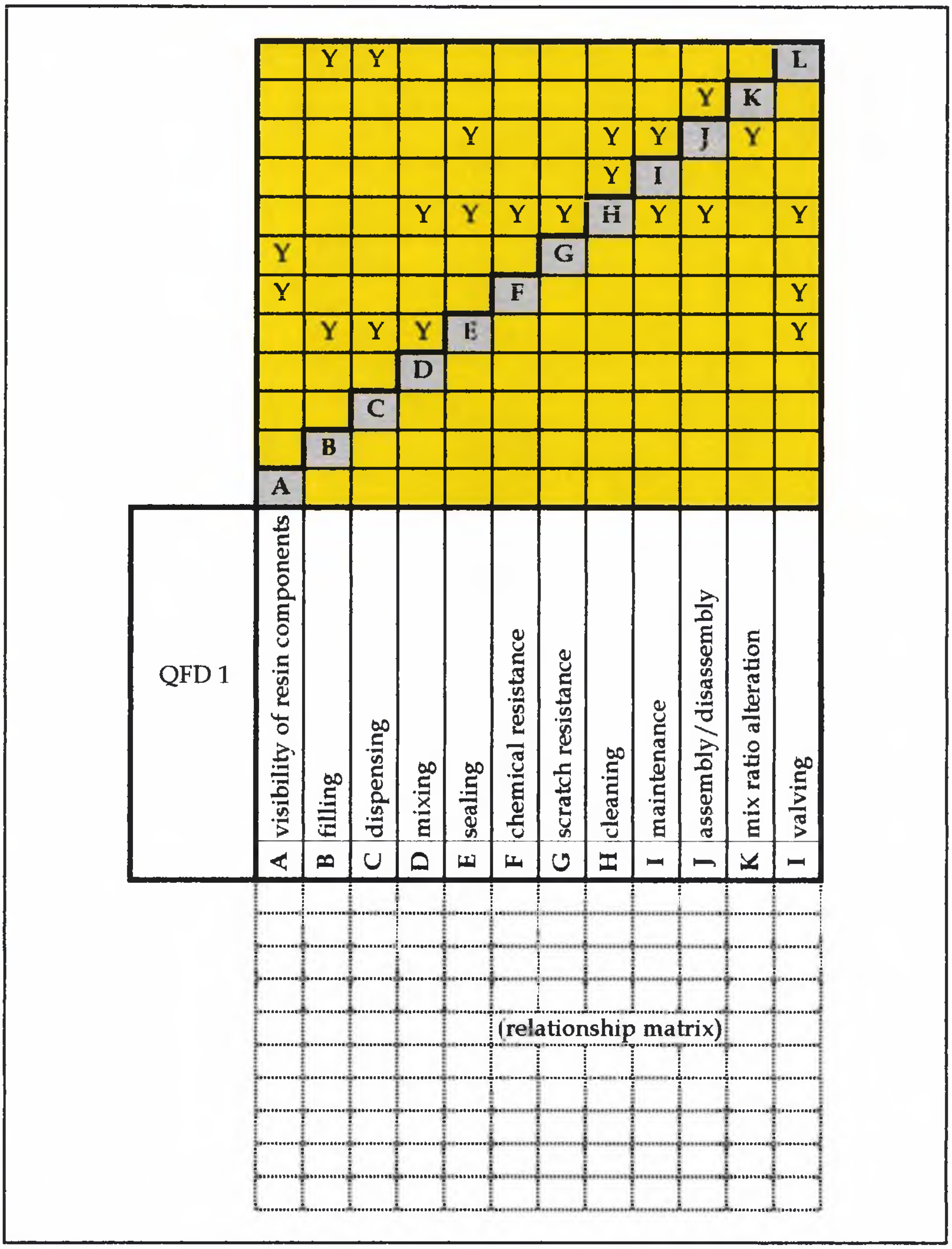


Fig. 4.1 **QFD phase 1 correlation roof for Resin Mixing System**

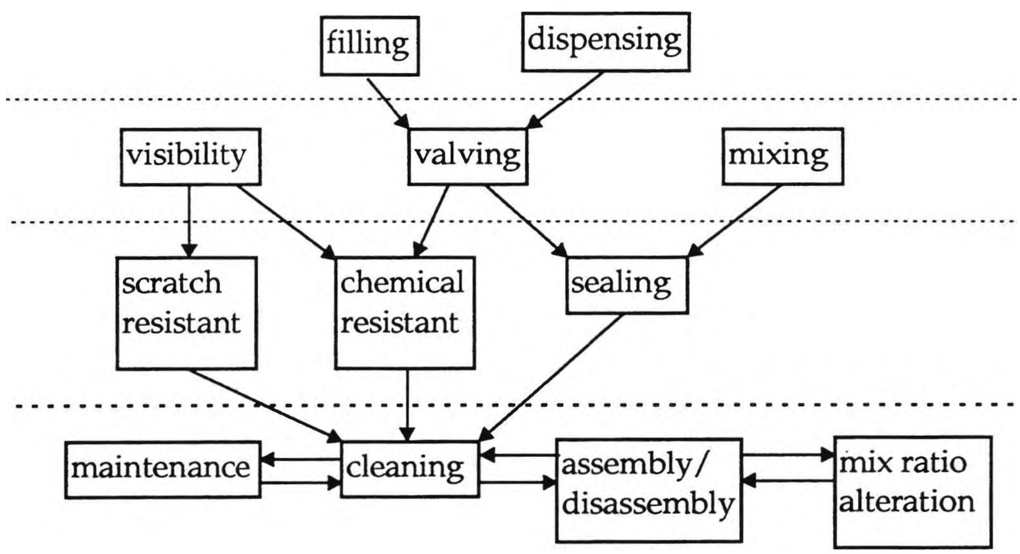


Fig. 4.2 Correlation chain hierarchy for embodiment design

4.3 Preparation for Robust Engineering Design

4.3.1 Mixing head embodiment design

The final embodiment design for the resin Mixing System is shown in Fig. 4.3 and Fig. 4.4.

The system fills with resin component material through simultaneously pulling the two pistons down by means of the handle acting on the guide block. Once the chambers are filled the handle is then raised and the resulting flow of material switches the valves causing the material to flow together down the mixing nozzle into the vacuum chamber reservoir.

The Mixing Head has been designed as a sandwich construction with quick-release fitting on the end plates for ease of assembly/disassembly. Cleaning is facilitated through the simple assembly, disposable mixing nozzles and valves, and also the use of polycarbonate, acrylic and stainless steels materials. Virtually all of the components that come into contact with the resin are transparent for maximum visibility. One of the piston/chamber pairs are changed in order to alter the mix ratios.

4.3.1(a) Physical effects

Developing the understanding of the system in more physical terms (i.e. adding detail to Fig 4.3 and Fig. 4.4) the primary physical function (or physical effect to differentiate it from the procedural design functions of phase 1) is mixing. Now by analysing the embodiment design we can breakdown the physical effects until a level is reached where the designer has control over the effects, which are design factors.

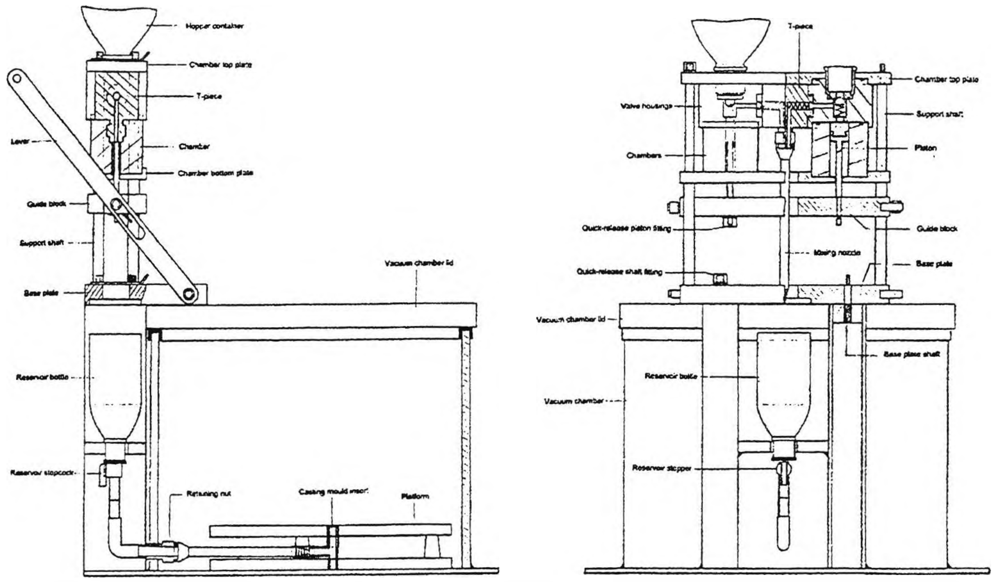


Fig. 4.3 Elevations of vacuum casting equipment (Cattini, 1997)

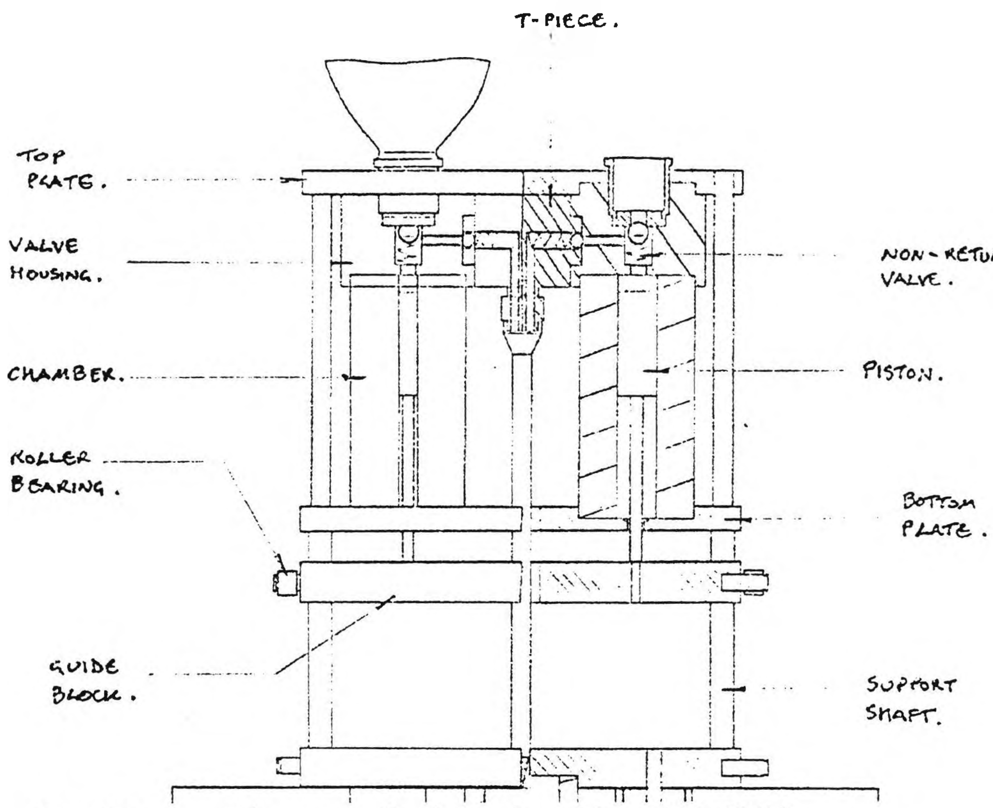


Fig. 4.4 Close-up of mixing head (Cattini, 1997)

4.3.1(b) Nozzle design factors

In Fig. 4.5 some of the physical effects are shown subjected to decomposition identifying a few of the associated design factors. Ideally the quality characteristic of the system would relate to the homogeneity of the mixed resin. However, to measure this quantitatively with sufficient precision could involve expensive and/or time-consuming techniques. In this particular case material properties tests (such as impact strength) on test specimens produced with the resin - are a practical proposition. From Fig. 4.5 we can consider partitioning the physical effects in order to keep the number of design factors small. Thus nozzle length and number of nozzle elements -which both establish the helix- together with nozzle diameter are highlighted for Robust Engineering Design experiments. The next stage would be to establish their interrelationship using dimensional analysis in order to set sliding factor levels if appropriate.

4.3.2 Dimensional analysis on mixing nozzle

In considering an appropriate choice of dependent variable for use in a dimensional analysis of mixing various measures are suggested such as diffusivity, vorticity and momentum. However, as it is clear that the homogeneity achieved with thorough mixing is strongly related to the ideal impact strength of the resin material then we could also consider impact strength as another option for the dimensional analysis.

For the mixing nozzle, the available design factors 'off-the-shelf' are:

d - the internal diameter.

l - the overall nozzle length.

Other relevant parameters are:

μ - aggregate dynamic viscosity of resin.

ρ - aggregate density of resin.

v - aggregate velocity of resin through nozzle.

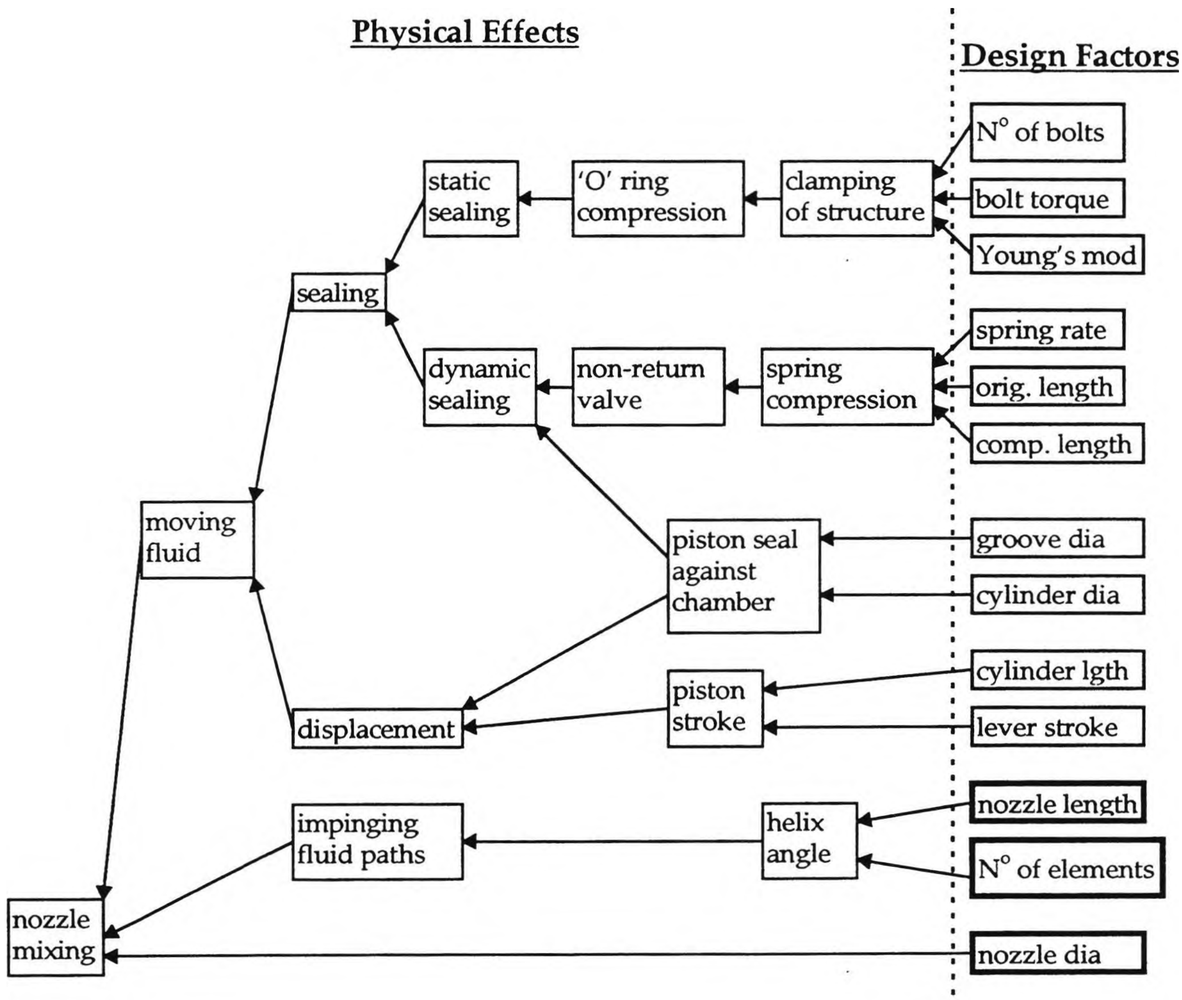


Fig. 4.5 Physical effects and potential design factors

Thus let the two dependent variables in the dimensional analysis be:

(i.) momentum

$$G = \phi\ (d^a l^b \mu^c \varrho^d v^e)$$

$$\therefore\ \frac{ML}{T} = \phi\ (L^a L^b \left[\frac{M}{LT}\right]^c \left[\frac{M}{L^3}\right]^d \left[\frac{L}{T}\right]^e)$$

Equating powers of M, L and T.

M: $1=c+d$

L: $1=a+b-c-3d+e$

T: $-1=-c-e$

$\therefore$ $a=2-b+e,\ c=1-e$ and $d=e$

$$\Rightarrow G = \phi\ (d^{2-b+e}\ l^b \mu^{1-e} \varrho^e v^e)$$

$$G = d^2 \mu\ \phi \left\{ \left(\frac{l}{d}\right)^b \left(\frac{d\varrho\, v}{\mu}\right)^e \right\}$$

(ii.) impact strength

$$S = \phi\ (d^a l^b \mu^c \varrho^d v^e)$$

$$\therefore\ \frac{M}{T^2} = \phi\ (L^a L^b \left[\frac{M}{LT}\right]^c \left[\frac{M}{L^3}\right]^d \left[\frac{L}{T}\right]^e)$$

Again equating powers of M, L and T.

M: $1=c+d$

L: $0=a+b-c-3d+e$

T: $-2=-c-e$

$\therefore$ $a=e-b-1,\ c=2-e$ and $d=e-1$

$$\Rightarrow S = \phi\ (d^{e-b-1}\ l^b \mu^{2-e} \varrho^{e-1} v^e)$$

$$S = \frac{\mu^2}{\varrho d}\ \phi \left\{ \left(\frac{l}{d}\right)^b \left(\frac{d\varrho\, v}{\mu}\right)^e \right\}$$

From section 3.3.2 the π groups are observed to be the three groupings in each case. Note that π_1 differs in each case according to the response output but the π_2 and π_3 groups are identical - representing the ratio of length:diameter and Reynolds (R_e) number respectively.

4.3.3 Experiment preparation

The design factors are *d* and *l* where several lengths are available for given internal diameters and no two nozzle lengths are the same. Therefore guided by π_2 we assign the ratio *l/d* to one column of an orthogonal array and *d* to another according to chapter 3. This is shown in Table 4.1 below.

L_4	*l/d*	column 2	*d*
Exp 1	1	1	1
Exp 2	1	2	2
Exp 3	2	1	2
Exp 4	2	2	1

Table 4.1 Proposed L_4 OA assignment

As the experiments are addressed at one resin only we shall assume that mix viscosity, μ, and mix density, ρ, remain constant. Thus in π_3 only nozzle diameter, *d* and resin flow velocity, *v*, can change. As *d* is a design factor and subject to the Orthogonal Array, then this leaves *v* as a noise factor. We appear to have identified *v*, as a significant noise factor as well as identifying the design factors sliding levels. In Tables 4.2 design factor values are based on proprietary nozzles and the noise factor levels are achieved by a normal and slow operation of the operating handle.

L_4	*l/d*	col 2	*d*	**noise level 1**	**noise level 2**
Exp 1	30	1	5mm	"normal pull"	"slow pull"
Exp 2	29.4	2	6.3mm	"normal pull"	"slow pull"
Exp 3	37.1	1	6.3mm	"normal pull"	"slow pull"
Exp 4	37.6	2	5mm	"normal pull"	"slow pull"

Table 4.2 Assignment of factor levels

4.4 Nozzle Experiments

4.4.1 Impact test data

The test pieces were tested according to BS2782 for an unnotched standard test piece on an Avery 6702 self-indicating impact testing machine.

Impact Strength in KJ/m^2					
L_4	*l/d*	col 2	*d*	noise level 1	noise level 2
Exp 1	30	1	5	2.4, 2.8, 2.3, 2.7, 2.2	2.1, 2.0, 2.5, 2.6, 2.4
Exp 2	29.4	2	6.3	3.0, 2.7, 2.5, 2.4, 2.3	2.8, 2.7, 2.3, 2.2, 2.8
Exp 3	37.1	1	6.3	2.8, 2.1, 2.4, 2.9, 2.8	2.7, 2.6, 2.6, 2.5, 2.5
Exp 4	37.6	2	5	2.2, 2.6, 2.4, 2.6, 2.1	2.5, 2.7, 2.4, 2.1, 2.4

Table 4.3 Impact test experiment data

4.4.2 Analysis

4.4.2(a) Significant design factor

The mean impact strength (ave) and Larger-the-Better Signal-to-Noise Ratio (S/N) for each experimental trial is shown in Table 4.4.

Run	1 L/d	2	3 d	impact stgh ave	impact stgh S/N
1	30 nom	1	5.0	2.40	7.47 dB
2	30 nom	2	6.3	2.57	8.07 dB
3	37 nom	1	6.3	2.59	8.16 dB
4	37 nom	2	5.0	2.40	7.51 dB

1x3

Table. 4.4 Mean impact strength and Larger-the-Better SNR for each experiment trial

The response table for the mean and Signal-to-Noise Ratio of the impact strength data is shown in Table 4.5.

Factor	Level	impact stgh (ave)	impact stgh (s/n)
L/d	30 nom	2.49	7.77
	37 nom	2.49	7.84
2	1	2.49	7.81
	2	2.49	7.79
d	5.0	2.40	7.49
	6.3	2.58	8.12

Table 4.5 Response table for impact data

From Table 4.5, Fig. 4.6 and Table 4.6 diameter, *d*, is shown to be the most significant factor effect for both mean (ave) and variability (S/N or Signal-to-Noise Ratio).

4.4.2(b) Avoiding interaction

Fig. 4.7 indicates that the interaction between *L/d* and *d* is very small by virtue of the parallelism between the lines. This result supports the choice of sliding the levels of *L* in the ratio *L/d*.

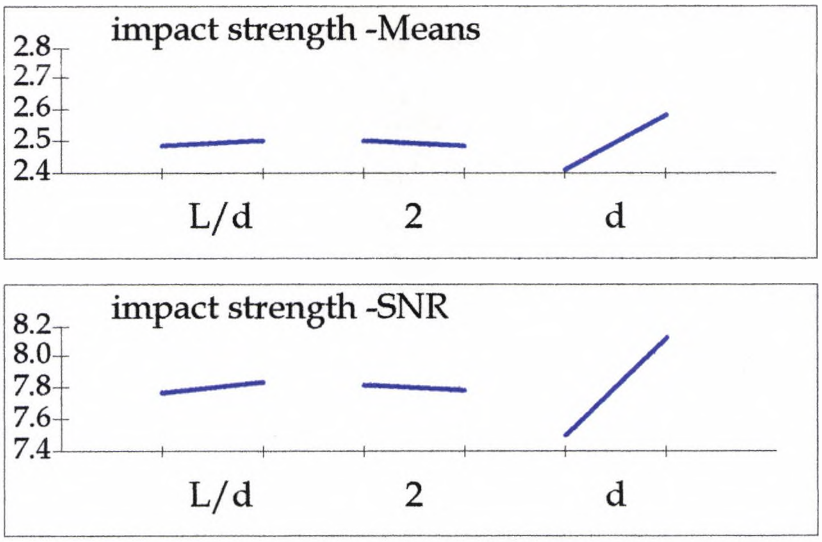


Fig. 4.6 Response graphs for impact data

Factor	impact stgh-S/N SS	d.o.f.	mean sq	F
d	0.39	1	0.39	816.2
L/d	0.00	1	0.00	9.2
error	0.00	1	0.00	

Factor	impact stgh-Mean SS	d.o.f.	mean sq	F
d	0.32	1	0.32	5.6
L/d	0.00	1	0.00	--
error	2.13	37	0.06	

Table. 4.6 ANOVA tables for mean (incorporating error within treatments) and SNR impact strength

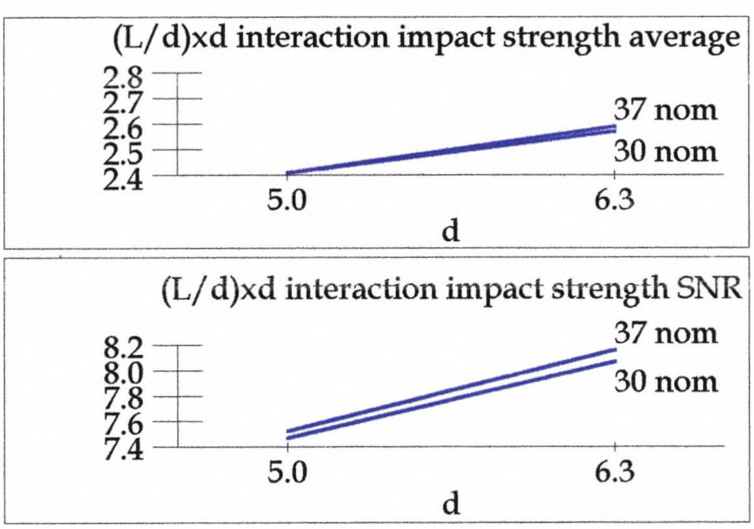


Fig. 4.7 Interaction plot of *d* and *l/d*

4.5 Summary of Mixing System Case Study

4.5.1 Discussion

The function decomposition exercised in completing the correlation roof of Quality Function Deployment phase 1 has relied on the designers' anticipation of the knowledge required in tackling the Mixing System design problem. A designer is likely to better understand the dependencies and interdependencies of the design requirements with experience of previous or similar products which suggests redesign problems would be well suited to this approach. From the correlation chains the mixing function was identified as an independent issue and targeted for Robust Engineering Design experimentation. Following embodiment design further function decomposition took place through identifying the physical effects of this subsystem and breaking them down until they were viewed as controllable by the designer. In other words design factors. The judgement of the design team in identifying the physical effects was necessary as no analytical means of gaining insight into the system function was used. However dimensional analysis did provide some front-end insight into the relationship between the quality characteristic of impact strength and flow parameters of the mixing nozzle. An interesting aspect of the Robust Engineering Design front-end was the identification of flow velocity as a noise factor from the dimensional analysis. Diameter of the mixing nozzle has been identified as the significant nozzle influence on impact strength of the specimens tested. Had resources allowed it would have been desirable to conduct a much larger Robust Engineering Design experiment with several three-level design factors in order to find optima values. However, in addition to the QFD/RED link demonstrated at phase 1 level, from Fig. 4.8 we can envisage using greater Robust Engineering Design activity to identify critical part characteristics (i.e. design factors).

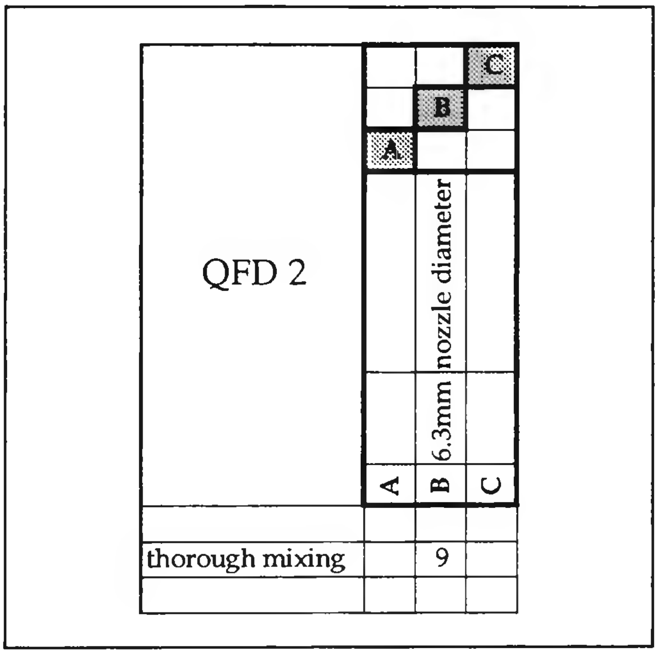


Fig. 4.8 Part of QFD phase 2 matrix relating to nozzle detail

4.5.2 Conclusions

We have demonstrated the partitioning of the design problem using correlation chains formed from the new correlation roof. The resultant design procedure has informed a basic Robust Engineering Design experiment in which design factor sliding levels were determined using dimensional analysis in order to achieve additivity. Dimensional analysis also led to the identification of handle pull speed as an influential noise factor.

Chapter 5. Loudspeaker Case Study

5.1 Introduction

5.1.1 Overview and purpose of case study

Loudspeaker performance will vary between any two speakers off the production line due to the inevitable variation in material properties, dimensions, and other parameters of the component parts. The two major sub-systems of a loudspeaker are the driver unit and its enclosure. The main aim of this case study was to investigate the main sources of unit-to-unit variation of driver units.

The equivalent of Quality Function Deployment phase 1 had already been conducted as the design requirements were clear and the concept embodiment well established. Thus the context is the (partial) completion of Quality Function Deployment phase 2. The effectiveness of bond graphs to identify significant factors was addressed in this case study. Sound Pressure Level (SPL) was chosen as the appropriate quality characteristic to measure because it is energy-related, measurable and an objective measure of loudspeaker performance accepted within the industry. However in the bond graph model we were only able to represent SPL with voice-coil velocity. Thus simulation results and the results of physical experiments have to be reconciled. The physical experiments show that coil resistance variation is significant to driver quality which was expected from the bond graph model. Approximately 30% of the total variation in performance (which was up to 3 decibels) amongst twenty drivers was observed to be due to variation in the electrical resistance of the voice coil. In addition coil resistance was observed to vary significantly by batch. However, about 60% residual error suggests that significant parameters were not included in experimentation. Thus the selection of parameters is open to further insight. The coils used in this investigation came from batches produced on five different dates. Their electrical resistance was observed to have distinctly different standard deviations suggesting a systematic cause but this was difficult to identify and warrants further investigation.

Some parameter levels in this case study are selected from the available production distribution rather than set as freely selectable levels. In Robust Engineering Design experiments on redesign problems, the incorporation of the production processes in the experimental design enables identification of design factors likely to have interaction with the noise factors causing unit-to-unit variation. This pragmatic approach is also aimed at incorporating representative levels of noise, or even correctly sampling noise space, as well as being an efficient way of searching local regions of design space. From the survey of noise factors in chapter 3 it was clear that selection based upon unit-to-unit noise factors will perhaps only account for approx. 20% of all the disturbing influences. This is a limitation of the approach presented here and so other considerations would need to be included in order to identify all significant design factors in the design experiment. In addition, correlations between parameters are identified in terms of their effect on the variability of the loudspeaker output which provides an opportunity to simplify further experimentation involving these design factors.

Bond graph simulation of the loudspeaker voice-coil highlights the issue of experiment resolution in terms of clearly understanding the link between the voice-coil performance (low-level) and the driver unit performance (high-level). Without this understanding factors effects found at the one level will not translate to the expected performance at the other level. Dimensional analysis is used to identify candidate voice-coils for assignment to an Orthogonal Array.

5.1.2 Loudspeaker driver unit parameters

The basic working principle of the moving-coil loudspeaker will be appreciated from the driver unit assembly shown in Fig. 5.1. Essentially a motor coil moves axially within a radial magnetic field driving a diaphragm at audible frequencies which then radiates sound from its surface into the air. Consideration of potential design factors in the driver unit for Robust Engineering Design experimentation highlights several groups or sub-systems even for this product with its relatively low parts count. The loudspeaker design factors will depend on the nature of the sub-system to which they are associated:

- **Surround** - material and adhesive bonding properties.
- **Diaphragm** - material properties and various dimensions.
- **Suspension** - dynamic characteristics.
- **Magnet** - magnetic properties and various dimensions.
- **Voice-coil** - energy properties and various dimensions.

Thus design factors from various 'levels' of the system can be readily identified, including:

(i) B - flux density of magnet.

(ii) l - coil wire length.

(iii) i - electrical current.

(iv) F - motor force, Bli.

(v) N - number of turns.

(vi) r - coil radius.

(vii) d - coil wire diameter

(viii) R_{coil} - electrical resistance of coil.

(ix) $R_{lead\text{-}out}$ - electrical resistance of the lead-out wire braid.

(x) R_e - overall driver unit resistance.

(xi) L - coil inductance.

(xii) M_{coil} - coil mass.

(xiii) M_{cone} - diaphragm cone mass.

(xiv) M_{air} - air mass.

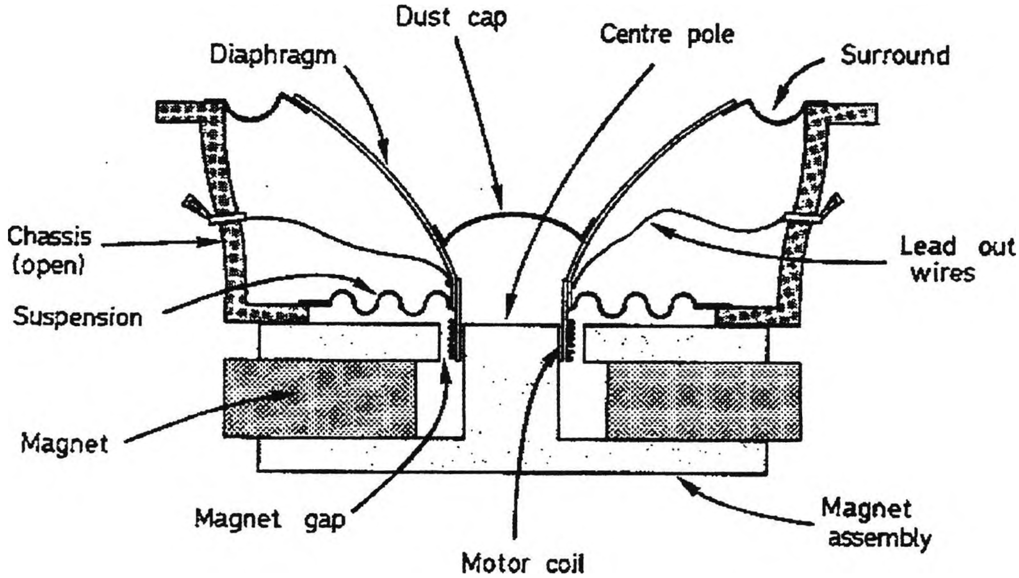


Fig. 5.1 Moving-coil loudspeaker driver unit (Colloms, 1991)

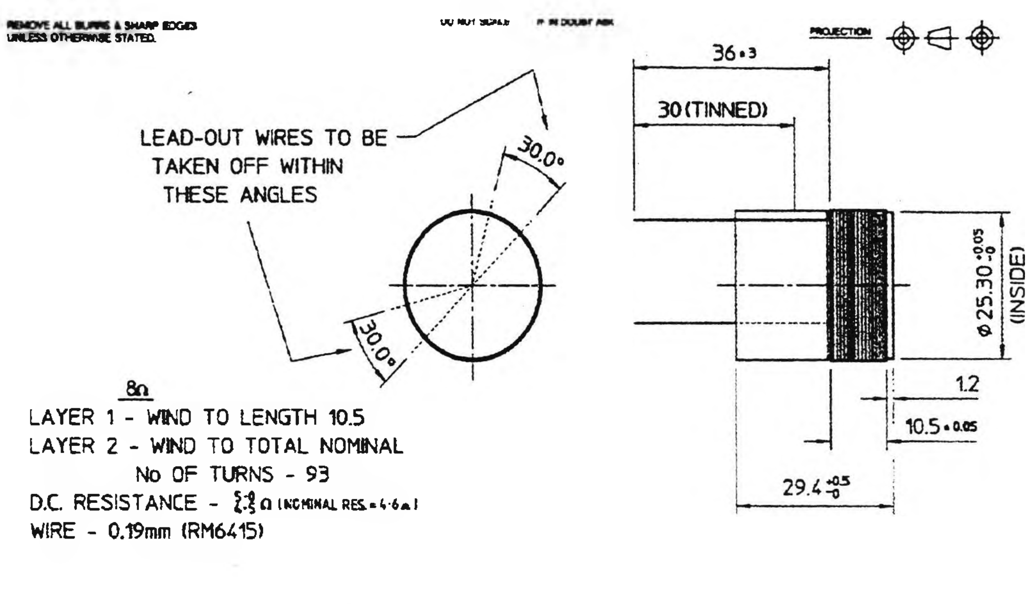


Fig. 5.2 Example of a loudspeaker voice-coil

(xv) M_{md} - total moving mass.

(xvi) R_{air} - air mechanical resistance.

(xvii) R_{cone} - mechanical resistance of cone material.

(xviii) R_{supp} - mechanical resistance of supports.

(xix) R_{ms} - total mechanical resistance.

(xx) C_{air} - mechanical compliance of air.

(xxi) C_{glue} - mechanical compliance of glue used to assemble rim to cone.

(xxii) C_{supp} - mechanical compliance of supports.

(xxiii) C_{ms} - total mechanical compliance.

(xxiv) R_{rim} - cone rim radius.

(xxv) R_{apex} - apex radius of cone.

(xxvi) alpha - cone angle.

(xxvii) h - cone material thickness.

(xxviii) E - Young's modulus of cone material.

(xxix) g - magnet gap.

(xxx) x - magnet thickness.

This is not an exhaustive list but does illustrate the need for a means of selection when only a few design factors can be included in the experiment. Choosing factors for experimentation from one system level is preferred in order to avoid interacting effects (Taguchi, 1987). An advantage of using bond graphs as a generalised modelling tool for Robust Engineering Design is that any design factors represented are all at the same 'level' within the system as the model is built up from a few generalised modelling elements. From this basic level (resolution) there is potential for more detail to be added by subdividing the system into more elements and connections. Let us follow steps (i) to (iii) from section 3.2.1(a) in Chapter 3 in order to gain insight from a bond graph model.

5.2 Bond Graph Selection of Design Factors

5.2.1 Bond graph model of voice-coil

Fig. 5.3 was utilised to highlight potential design factors for selection from the large number of parameters indicated above. This bond graph is a lumped parameter model. Distributed parameter models are a more advanced bond graph approach and would involve considerable time to model. More advanced models for voice-coils have not been presented in the bond graph literature (Sharpe, 1995).

In choosing the design factors for this investigation, the bond graph in Fig. 5.3 highlights parameters at a common basic level linked with the flow of power through the voice-coil device, namely:

(i) **R_e** - the electrical resistance of the driver unit, made up almost entirely by that of the coil with a small amount contributed by the lead-out braid.

(ii) **Bl** - the motor 'shove factor', determined by the coil turns on the voice coil and the magnetic flux generated in the gap between magnet and coil.

(iii) **M_{md}** - the total moving mass, which is mainly that of the voice coil and the cone diaphragm.

(iv) **R_{ms}** - the total mechanical resistance offered from elements such as the surround and support.

(v) **C_{ms}** - the total mechanical compliance of the supports.

The coil inductance, I (L in the list above), was not selected under guidance of the design team, instead three dimensionless parameters of specific interest to the loudspeaker design engineers were included:

(vi) **Q_{es}** - the electrical damping ratio defined as $(2\pi f_s M_{md} R_e)/(Bl)^2$.

(vii) **Q_{ms}** - the mechanical damping ratio defined as $2\pi f_s M_{md}/R_{ms}$.

(viii) **Q_{ts}** - the total system damping ratio defined as $1/((1/Q_{ms})+(1/Q_{es}))$.

Where f_s is the free air resonance frequency.

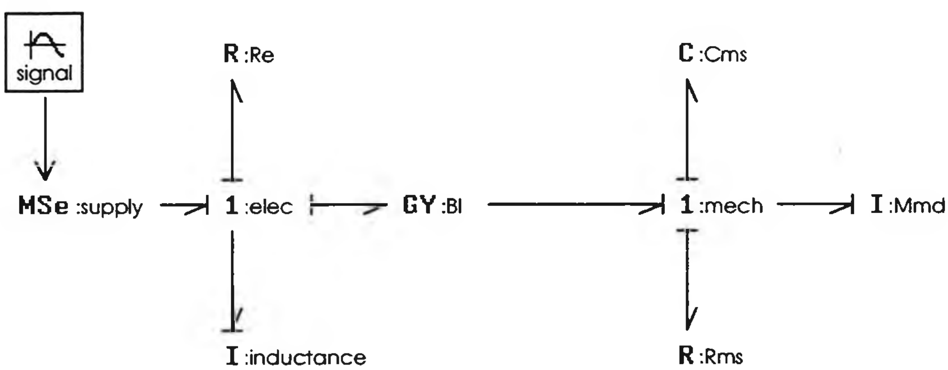


Fig. 5.3 Bond graph model of loudspeaker voice-coil

5.2.2 State-space equations for design factor selection

Here we shall quickly note the state-space equations for the purposes of illustration. The power bonds are numbered clockwise around each junction starting with the supply as #1 and finishing with the R_{ms} as #8.

$$\frac{dp_4}{dt} = e_1 - e_2 - e_3 = S_e - R_e f_4 - Blf_7$$

where $\dfrac{dp_4}{dt} = I\dfrac{df_4}{dt}$

$$\therefore \frac{df_4}{dt} = \frac{1}{I}(S_e - R_e f_4 - Blf_7)$$

$$\frac{dq_6}{dt} = f_7 \text{ where } \frac{dq_6}{dt} = C_{ms}\frac{de_6}{dt} \quad \therefore \frac{de_6}{dt} = \frac{1}{C_{ms}} f_7$$

$$\frac{dp_7}{dt} = e_5 - e_6 - e_8 = Blf_4 - R_{ms} f_7$$

where $\dfrac{dp_7}{dt} = M_{md}\dfrac{df_7}{dt}$

$$\therefore \frac{df_7}{dt} = \frac{1}{M_{md}}(Blf_4 - e_6 - R_{ms} f_7)$$

Putting these equations in matrix form:

$$\frac{d}{dt}\begin{bmatrix} f_4 \\ e_6 \\ f_7 \end{bmatrix} = \begin{bmatrix} \frac{R_e}{I} & 0 & -\frac{Bl}{I} \\ 0 & \frac{1}{C_{ms}} & 0 \\ \frac{Bl}{M} & \frac{1}{M} & -\frac{R_{ms}}{M} \end{bmatrix}\begin{bmatrix} f_4 \\ e_6 \\ f_7 \end{bmatrix} + \begin{bmatrix} \frac{1}{I} \\ 0 \\ 0 \end{bmatrix}[S_e]$$

and inserting nominal values

$$\frac{d}{dt}\begin{bmatrix} f_4 \\ e_6 \\ f_7 \end{bmatrix} = \begin{bmatrix} \frac{5}{0.00025} & 0 & -\frac{6}{0.00025} \\ 0 & \frac{1}{1\times10^{-3}} & 0 \\ \frac{6}{8\times10^{-3}} & \frac{1}{8\times10^{-3}} & -\frac{0.4}{8\times10^{-3}} \end{bmatrix}\begin{bmatrix} f_4 \\ e_6 \\ f_7 \end{bmatrix} + \begin{bmatrix} \frac{1}{0.00025} \\ 0 \\ 0 \end{bmatrix}[S_e]$$

or

$$\frac{d}{dt}\begin{bmatrix} f_4 \\ e_6 \\ f_7 \end{bmatrix} = \begin{bmatrix} 20000 & 0 & -24000 \\ 0 & 1000 & 0 \\ 750 & 125 & -50 \end{bmatrix}\begin{bmatrix} f_4 \\ e_6 \\ f_7 \end{bmatrix} + \begin{bmatrix} 4000 \\ 0 \\ 0 \end{bmatrix}[S_e]$$

The relative significance of the design factors in the main matrix can be estimated after scaling the matrix so as to equalise all numerical values (Martens & Bell, 1972). First estimates of the nominal values of f_4, e_6 and f_7 are required.

Let us consider $f_4 = 3A$, $e_6 = 1N$ and $f_7 = 1m/s$. Then scaling e_6 and f_7 by 3 the following equations result.

$$\frac{d}{dt}\begin{bmatrix} f_4 \\ 3e_6 \\ 3f_7 \end{bmatrix} = \begin{bmatrix} 20000 & 0 & -8000 \\ 0 & 3000 & 0 \\ 2250 & 125 & -50 \end{bmatrix}\begin{bmatrix} f_4 \\ 3e_6 \\ 3f_7 \end{bmatrix} + \begin{bmatrix} 4000 \\ 0 \\ 0 \end{bmatrix}[S_e]$$

The two largest values indicate that from the design factors considered, R_e and Bl may have significant influence on the energy flow through the voice-coil. Furthermore the values in the leading diagonal are first approximations of the system time constants.

5.2.3 Tracing causality for possible interactions

Back to Fig. 5.3:

(i) Inductance, I, has not been included in the design factor group. However as it determines the first flow junction we follow its flow causation which acts upon R_e and also through Bl switching to effort causation which acts on M_{md}.

(ii) The mass is shown to determine the final flow junction and as such acts upon R_{ms}, C_{ms}, and also back through Bl switching to an effort which acts upon I.

(iii) Mechanical compliance, C_{ms}, *effort* acts on the final *flow* junction and therefore potential interactions are limited to that with M_{md}.

Thus the clearest link is between I, Bl and M_{md}, that is Bl X M_{md} from the design factors identified. We are now in a position to partially estimate the QFD phase 2 correlation roof until physical experiments are performed (Fig. 5.4). In a design team situation this could assist other members of the team to progress their design work if initial estimates of design factors and interactions were released.

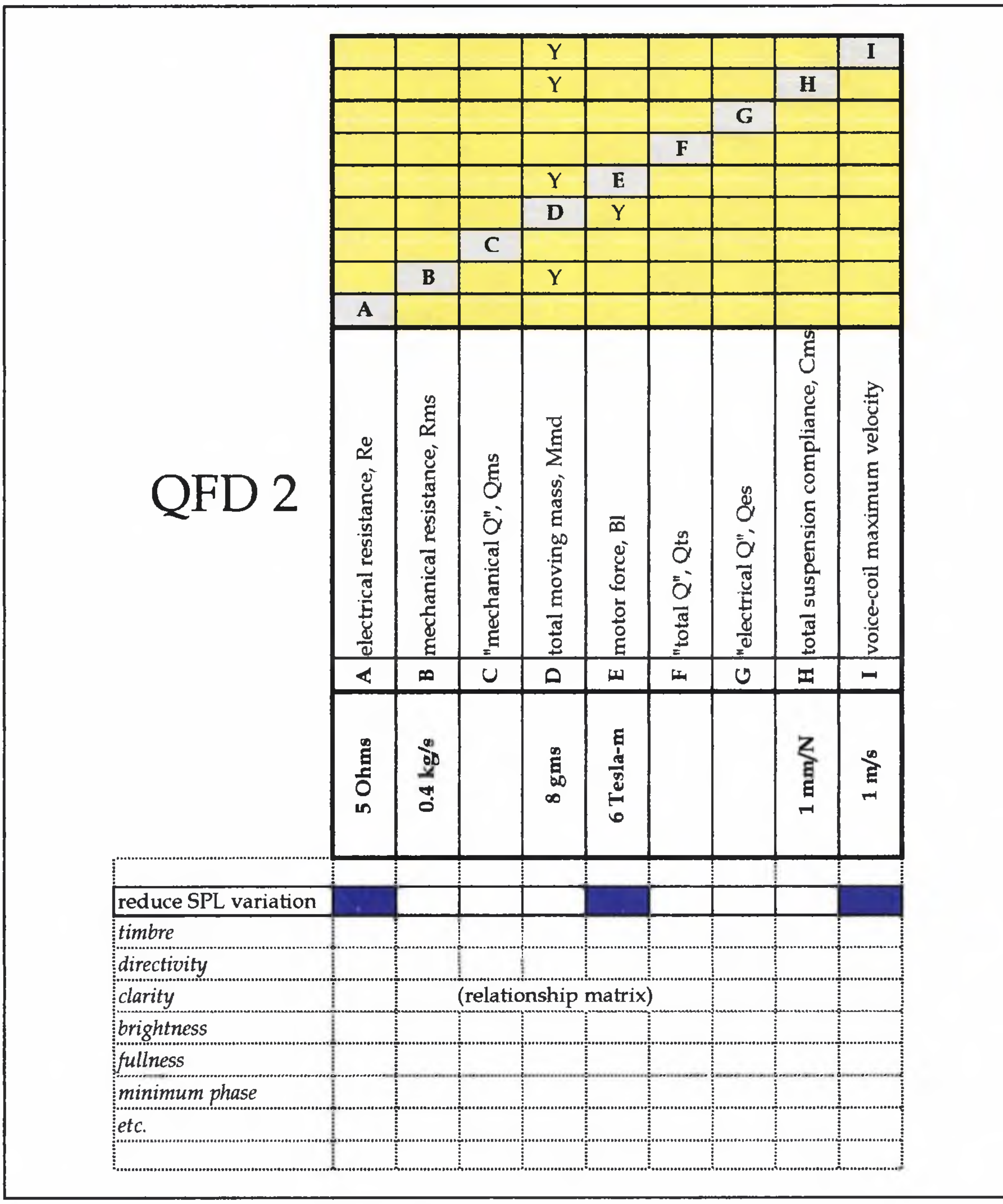


Fig. 5.4 **Partial estimate of QFD phase 2 from bond graph**

5.3 Loudspeaker Experiment

5.3.1 Observations on where unit-to-unit noise enters the production of driver units

As a loudspeaker driver unit is a product made as an assembly then it is important to consider the role of unit-to-unit noise in product performance, that is noise that affects the intended value of a design factor.

For the driver unit production line studied, manufacture of the voice-coil sub-assembly was the most involved (compared with the magnet and cone sub-assemblies), with various despooling, tensioning, winding and coating processes taking place. In comparison, the magnet sub-assembly and cone diaphragm sub-assembly (both basically assemblies of bought-in parts) appeared to involve significantly fewer contributions towards the overall unit-to-unit variation.

Referring to the five factors (a-e) above, R_{ms} and C_{ms} are the most difficult for which to identify associated unit-to-unit noise factors amongst the various production line activities. Whereas for R_e it was clear that in addition to wire supply variations there were many potential unit-to-unit noise contributions in the form of resistance changes due to for example the effects of wire tensioning, acceleration forces, friction forces, coating adhesive curing temperatures, wire trimming and wire lead-out soldering. Note that in this case the majority are energy-related.

From the above practical observations, R_e was expected to exhibit the greatest interaction with unit-to-unit noise factors in the subsequent experimentation.

5.3.2 Voice coil and driver unit tests to establish design factor values

5.3.2(a) Voice-coil test

Twenty five voice coil units were used comprising batches of five taken off the production line on five different dates. The electrical resistance (R_{coil}) and motor 'shove factor' (Bl) of the remaining voice coils was measured and recorded (Table 5.1). One voice coil from each batch was destructively tested in order to establish a sample of the number of winding turns as no direct reliable measure was available.

Coil No	R_{coil} Ohms	Bl Tesla-m
1	4.40	5.943
2	4.62	6.280
3	4.51	6.068
4	4.51	5.863
5	4.58	6.145
6	4.70	6.080
7	4.59	6.203
8	4.51	6.163
9	4.67	6.105
10	4.57	6.193
11	4.51	6.108
12	4.66	6.318
13	4.50	5.883
14	4.73	6.130
15	4.73	6.195
16	4.62	6.240
17	4.74	6.193
18	4.48	6.223
19	4.61	6.330
20	4.55	6.243

Table 5.1 Voice-coil parameter values

5.3.2(b) Driver unit tests

The twenty voice coils remaining were assembled into driver units using parts specifically selected off the production line for their near-nominal values. That is apart from the variation in voice coil parameters the driver units were considered to be 'best practice'.

The small-signal parameters (Q_{ms}, Q_{es}, Q_{ts}, M_{md}, C_{ms}, R_{ms}) of the driver units were measured using an FFT analyser with 100 Hz bandwidth pseudo-random noise together with R_e, the electrical resistance across the driver unit. (Table 5.2).

Driver Unit	R_e Ohms	Q_{ms}	Q_{ts}	Q_{es}	M_{md} grams	C_{ms} 10^{-3}m/N	R_{ms} kg/s
1	4.675	7.451	0.363	0.381	7.835	1.015	0.388
2	4.750	7.149	0.322	0.337	8.393	1.143	0.393
3	4.938	7.390	0.368	0.388	7.883	1.013	0.390
4	4.858	7.430	0.386	0.408	7.855	1.013	0.388
5	4.848	7.385	0.361	0.380	8.043	0.983	0.400
6	4.865	7.690	0.365	0.383	8.120	1.023	0.380
7	4.858	7.501	0.351	0.368	8.125	1.023	0.388
8	4.758	8.468	0.352	0.367	8.168	1.020	0.343
9	4.918	7.200	0.362	0.381	7.968	1.023	0.403
10	4.833	7.846	0.349	0.365	8.005	1.025	0.370
11	4.848	7.166	0.364	0.385	8.315	1.018	0.413
12	4.915	7.594	0.342	0.359	8.303	1.048	0.383
13	4.740	8.087	0.363	0.380	7.578	1.063	0.343
14	4.973	7.741	0.356	0.373	8.038	1.080	0.368
15	4.998	7.533	0.355	0.373	8.135	1.063	0.383
16	4.763	7.411	0.312	0.326	8.093	1.223	0.358
17	4.915	7.893	0.368	0.386	8.198	0.965	0.380
18	4.860	7.409	0.350	0.367	8.243	1.030	0.393
19	4.870	6.8519	0.321	0.336	8.263	1.153	0.403
20	4.790	7.743	0.345	0.361	8.497	1.057	0.380

Table 5.2 Driver-unit parameter values

5.3.3 Sound Pressure Level measurement procedure and SPL measurement error

5.3.3(a) Sound Pressure Level measurement procedure

The procedure for measuring Sound Pressure Level (SPL) and dynamic input impedance (Z) in an infinite baffle anechoic chamber was as follows:

(i.) Select driver unit and screw in place on chamber trap-door
(ii.) Connect wires to driver and close door
(iii.) With the appropriate software running on the dedicated PC and the external switch in the 'SPL' position start the SPL reading
(iv.) When finished, press the switch, and measure Z
(v.) Return switch to SPL position and remove driver unit
(vi.) Save data file.

This process was repeated for each driver unit in turn.

5.3.3(b) SPL measurement error

(i) Test 1

A measurement of SPL and Z for each of the 20 driver units was undertaken. This initial study revealed higher than expected variation in SPL for the 20 driver units. To investigate this a separate study was made on a randomly selected driver unit to quantify SPL measurement error.

The action of pressing the external switch (step iv in 5.3.3(a)) was identified as a possible source of measurement error and the test software was reconfigured to remove the need to use the switch by measuring SPL only. The five test measurements were repeated and showed minimal measurement error (Fig. 5.5).

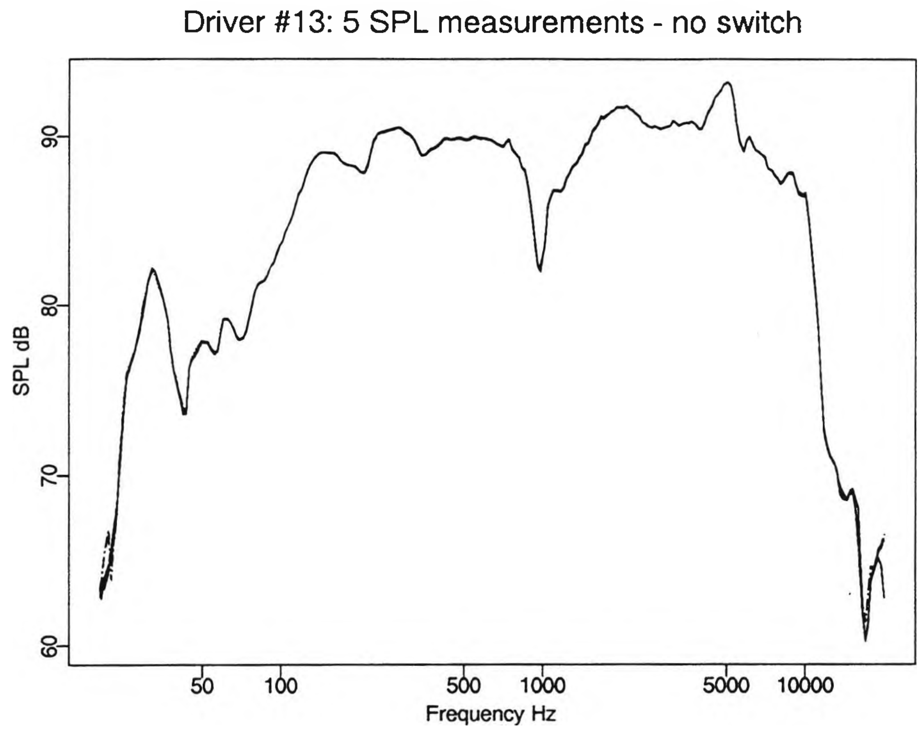


Fig. 5.5 Five SPL measurements of driver #13 without Z switch

To try and pinpoint the source of error the SPL and Z measurements on driver #13 were repeated. The test software for processing SPL and Z measurements was reloaded and the switch used between measurements. The results of this test show no measurement error and so the switch could not be pinpointed as the source of error.

(ii) Test 2

The SPL measurements for all 20 driver units were recorded with each measurement repeated five times with the driver in place. All measurements were shown to have no detectable error.

(iii) Test 3

To measure the effect of inserting and removing driver units in the chamber a third set of SPL measurements were made, each of the 20 driver units having its SPL measured once only. Comparing measurement #1 from Test 2 with the measurement from Test 3 for each driver then gives an indication of the effect of inserting and removing driver units in the chamber. This effect was also found to be negligible.

Thus negligible measurement error was achieved despite problems with measurement in earlier tests and the SPL measurements of Test 3 were then used in the statistical analysis.

5.3.4 SPL data

The SPL data obtained from Test 3 are shown in Table 5.3 below.

Driver Unit	100 Hz	200 Hz	500 Hz	800 Hz	1 kHz	1.4 kHz	2 kHz	3 kHz
1	83.6091	88.0316	89.8012	89.3319	85.5220	89.9540	91.8707	91.5123
2	83.6852	87.9973	89.8528	87.4447	86.7519	89.1242	91.5717	90.8887
3	83.5608	87.7721	89.6791	89.2092	85.7419	89.2003	91.8783	91.1258
4	83.7099	87.8210	89.6462	88.3919	86.1165	89.2514	91.8016	90.9128
5	83.3854	87.7405	89.7060	88.6908	85.1952	89.0794	91.4553	91.0764
6	83.6665	87.8540	89.7195	88.2060	85.1329	89.1102	91.5475	90.5846
7	83.6809	87.9750	89.7617	88.6036	84.5002	89.3979	91.7010	90.7354
8	83.7086	88.0463	89.9572	87.6803	86.7579	89.2429	91.7350	91.3731
9	83.5521	87.6051	89.3677	88.0153	86.8567	88.6704	91.4205	90.6547
10	83.7162	87.8785	89.8895	88.3521	84.7779	89.6506	92.4148	91.4718
11	83.4653	87.7820	89.6149	88.9644	82.3296	89.1720	91.6089	91.0309
12	83.6517	88.1350	90.0098	87.3279	85.1680	89.1186	91.9694	91.5345
13	83.6659	87.9898	89.8635	88.8080	83.1343	88.9299	91.6727	90.5946
14	83.5542	87.7315	89.4736	88.6019	81.7606	88.5988	91.0204	90.9025
15	83.6047	87.9347	89.8589	89.3232	83.7124	88.8943	91.5308	90.8441
16	83.7765	88.1526	89.9511	88.3939	84.1345	89.4240	91.7217	91.1789
17	83.5079	87.7207	89.5015	88.8349	83.3493	88.8670	91.4059	90.7624
18	83.5870	87.8834	89.7753	88.8404	83.8234	89.1467	91.7066	90.9612
19	83.4617	87.9138	89.8742	89.6700	84.6360	89.4647	91.9402	91.3549
20	83.7795	88.0379	89.9479	88.6075	83.7135	88.7857	91.4388	91.0694

Table 5.3 SPL against frequency for 20 driver units (Test 3)

5.4 Analysis

5.4.1 SPL variation largely dependent on resistance

5.4.1(a) Factors modelled

Twenty loudspeakers were tested. In the analysis two replications were used for each coil in each of which a full frequency response curve was produced. The explanatory factors modelled are:

(i) coil electrical resistance including connections (Re).

(ii) "mechanical Q" (Qms).

(iii) "electrical Q" (Qes).

(iv) "total Q" (Qts).

(v) total moving mass (Mmd).

(vi) total suspension compliance (Cms).

(vii) motor 'shove factor' (Bl).

(viii) mechanical damping (Rms).

5.4.1(b) Correlation groups

A simple correlation analysis shows that these factors split into four correlation groups:

{Re}, {Qms, Rms}, {Mmd, Bl}, {Qts, Qes, Cms}.

It would be interesting to investigate the physical explanation of these correlations but within these groups separate factor effects other than Re cannot be established from the data collected. However, it is important to note the following points:

(i) Correlation is a measure of the linear fit only of a line through the data.

(ii) Correlation does not imply causation. There may seem to be correlation between two parameters when they are related only to a third (untested) variable.

5.4.1(c) Correlation values

Table 5.4 shows the correlation index between the factors investigated.

(i) A value of +1 is a strong positive correlation.

(ii) A value of -1 is a strong negative correlation.

(iii) A value of zero indicates no relationship.

(iv) Values between -0.5 and +0.5 are uncertain without going into t-tests for significance.

The corresponding data is presented graphically in Figure 5.5.

	R_e	Q_{ms}	Q_{es}	Q_{ts}	M_{md}	C_{ms}	Bl	R_{ms}
R_e	1.00							
Q_{ms}	-0.17	1.00						
Q_{es}	0.26	0.27	1.00					
Q_{ts}	0.27	0.23	**0.99**	1.00				
M_{md}	0.12	-0.22	-0.50	-0.49	1.00			
C_{ms}	-0.22	-0.32	**-0.85**	**-0.85**	0.21	1.00		
Bl	0.23	-0.22	**-0.75**	**-0.75**	**0.81**	0.42	1.00	
R_{ms}	0.31	**-0.84**	0.10	0.14	0.33	-0.20	0.18	1.00

Table 5.4 Correlation indices between factors

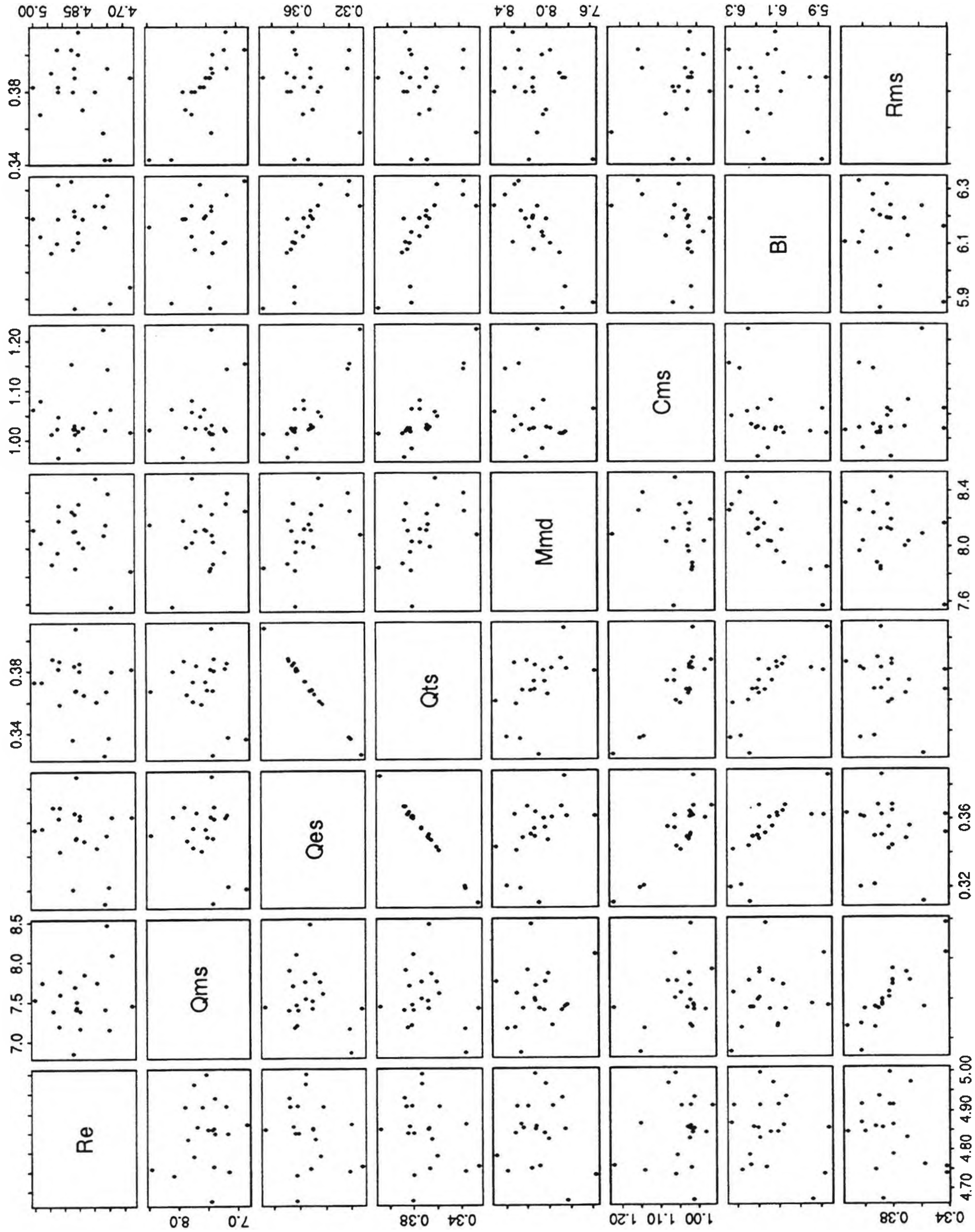


Fig. 5.6 **Correlations between factors**

5.4.1(d) Contributions of each correlation group

Fig. 5.6 illustrates the correlations between factors. For example,

(i) Qts and Qes are almost perfectly positively correlated. This is expected from the relationship:

$$Q_{ts} = \frac{1}{\frac{1}{Q_{es}} + \frac{1}{Q_{ms}}} = \frac{Q_{es}Q_{ms}}{Q_{es} + Q_{ms}}$$

(ii) Bl and Mmd are positively correlated. There is no obvious reason for this according to loudspeaker theory (Roberts, 1996).

(iii) Qms and Rms are negatively correlated. These would normally be expected since they have a direct linear relationship in theory.

(iv) Qts and Cms are negatively correlated. Again a direct linear relationship would be expected.

Thus it was decided to take only one factor from each group, namely Re, Qms, Qts, Bl, in order to avoid colinearity in the regression. That is, where two factors exhibit colinearity (correlation), the impact is to reduce the predictive power of each in any model by the extent to which they are associated with each other - they share predictive power.

Output (SPL) was taken to be the amplitude at each of the frequencies leading to two 'Y-values' (one for each replication) at each frequency.
A linear multiple regression was performed with Re, Qms, Qts and Bl. One analysis of variance was conducted for each of the eight frequencies along the curve and the results are shown below in Fig. 5.7.

From Fig. 5.7 the significant contributions of each factor are seen to be:

R_e: 24%@100Hz, 36%@200Hz, 26%@500Hz, 20%@1400Hz & 6%@3000Hz

'Q_{ms}': 9.5%@100Hz, 8%@800Hz & 7%@1400Hz

'Q_{ts}': 5%@200Hz, 5%@500Hz, 20%@800Hz, & 5%@3000Hz

'Bl': 5%@3000Hz

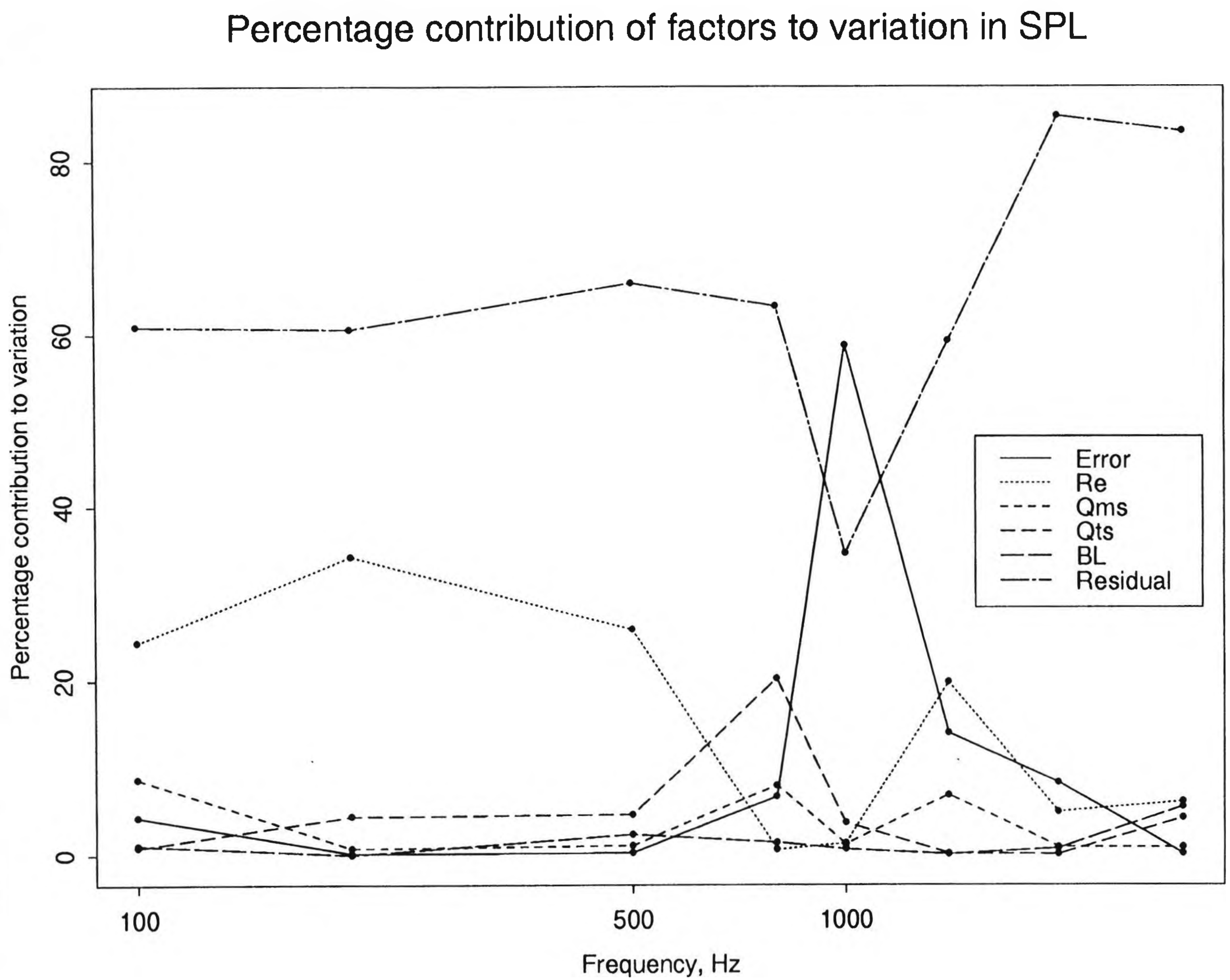


Fig. 5.7 Results of ANOVA @ 100, 200, 500, 800, 1000, 1400, 2000, 3000Hz

Statistical modelling of the factors indicates that in general the most significant design factor from those considered is R_e, electrical resistance of the coil. The results in Fig. 5.7 depend on the order in which the regression terms are fitted and also the correlations between successive frequency measurements (giving the general shape of the SPL) have been ignored.

Reducing electrical resistance variation on the driver unit will improve the quality of the loudspeaker product in terms of SPL. R_e will have a greater effect at low frequencies since higher up the range coil inductance dominates. It is interesting to note the correlation of the two "Q" parameters at frequencies well above fundamental resonance. In particular, there may be a significant clue in the fact that Q_{ms} is correlated to SPL at 1400 Hz, albeit small. The possible cause behind this is that 1400 Hz is close to the second main vibrational mode in the diaphragm (the first being fundamental resonance) when the rubber surround - the main mechanical damping element - decouples. This behaviour is so strong that it is reflected in the coil impedance around that frequency since the surround resonance affects the motion of the cone/coil portion of the diaphragm resulting in a peak in the electrical impedance.

The high value (60% or more) for residual error in Fig. 5.7 indicates that there are other significant factors, not included in this experimentation, that should be investigated.

5.4.2 Resistance varies between production batch

There is a significant difference in electrical resistance between production batches from different dates and it is not predicted by the initial coil resistance. Figure 5.8 shows the electrical resistance (R_e) of the twenty driver units plotted against coil resistance (R_{coil}) and grouped by date of coil manufacture. From the plot R_e has a maximum range of approx. 0.15 ohms within batch but up to approx. 0.3 ohms overall.

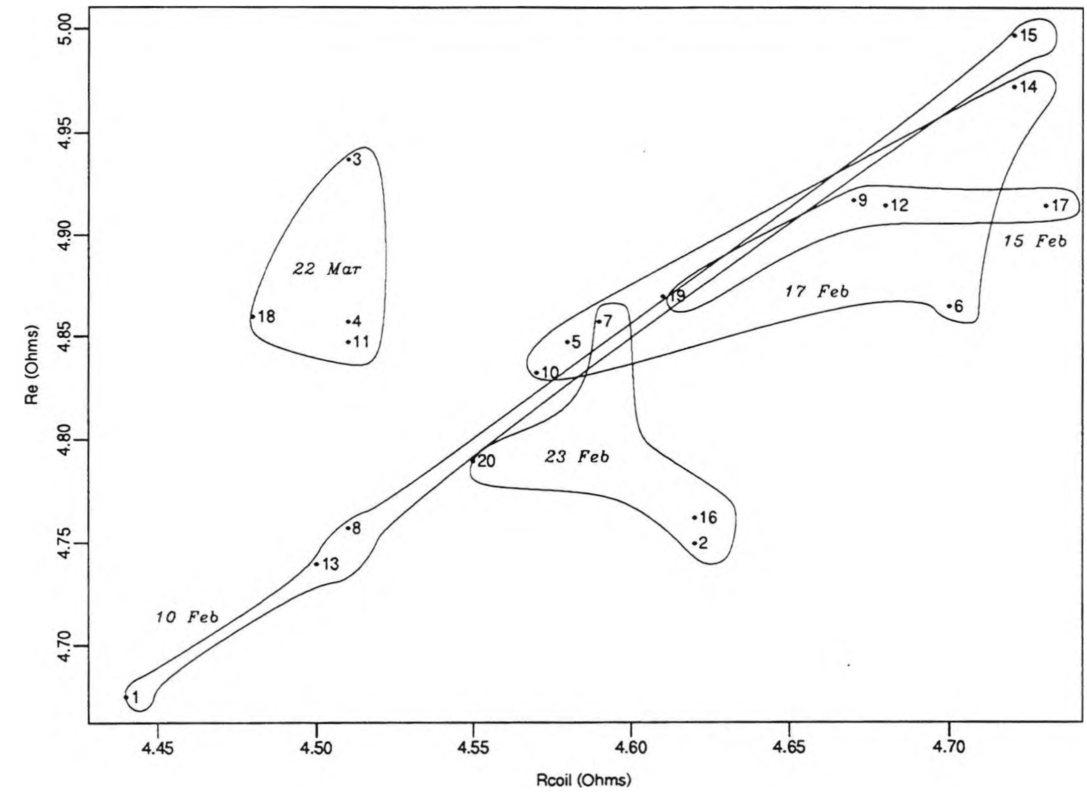


Fig. 5.8 Re versus Rcoil for twenty driver units

Two possible causes of the observed changes in variation of R_e and R_{coil} against date of manufacture have been investigated:

5.4.2(a) Cold working of copper

Cold working of the wire as it passes through the de-spooling and tensioning devices on the production wire could feasibly increase the electrical resistance of the wire by as much as 0.3 ohms. However, R_{coil} is measured after this working has occurred and R_e is measured once the wire has been trimmed and soldered. There are no other processes between these two measurements. Reversing cold working requires a significant (at above 200°C) amount of thermal energy. There is no evidence to suggest that the thermal energy required is present between the two measurements.

5.4.2(b) Coil resistance measurement error

15 voice coils of various sizes were measured using test equipment configured for 4-wire measurement. Approximately 12 resistance measurements were taken for each coil (Table 5.5). The variations in readings obtained were all within the +/- 4% stated accuracy of the equipment and for three coils the measurements were obtained with zero standard deviation. The ambient temperature throughout was between 18 & 20 °C (c.f. 23°C for Celestion tests) which could therefore account for a discrepancy of approximately up to 1.75% (Colloms, 1991). This is taken into consideration in making the decision in the final column as to whether the two readings agree.

Coil No	original factory measurement	4-wire measurement			Agree ?
		mean	+/- 3std dv	+/- 4% limits	
1	11.66	11.44	-	10.54/11.86	yes
2	3.17	2.94	2.83/3.05	2.82/3.06	**no**
3	25.9	24.0	-	23.04/24.96	**no**
4	2.77	2.67	2.56/2.78	2.56/2.78	yes
5	5.49	5.54	5.49/5.60	5.32/5.76	yes
6	5.57	5.42	5.30/5.54	5.20/5.64	yes
7	5.44	5.35	-	5.14/5.56	yes
8**	11.33	11.45	11.28/11.62	10.99/11.91	yes
9	25.8	25.77	25.31/26.24	24.74/26.80	yes
10	5.64	5.73	5.64/5.81	5.50/5.96	yes
11	3.23	3.00	2.94/3.06	2.88/3.12	**no**
12	5.20	5.23	5.16/5.30	5.02/5.44	yes
13	3.20	3.00	2.91/3.08	2.88/3.12	**no**
14	6.44	6.34	6.25/6.44	6.09/6.59	yes
15	6.49	6.41	6.13/6.68	6.15/6.69	yes

** wires broke 3 times - coil appeared to be 'cooked'.

Table 5.5 Resistance measurement comparisons for various voice-coils

5.4.3 Further experimental work required

The results also indicate that most of the variability is dependent on factors yet to be investigated.

(i) It is worth investigating the cause of variation in electrical resistance, possibly the soldering of leads on to the coils introduces noise into the system. This could involve physical experiments on this section of the production line.

(ii) Assuming that the problem experienced with error in measuring SPL is associated with the external switch attached to the dedicated PC for the anechoic chamber, then the actual cause needs to be investigated further to avoid corrupt data in the future. The method of resistance measurement should also be checked.

(iii) As the effects of factors that are correlated cannot be separated, more extensive experimentation is required to decide which factor within each correlation group contributes most to variation in SPL.

(iv) Further Robust Engineering Design work could improve the quality of driver units and yield bigger gains still by reducing reliance on tight parameter tolerances. This could take the form of thorough investigations into sub-systems, such as the voice coil, in order to get a firm grip on the sources of performance variability.

5.5 Comparing Experiment with Bond Graph Insight

5.5.1 The qualitative insight provided by the bond graph front-end

The performance variation between driver units is largely dependent upon differences in their electrical resistance, R_e. R_e is not effectively under control and varies significantly between batches. In step (ii) of the bond graph front-end approach it was predicted that R_e would be a significant influence on voice-coil performance. The correlated design factor effects in the results means that comparisons are more difficult for the other design factors, however the Bl X M_{md} correlation was predicted. The significance of the Bl X M_{md} correlation group was indicated by virtue of Bl being predicted to be a significant influence. There is also a hint of the expected M_{md} X Cms and M_{md} X Rms correlations (where M_{md} was causal) in the results through the fact that M_{md} is a term in Qms and Qts but this is perhaps a rather tenuous link.

5.5.2 Bond graph simulation results for voice-coils in relation to SPL measurements

The design factors investigated have values obtained off the production line which are difficult to set as precise levels for assignment to an orthogonal array. The SPL variation observed in the physical experiments was small and the high value for residual error suggests that significant unobserved factors have varied between driver units. Experimenting directly with the voice-coils would remove many such nuisance factors but presents problems in measuring the velocity output in a production environment.

Therefore let us run a bond graph simulation of each of the 20 voice-coils in order to obtain relative values of output velocity for comparison with the actual SPL measurements. Inputting the model of Fig. 5.3 into the 20-sim package (produced by Twente University, Holland) rapidly produces a simulation of the voice-coil. Typical graphical output in Fig. 5.9 shows the electrical input signal and mechanical output velocity over a 0.5 second simulated time period and Table 5.6 presents simulation results for all the voice coils. Nominal values have been used for inductance (L), supply voltage amplitude (S_e) and frequency (omega).

coil no	Rms	Bl	Cms	Mmd	Re	omega	L	Se	vmax	
1	0.388	5.943	0.001015	0.007835	4.675	100	0.00025	10	1.0518	
2	0.393	6.280	0.001143	0.008393	4.750	100	0.00025	10	1.1219	
3	0.390	6.068	0.001013	0.007883	4.938	100	0.00025	10	1.0213	
4	0.388	5.863	0.001013	0.007855	4.858	100	0.00025	10	1.0239	
5	0.400	6.145	0.000983	0.008043	4.848	100	0.00025	10	1.0162	
6	0.380	6.080	0.001023	0.008120	4.865	100	0.00025	10	1.0389	
7	0.388	6.203	0.001023	0.008125	4.858	100	0.00025	10	1.0422	
8	0.343	6.163	0.001020	0.008168	4.758	100	0.00025	10	1.0546	
9	0.403	6.105	0.001023	0.007968	4.918	100	0.00025	10	1.0309	
10	0.370	6.193	0.001025	0.008005	4.833	100	0.00025	10	1.0465	
11	0.413	6.108	0.001018	0.008315	4.848	100	0.00025	10	1.0380	
12	0.383	6.318	0.001048	0.008303	4.915	100	0.00025	10	1.0533	
13	0.343	5.883	0.001063	0.007578	4.740	100	0.00025	10	1.0725	
14	0.368	6.130	0.001080	0.008038	4.973	100	0.00025	10	1.0612	
15	0.383	6.195	0.001063	0.008135	4.998	100	0.00025	10	1.0494	
16	0.358	6.240	0.001223	0.008093	4.763	100	0.00025	10	1.1592	
17	0.380	6.193	0.000965	0.008198	4.915	100	0.00025	10	0.9999	
18	0.393	6.223	0.001030	0.008243	4.860	100	0.00025	10	1.0470	
19	0.403	6.330	0.001153	0.008263	4.870	100	0.00025	10	1.1116	
20	0.380	6.243	0.001057	0.008497	4.790	100	0.00025	10	1.0735	
									max diff	0.1593

Table 5.6 Results of bond graph simulation of 20 voice-coils.

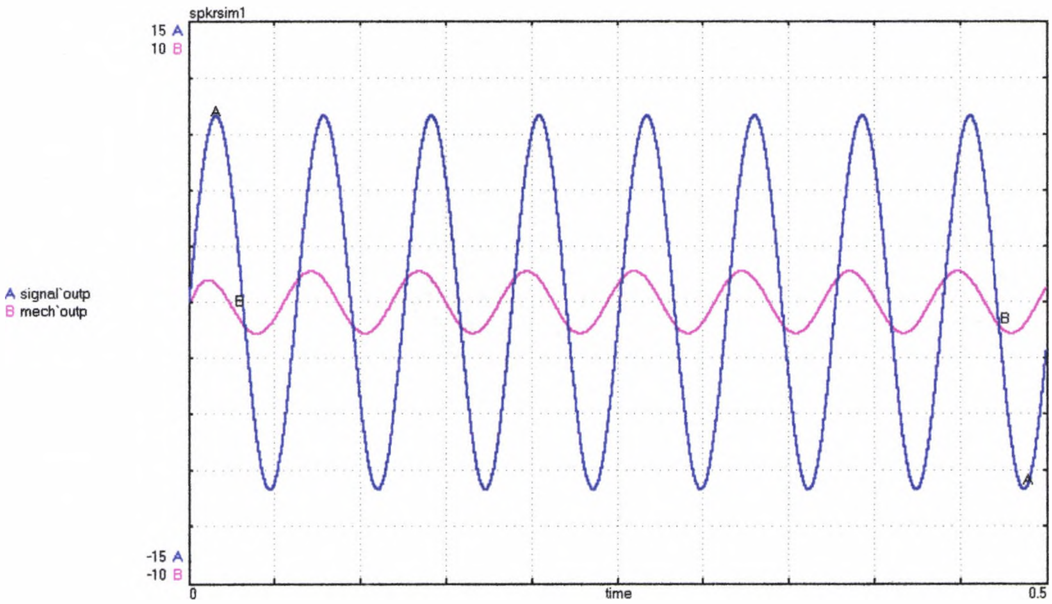


Fig. 5.9 Simulation output for bond graph model of voice-coil

Comparing the simulated voice-coil maximum velocity outputs with the means of the measured SPL readings (Table 5.7) in Fig. 5.10 highlights that that the correlation is weak should be expected from Fig. 5.5 as v_{max} is related to frequency.

coil no	v_{max}	mean SPL
17	0.9999	87.9937
5	1.0162	88.2911
3	1.0213	88.5209
4	1.0239	88.4564
9	1.0309	88.2678
11	1.0380	87.9960
6	1.0389	88.2277
7	1.0422	88.2945
10	1.0465	88.5189
18	1.0470	88.2155
15	1.0494	88.2129
1	1.0518	88.7041
12	1.0533	88.3644
8	1.0546	88.5627
14	1.0612	87.7054
13	1.0725	88.0823
20	1.0735	88.1725
19	1.1116	88.5394
2	1.1219	88.4146
16	1.1592	88.3417

Table 5.7 Mean measured SPL versus simulated maximum velocity

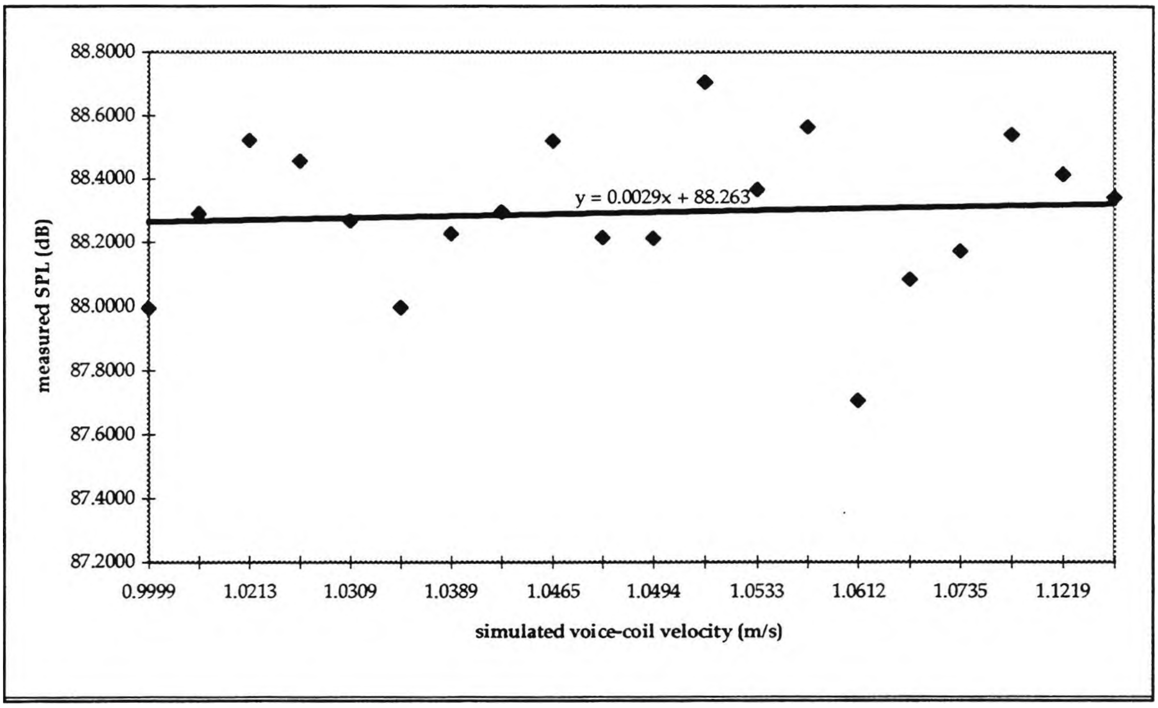


Fig. 5.10 Comparison of experimental and simulation results

5.5.3 Incorporating dimensional analysis in order to study dynamic similarity

Experimental design could be described as exploring dynamically dissimilar configurations between experimental groups and dynamically similar configurations within groups. Therefore it would be of interest to know which configurations of the 20 voice-coils share dynamic similarity using the parameter values in a dimensional analysis.

Expressing the parameters in terms of principal dimensions:

$$Bl = \left[\frac{ML}{AT^2}\right]^a \quad R_e = \left[\frac{ML^2}{A^2T^3}\right]^b \quad M_{md} = [M]^c \quad R_{ms} = \left[\frac{M}{T}\right]^d \quad C_{ms} = \left[\frac{T^2}{M}\right]^e$$

$$L = \left[\frac{ML^2}{A^2T^2}\right]^f \quad S_e = \left[\frac{ML^2}{AT^3}\right]^g \quad \text{and output velocity, } v_{max} = \left[\frac{L}{T}\right]$$

From the Buckingham π-theorem, there will be four dimensional groups formed. Equating powers of M, L, T and A,

M: $0 = a + b + c + d - e + f + g$

L: $-1 = a + 2b + 2f + 2g$

T: $1 = -2a - 3b - d + 2e - 2f - 3g$

A: $0 = -a - 2b - 2f - g$

There are seven unknown powers and four equations, therefore solving four in terms of the other three:

$a = -2b - 2f - 1$

$c = -e - f$

$d = b + 2e + 2f$

$g = 1$

Thus the π groups are:

$$\pi_1 = \frac{Blv_{max}}{S_e} \quad \pi_2 = \left[\frac{M_{md}}{R_{ms}{}^2C_{ms}}\right]^e \quad \pi_3 = \left[\frac{R_eR_{ms}}{(Bl)^2}\right]^b \quad \pi_4 = \left[\frac{R_{ms}{}^2L}{(Bl)^2M_{md}}\right]^f$$

Note that in π_1 that the only design factor is Bl. Which means that at this level of experiment resolution π_1 cannot be used for sliding design factor levels. At a higher resolution (i.e. lower level) B and l might be separate design factors and therefore be related through sliding levels. Thus at this stage we use π_2, π_3, and π_4 to identify voice-coils potentially sharing dynamic similarity. Table 5.8 shows the values of all four of the π groups for each voice-coil.

coil no	(reciprocal) pi 1	pi 2	(reciprocal) pi 3	(reciprocal) pi 4
1	1.600	51.3	19.5	7353
2	1.419	47.5	21.1	8573
3	1.614	51.2	19.1	7633
4	1.666	51.5	18.2	7174
5	1.601	51.1	19.5	7593
6	1.583	55.0	20.0	8315
7	1.547	52.8	20.4	8307
8	1.539	68.1	23.3	10548
9	1.589	48.0	18.8	7314
10	1.543	57.0	21.4	8971
11	1.577	47.9	18.6	7275
12	1.503	54.0	21.2	9038
13	1.585	60.6	21.3	8917
14	1.537	55.0	20.5	8921
15	1.538	52.2	20.0	8513
16	1.382	51.6	22.8	9835
17	1.615	58.8	20.5	8710
18	1.535	51.8	20.3	8267
19	1.421	44.1	20.4	8154
20	1.492	55.7	21.4	9174
max diff	0.283	23.9	5.0	3374

Table 5.8 Values of π groups for each voice-coil

The following procedure was then followed in order to identify pairs of voice-coils with likely dynamic similarity.

(i) For each column of π values compute the difference pair-wise between voice-coils.

(ii) For each pair-wise difference value discard those falling outside limits as follows:

$\pi_2 = \pm 10\%$ or approximately ± 2.4

$\pi_3 = \pm 10\%$ or approximately ± 0.5

$\pi_4 = \pm 2\%$ or approximately ± 68

(iii) Determine the voice-coil pairs that fall within the limits for all three π groups.

These pairs are shown in Table 5.9.

voice-coil pair	π_2 difference	π_3 difference	π_4 difference
3&5	0.02	0.35	41
6&7	2.21	0.42	8
7&18	0.94	0.14	39
9&11	0.07	0.17	39

Table 5.9 Dynamically similar pairs suggested by π_2, π_3, and π_4

The simulation results for v_{max} can then be used to determine π_1 difference values for the pairs (Table 5.10). This shows that for all the pairs except pair 6&7 the difference is much less than 10% therefore confirming dynamic similarity within the pairs 3&5; 7&18; and 9&11.

voice-coil pair	π_1 difference
3&5	0.012
6&7	0.036
7&18	0.012
9&11	0.012

Table 5.10 π_1 value differences for voice-coil pairs

These close π_1 values are a confirmation that dimension analysis has identified similar voice coils. Furthermore we have opened up the possibility of investigating the driver units containing these voice-coils in order to identify any differences that might be the source of the SPL variation that is still apparent in the associated driver units.

5.5.4 Quantifying QFD phase 2 correlation chains

The experimental correlations have been identified and related design factors to SPL, the quality characteristic under investigation as well as each other. Thus we are now able to update Fig. 5.4, the qualitative estimate of QFD phase 2, with quantitative information in order to more accurately evaluate any subsequent design modifications. Fig. 5.11 conveys an objective of the design as the improvement of loudspeaker quality in terms of sound pressure level amongst a host of other candidate quality characteristics. The associated correlation chain for variability has been taken from the values of Table 5.4. The nature of the stronger correlations is shown together with a further weak correlation between two correlation groups i.e. between {Bl, M_{md}} and {Q_{ts}, Q_{es}, C_{ms}}.

In QFD3 the possible interactions between design factors and unit-to-unit noise factors could be recorded in order to identify the influence these noise factors might exert on overall unit-to-unit variation. For example, coil wire supply variation might be identified (column-wise) as the most significant single potential unit-to-unit noise source within the voice-coil sub-assembly.

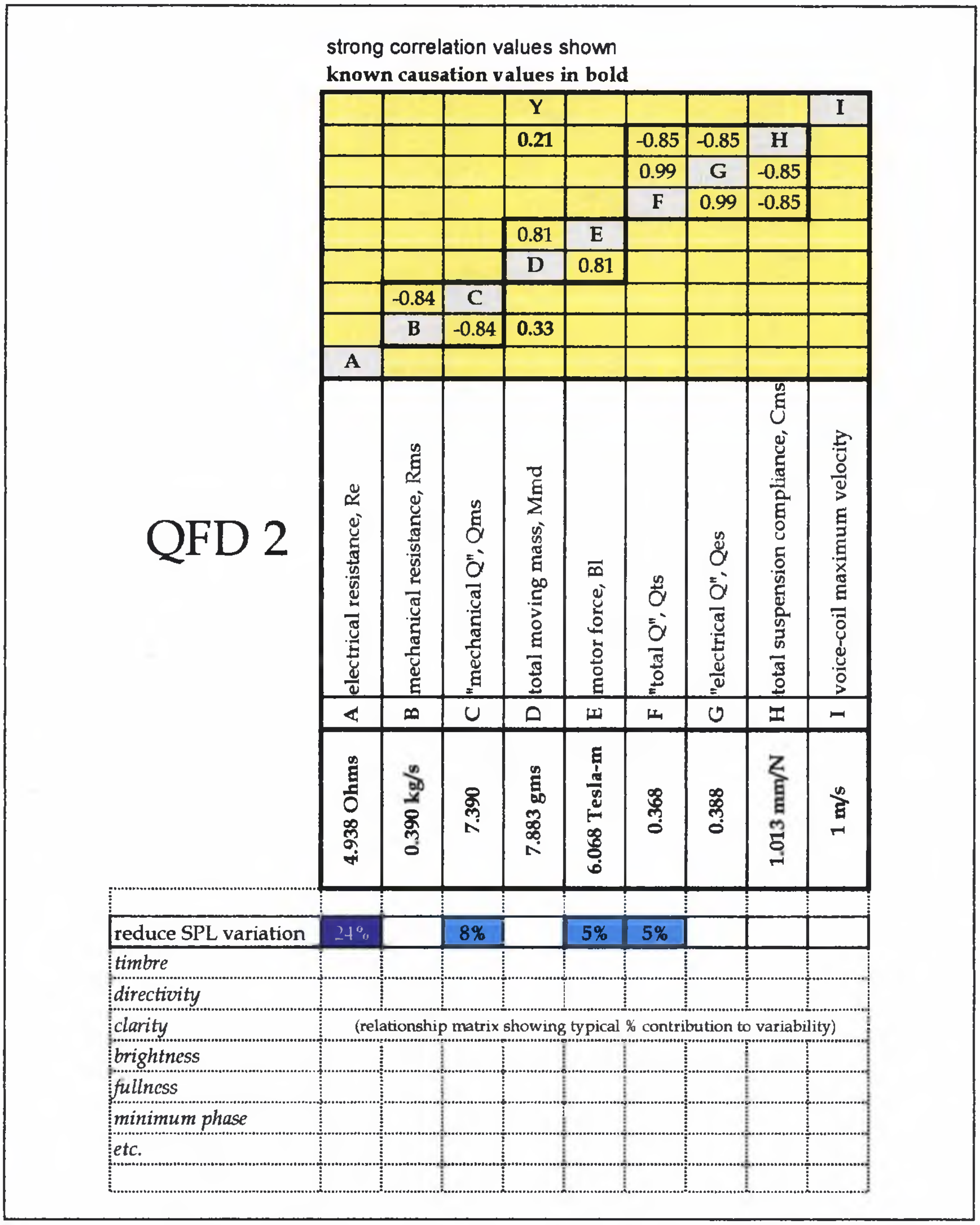


Fig. 5.11 Incorporation of experimental results into correlation roof

5.6 Summary of Loudspeaker Case Study

5.6.1 Discussion

Had there been scope to conduct designed experiments then this would have yielded a clearer picture of the contributions of each design factor. We have shown how to identify voice coils with dynamic similarity from a production batch. The π-groups offer scope for assigning voice-coil units of two or three dynamic characteristic levels from the production line to a column of an Orthogonal Array. This would test the (dimensionless) role of the voice coil in the overall loudspeaker system. Alternatively, insight from the bond graph suggests experiments on the voice-coil focused at a lower level might reveal important information about the cause of resistance variation and the roles of design factors within the correlated groups. Further case studies should aim to achieve closer correlation between the bond graph model output and the experiment quality characteristic. This could perhaps be termed as an issue of resolution, scale or level.

5.6.2 Conclusions

Bond graphs have offered some insight into the relationships to be found in a physical experiment on voice-coils and driver units. The Quality Function Deployment phase 2 correlation roof provides an appropriate place to communicate significant correlations observed in experimentation to the loudspeaker designer for design retrieval purposes. The dynamic similarity of voice-coils found from dimensional analysis enables meaningful comparisons to made between randomly varying products.

Chapter 6. Hedgetrimmer Case Study

6.1 Introduction

6.1.1 Overview and purpose of case study

In this case study Quality Function Deployment phase 1 correlation chains and bond graph simulation for Robust Engineering Design are considered together, as part of the process of designing a hedgetrimmer, in order to further demonstrate the linking of QFD and RED. This work was conducted in collaboration with a major manufacturer of garden power tool equipment. Two teams of designers were introduced to the Quality Function Deployment methodology and then guided through a project on the design of a hedgetrimmer in consultation with the client. The client briefed the teams on four market segments which are approximately represented by the four quadrants of two axes defined as enthusiasm and garden size. The focus was on two of these segments: *creative enthusiasts* - enthusiastic gardeners with large gardens, and *careful devotees* - those with small gardens who were also keen on gardening.

We aim to follow the design partitioning that results from the correlation chains in configuring the Robust Engineering Design experiment. However the strongest link between Quality Function Deployment and Robust Engineering Design is demonstrated to be by virtue of using bond graphs both as a front-end to RED experiments and as a means of estimating critical part characteristics in QFD phase 2. Furthermore in this application we specifically employ more advanced bond graph modelling than was attempted for the loudspeaker voice-coil in order to compare more clearly the simulation results with those from physical Robust Engineering Design experiments.

6.1.2 Partitioning the Design Problem Using Correlation Chains

6.1.2(a) Completing the QFD phase 1 correlation roof

Customer requirements were gathered by the design teams through structured interviewing of 38 users and also with reference to consumer reports and surveys. Examples of the resultant QFD phase 1 chart are shown in Appendix B.

The QFD phase 1 output (de Wildt, 1996 and King, 1996 - examples in Appendix B) was used to generate the abridged correlation roof shown in Fig. 6.1. The # symbol is used here to indicate where the procedural causal relationship is uncertain, in fact each should be viewed as a two-way relationship. For example, 'product weight' is largely dependent on the actual weights of the blade and motor but a product weight target is also desirable at the outset before these subsystems are determined. This type of dilemma may be considered either a trivial issue easily avoided or an important interdependence to be addressed. However, let us focus on causality and note that blade speed (D) is viewed here to be a significant influence on motor power rating (F) and not the other way round. This is because in the embodiment design stage the procedure is that we determine the blade design and the speed required and then select a motor of sufficient power to achieve it. The physical reality is the opposite, that is blade speed is determined by motor rating as well as other factors. Thus the correlation roof of phase 1 should be completed in the context of design requirements in information terms that have a direct and significant influence on the outcomes of others, bearing in mind that the physical causation may well be the opposite way round. This is consistent with how we might address embodiment design where, faced with two design requirements to be addressed, we prefer to configure the one which has bearing on the configuration of the other for efficient design. Making all the pair-wise comparisons in this way provides the basis for determining a design procedure.

QFD 1		A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
A	product weight	A	#				#				#								#
B	blade length	#	B																#
C	blade tooth form design			C															
D	blade speed		Y	Y	D														
E	blade braking				Y	E													
F	motor power rating	#		Y	Y		F												
G	thermal cut-out						Y	G											
H	noise						Y		H	Y									
I	ventilation						Y			I									
J	grip placement	#	Y								J								#
K	grip diameter/size											K					Y		
L	cable protection		Y										L						
M	cable length													M					
N	cable/body connection														N				
O	switch design										Y					O	Y		
P	switch force																P		
Q	guarding																	Q	
R	reach	#	#								#			Y					R

(relationship matrix)

Fig. 6.1 QFD phase 1 correlation roof for hedgetrimmer

6.1.2(b) Forming the correlation chains

In Fig. 6.2 a raw network of correlation chains is developed from the causal relationships identified. The two square nodes are target attributes of the design which act as reference points for the emerging design - effectively behaving as iterative loops similar to those described for the solar car in chapter 3.

In Fig. 6.3 the nodes are grouped to highlight their associated subsystems.

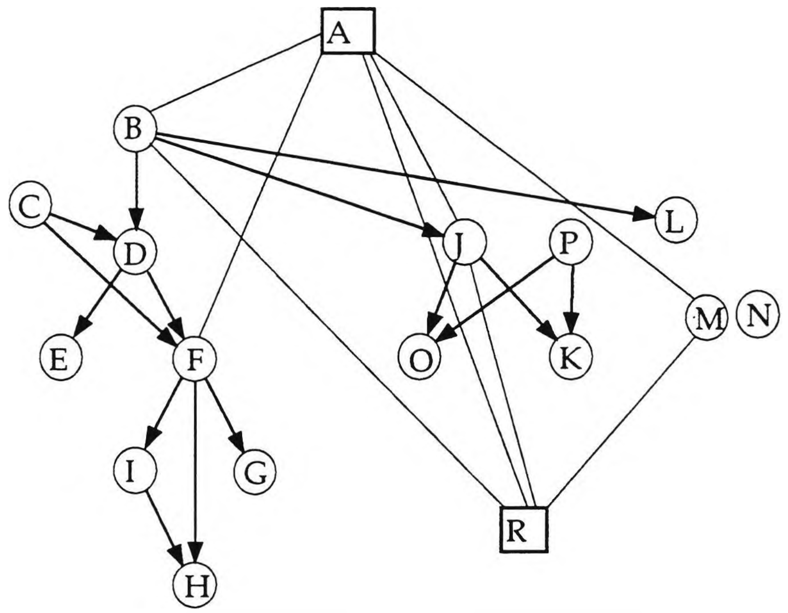


Fig. 6.2 Raw correlation chain network for hedgetrimmer

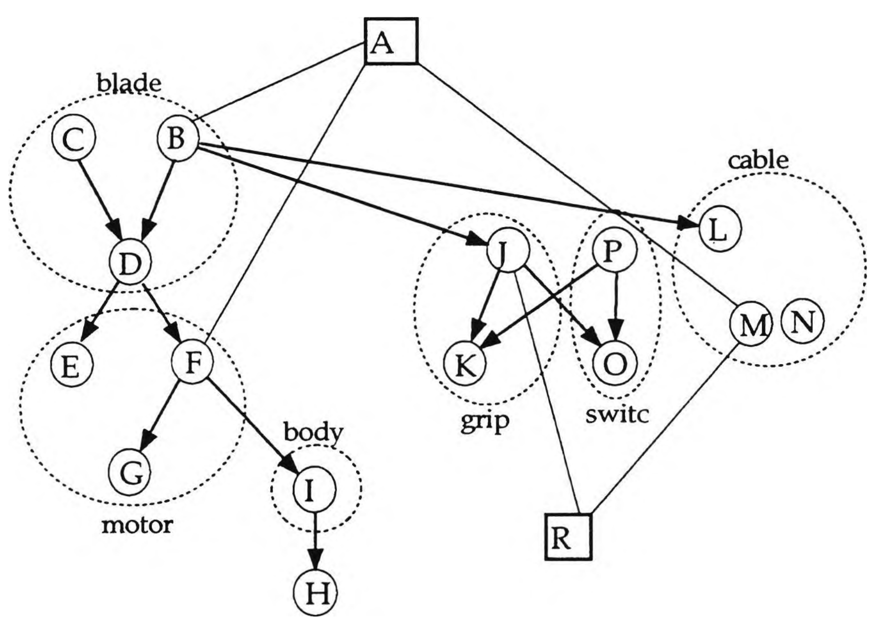


Fig. 6.3 Rationalised correlation chain network

6.1.2(c) Combining dependent and interdependent requirements

In Fig. 6.4 the correlation chains have been adjusted into a hierarchy separating connected nodes by one stage. In this case a design procedure for tackling subsystems in some kind of order is clearly put forward. Weight and reach are not aspects of the design to be worked on independently. At the concept design stage thought processes are complex and often parallel but towards the end of concept design comes the embodiment design and with this a more ordered set of thought processes is required. This design procedure keeps the customer requirements firmly at the forefront as the design is addressed, and for concept design it is helpful to have such a simple but effective picture or 'requirements mind map' to work with. Furthermore as the design moves towards embodiment the design team have a means of dividing and scheduling the work. The links show where communication between design activities is required. Fig. 6.4 clearly promotes a combined team working on the grip and switch design, it would also appear prudent to combine motor and blade design into one team by virtue of the exclusive flow of information.

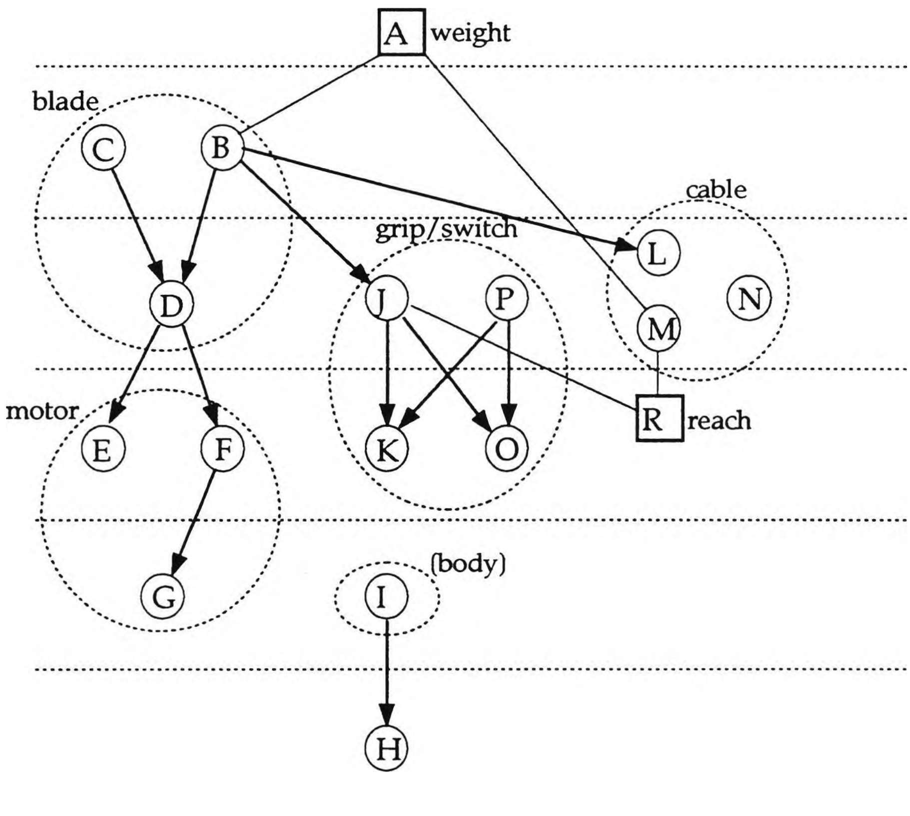


Fig. 6.4 **Correlation chain hierarchy**

6.2 Bond Graph Front-End for Parameter Selection

Again we can follow the three-step bond graph procedure highlighted in 3.2.1 (a) for gaining an insight into the system:

6.2.1 Constructing the motor-blade bond graph

Using the energy-related parameters of the motor and blade subsystems a bond graph representation of the hedgetrimmer was constructed (Fig. 6.5) with the aim of studying the effect of changes in key parameter values on the output of the system according to their expected variability. The simulation results were to be compared with physical Robust Engineering Design experiments conducted on hedgetrimmers (de Wildt, 1997; King, 1997) and also for estimating the critical part characteristics of QFD phase 2.

The model has been developed incorporating signal flows in order to achieve a representation of the reciprocating motion of the blade and the intermittent nature of the load. The load is configured to always work against motion, peaking at half-stroke, i.e. out of phase with the blade motion. Typical values of each parameter were established from physical measurements of motors and blades, and also test data from the client.

(i) $\mathbf{R_e}$ - the electrical resistance of the motor (including armature and field windings, brushes and internal wiring to the switch). Measured as 30.3 Ohms on a typical motor.

(ii) $\mathbf{I_{ind}}$ - the motor inductance. Calculated to be 0.152 H with knowledge of the power factor and other electrical data.

(iii) **r** - modulus of the motor gyrator element. A value of approximately 0.074 determined from $r = \frac{V_s - iR}{w} = \frac{240-(0.94\times 30.3)}{2847}$ (characteristics of a typical motor operating at 27000 rpm provided by the client).

(iv) **I** - moment of inertia of motor armature and gearbox calculated from client drawings as 4.54 $\times 10^{-5}$ kgm^2.

(v) **R_{ft}** - friction torque due to bearings, motor brushes, gears and yoke/eccentric mechanism. Estimated as 15.9×10^{-6} Nms/rad^2 (see below).

The friction torque was established as follows. For typical motor characteristics at no load, total power loss due to friction is $P_f = P_{in} - i^2R = 221.7W - (0.94)^2 30.3 = 194.93W$.

- Gearbox friction assumed to be approximately 4% (Hurricks, 1994) or 8.8W.
- Bearing friction based on load of 2.5N due to weight, F, of armature in a plain bush of diameter 8mm with coefficient of friction, $\mu = 0.2$, (Hurricks, 1994): $M = \mu Fd/2 = 0.2*2.5N*0.004m = 4\times10^{-3}$ *Nm* or 11.4W.
- Two motor brushes each applying 0.5N on a 20mm diameter commutator with coefficient of friction, $\mu = 0.3$ (Hurricks, 1994) producing a friction torque of $1N*0.3*0.01m = 3\times10^{-3}$ *Nm* or 8.6W.
- Remaining 166.1W of power lost to friction is split between friction in the yoke and the blades in the ratio 100:66 reflecting experience of the client (Stones, 1997). Thus 100W associated with yoke friction.
- Therefore total power lost to rotary friction is 128.6W. Now from power = torque x speed where from bond graph constitutive equation, R_{ft} = torque/speed, then R_{ft} = power/(speed)^2 = $128.6/(2847)^2$ thus $R_{ft} = 15.9\times10^{-6}$ Nms/rad^2.

(vi) **m_g** - the modulus of the gearbox transformer, typical value based on 6/73 ratio = 0.082.

(vii) **m_c** - the modulus of the yoke crank modulated transformer with a crank throw of approximately 0.0125m.

(viii) C - to represent the mechanical compliance or stiffness of the system. 1×10^{-5}m/N recommended (Kleijn, 1997).

(ix) **M** - the expected mass of the blade. 0.5 kg.

(x) $\mathbf{R_{bf}}$ - the blade friction. 66.1W due to linear friction remains from the above friction power loss calculations. Now power = force x velocity and from bond graph constitutive equation R_{bf} = force/velocity. Thus R_{bf} = power/(velocity)^2 = 66.1/(1.86)^2 = 19.1 Ns/m.

(xi) $\mathbf{S_l}$ = the cutting load opposing motion. Estimated as between 25N and 45N (King, 1997).

6.2.2 Obtaining quantitative insight into the system from the state-space equations

Recalling that the state-space equations are generated from consideration of each inertia and capacitor element in the system. From Fig. 6.5 each power bond considered below is assigned a number clockwise around each 1-junction and 0-junction starting with the supply as #1; the gyrator output as #5; the gearbox output as #9; the crank output as #11; and finishes with the mass as #16.

Thus at the first 1-junction:

$$\frac{dp_2}{dt} = e_1 - e_3 - e_4 = S_e - rf_5 - R_e f_4 = S_e - rf_6 - R_e f_2$$

where $\dfrac{dp_2}{dt} = I_{ind}\dfrac{df_2}{dt}$

$$\therefore \frac{df_2}{dt} = \frac{1}{I_{ind}}(S_e - R_e f_2 - rf_6)$$

and for the second 1-junction:

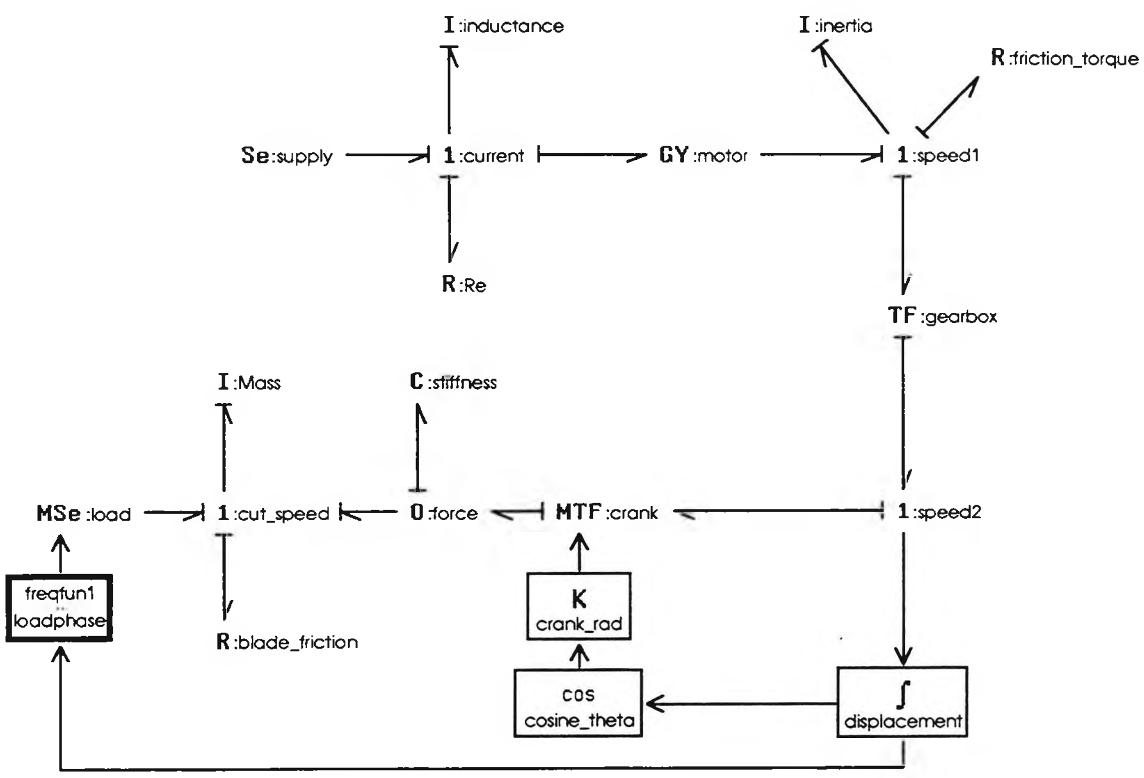


Fig. 6.5 **Bond graph of motor-blade system**

$$\frac{dp_6}{dt} = e_5 - e_7 - e_8 = rf_3 - R_{ft} f_7 - m_g e_9 = rf_2 - R_{ft} f_6 - m_g e_{10}$$
$$= rf_2 - R_{ft} f_6 - m_g m_c e_{11} = rf_2 - R_{ft} f_6 - m_g m_c e_{13}$$

where $\frac{dp_6}{dt} = I\frac{df_6}{dt}$

$$\therefore \frac{df_2}{dt} = \frac{1}{I}(rf_2 - R_{ft} f_6 - m_g m_c e_{13})$$

for the 0-junction:

$$\frac{dq_{13}}{dt} = f_{11} - f_{12} = m_c f_{10} - f_{16} = m_c f_9 - f_{16} = m_c m_g f_8 - f_{16} = m_c m_g f_6 - f_{16}$$

where $\frac{dq_{13}}{dt} = C\frac{de_{13}}{dt}$

$$\therefore \frac{de_{13}}{dt} = \frac{1}{C}(m_c m_g f_6 - f_{16})$$

and for the final 1-junction:

$$\frac{dp_{16}}{dt} = e_{12} - e_{14} + e_{15} = e_{13} - R_{bf} f_{14} + S_l$$

where $\frac{dp_{16}}{dt} = M\frac{df_{16}}{dt}$

$$\therefore \frac{df_{16}}{dt} = \frac{1}{M}(e_{13} - R_{bf} f_{16} + S_l)$$

Putting these equations into matrix form.

$$\frac{d}{dt}\begin{bmatrix} f_2 \\ f_6 \\ e_{13} \\ f_{16} \end{bmatrix} = \begin{bmatrix} \frac{-R_e}{I_{ind}} & \frac{-r}{I_{ind}} & 0 & 0 \\ \frac{r}{I} & \frac{-R_{ft}}{I} & \frac{-m_g m_c}{I} & 0 \\ 0 & \frac{m_c m_g}{C} & 0 & \frac{-1}{C} \\ 0 & 0 & \frac{1}{M} & \frac{-R_{bf}}{M} \end{bmatrix} \begin{bmatrix} f_2 \\ f_6 \\ e_{13} \\ f_{16} \end{bmatrix} + \begin{bmatrix} \frac{1}{I_{ind}} & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & \frac{1}{M} \end{bmatrix} \begin{bmatrix} S_e \\ S_l \end{bmatrix}$$

Inserting the parameter values from above.

$$\frac{d}{dt}\begin{bmatrix} f_2 \\ f_6 \\ e_{13} \\ f_{16} \end{bmatrix} = \begin{bmatrix} -199.3 & -0.49 & 0 & 0 \\ 1636 & -0.35 & -22.6 & 0 \\ 0 & 102.7 & 0 & 100{,}000 \\ 0 & 0 & 2 & -38.2 \end{bmatrix} \begin{bmatrix} f_2 \\ f_6 \\ e_{13} \\ f_{16} \end{bmatrix} + \begin{bmatrix} 6.6 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} S_e \\ S_I \end{bmatrix}$$

As was shown for the voice-coil, the relative significance of the design factors in the main matrix can be estimated after scaling the matrix so as to equalise all numerical values (Martens & Bell, 1972). However, estimates of the nominal values of f_2, f_6, e_{13} and f_{16} are first required.

From motor data corresponding to approximate anticipated blade running speed of 1800 rpm, f_2 = 1.33A, f_6 = 2847 rad/s and f_{16} = 1.86 m/s. However, e_{13} is more difficult to estimate but let us use the sum of output power and power lost to blade friction = 74W + 66W = 140W. Based on power = force x velocity then force, e_{13} = 140/1.86 = 75N.

We can then scale each equation to unity and the main matrix becomes:

$$\frac{d}{dt}\begin{bmatrix} \frac{f_2}{1.33} \\ \frac{f_6}{2847} \\ \frac{e_{13}}{75} \\ \frac{f_{16}}{1.86} \end{bmatrix} = \begin{bmatrix} -199.3 & -0.49\times\frac{2847}{1.33} & 0 & 0 \\ 1636\times\frac{1.33}{2847} & -0.35 & -22.6\times\frac{75}{2847} & 0 \\ 0 & 102.7\times\frac{2847}{75} & 0 & 100{,}000\times\frac{1.86}{75} \\ 0 & 0 & 2\times\frac{2847}{1.86} & -38.2 \end{bmatrix} \begin{bmatrix} \frac{f_2}{1.33} \\ \frac{f_6}{2847} \\ \frac{e_{13}}{75} \\ \frac{f_{16}}{1.86} \end{bmatrix}$$

Therefore

$$\frac{d}{dt}\begin{bmatrix} \frac{f_2}{1.33} \\ \frac{f_6}{2847} \\ \frac{e_{13}}{75} \\ \frac{f_{16}}{1.86} \end{bmatrix} = \begin{bmatrix} -199.3 & -1049 & 0 & 0 \\ 0.76 & -0.35 & -0.6 & 0 \\ 0 & 3898 & 0 & 2480 \\ 0 & 0 & 3061 & -38.2 \end{bmatrix} \begin{bmatrix} \frac{f_2}{1.33} \\ \frac{f_6}{2847} \\ \frac{e_{13}}{75} \\ \frac{f_{16}}{1.86} \end{bmatrix} + \begin{bmatrix} 4.96 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 1.08 \end{bmatrix} \begin{bmatrix} S_e \\ S_I \end{bmatrix}$$

Mass, M, and stiffness, C, in particular are parameters that are indicated to have a potentially significant influence on the system. However, greater insight will be obtained through utilising the expected variation of each parameter value as is used in control theory (Skogestad & Postlethwaite, 1996) by multiplying each value in the matrix by the ratio of expected variation/nominal value for each parameter.

Furthermore, at this point let us confine the parameters considered to the design factors to be investigated in physical experiments later, which relate to R_e, M, R_{ft} and R_{bf}. Only the main matrix values modified by these design factors are shown below. In each case we have used the anticipated experimental range value as the expected variation value.

$$\text{main matrix} = \begin{bmatrix} -199.3 \times \frac{0.05}{30.3} & - & - & - \\ - & -0.35 \times \frac{0.39}{16.25} & - & - \\ - & - & - & - \\ - & - & 3061 \times \frac{0.62}{0.5} & -38.2 \times \frac{14.3}{19.1} \end{bmatrix}$$

$$\text{main matrix} = \begin{bmatrix} -0.32 & - & - & - \\ - & -8.4 \times 10^{-3} & - & - \\ - & - & - & - \\ - & - & 3796 & -28.6 \end{bmatrix}$$

Note that from this analysis mass, M, is the strongest candidate followed by blade friction, R_{bf}.

6.2.3 Investigation of the causal links between design factors

Referring to Fig. 6.5 and limiting our consideration to the four factors R_e, M, R_{ft} and R_{bf} chosen for physical experiments later, we observe that the effort from M acts upon R_{bf} suggesting a possible interaction.

6.3 RED Simulation Experiments

6.3.1 Designing the simulation experiment

The estimated nominal values of the four design factors to be investigated, R_e, R_{ft}, M and R_{bf} have already been used above. Using an L_9 Orthogonal Array (Table 6.1) requires three levels to be set for each as follows:

(i) **Blade mass, M** - values of 0.5, 0.81 and 1.12 kg represent three lengths of blade.

(ii) **Blade friction, R_{bf}** - values of 19.1, 6.3 and 4.8 Ns/m represent reductions in blade friction achieved through changes to contacting faces and clamping bolt torque.

(iii) **Friction torque, R_{ft}** - values of 15.86×10^{-6}, 16.06×10^{-6} and 16.25×10^{-6} Nms/rad represent the changes in friction torque caused by using different lengths of motor brush springs. These lengths represent 1N, 1.18N and 1.36N brush spring force respectively.

(iv) **Resistance, R_e** - it was decided to investigate the effect of changes to the internal wiring connecting the switch to the motor such that the total motor resistance in each case was 30.3Ω, 30.26Ω and 30.25Ω.

Run	1 blade mass	2 blade friction	3 frict torque	4 motor res
1	0.5 kg	19.1 Ns/m	15.86e-6 Nms/r	30.30 Ohms
2	0.5 kg	6.3 Ns/m	16.06e-6 Nms/r	30.26 Ohms
3	0.5 kg	4.8 Ns/m	16.25e-6 Nms/r	30.25 Ohms
4	0.81 kg	19.1 Ns/m	16.06e-6 Nms/r	30.25 Ohms
5	0.81 kg	6.3 Ns/m	16.25e-6 Nms/r	30.30 Ohms
6	0.81 kg	4.8 Ns/m	15.86e-6 Nms/r	30.26 Ohms
7	1.12 kg	19.1 Ns/m	16.25e-6 Nms/r	30.26 Ohms
8	1.12 kg	6.3 Ns/m	15.86e-6 Nms/r	30.25 Ohms
9	1.12 kg	4.8 Ns/m	16.06e-6 Nms/r	30.30 Ohms

Table 6.1 L_9 Orthogonal Array for hedgetrimmer experiment

The noise factor used was cutting load representing the effect of foliage being cut on the performance of the system. Three values of 0N, 25N and 45N were used as an approximation. Thus 27 simulation experiments in total were run.

6.3.2 Simulation output and results

The simulation conducted on 20-sim, a proprietary bond graph simulation package produced by the University of Twente, Holland. The blade cut velocity and the load were plotted for each simulation experiment. The mean blade speed was determined from the average cycle time measured off the plot (Fig. 6.6). The results are shown in Table 6.2.

Results

Exp	no load	load = 25 N	load = 45 N
1	2142	2085	2042
2	2258	2194	2144
3	2273	2206	2156
4	2061	2005	1964
5	2212	2140	2086
6	2239	2165	2109
7	1969	1917	1876
8	2143	2071	2016
9	2173	2094	2036

Table 6.2 Mean blade speed established from simulation results.

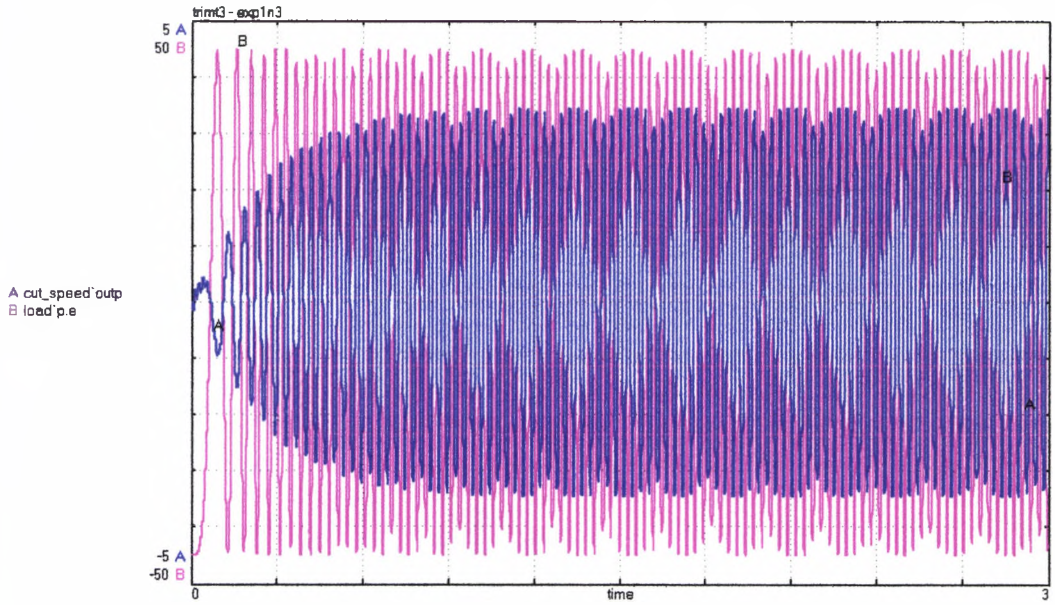


Fig. 6.6 **Simulation output of hedgetrimmer from 20-sim package.**

6.3.3 Analysis of the simulation results

The mean and Signal-to-Noise Ratio values for a Larger-the-Better quality characteristic are shown for the experiment data in Table 6.3 below.

Factor	Level	speed(LB) (ave)	speed(LB) (s/n)
blade mass	0.5 kg	2166.67	66.71
	0.81 kg	2109.00	66.47
	1.12 kg	2032.78	66.15
blade friction	19.1 Ns/m	2006.78	66.04
	6.3 Ns/m	2140.44	66.60
	4.8 Ns/m	2161.22	66.68
frict torque	15.86e-6 Nms/r	2112.44	66.49
	16.06e-6 Nms/r	2103.22	66.45
	16.25e-6 Nms/r	2092.78	66.39
motor res	30.30 Ohms	2112.22	66.49
	30.26 Ohms	2096.78	66.41
	30.25 Ohms	2099.44	66.43

Table 6.3 Response table of level effects for each design factor

From Table 6.3 and Fig. 6.7 it will be seen that blade mass and blade friction are the most significant design factors affecting mean blade speed and the Signal-to-Noise Ratio. The Analysis Of Variance summarised in Table 6.4 quantifies the significance of these factor effects with high values for blade friction and blade mass.

6.3.4 Comparison of simulation results with physical experiments

For the hedgetrimmer the two design teams conducted separate experiments working to a brief of focusing on energy-related parameters. One team investigated the performance of the hedgetrimmer in terms of blade cutting speed and the other in terms of blade stop time (Appendix B). The results for the blade speed experiment are summarised in Table 6.5 below and the design factors 'internal wire c.s.a.' and 'motor brush

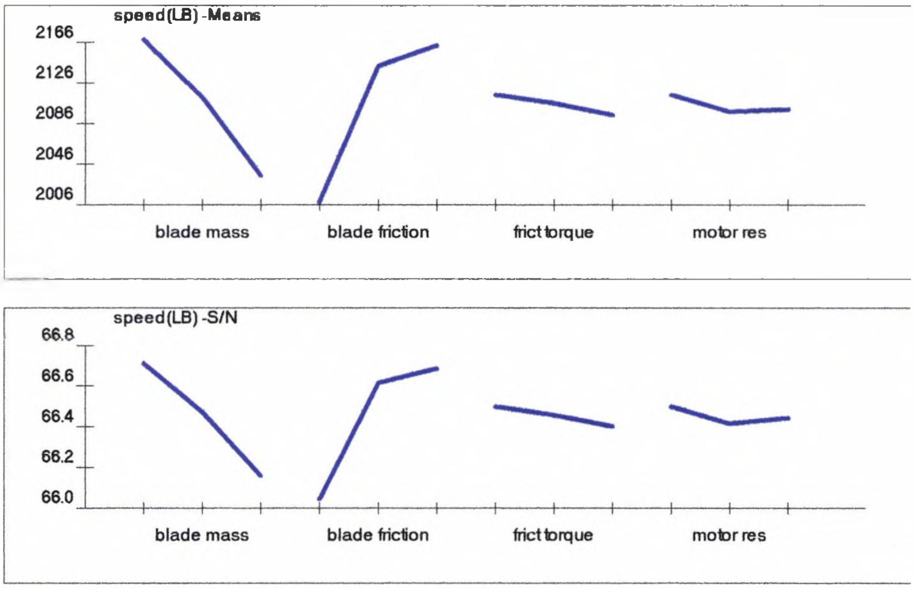


Fig. 6.7 Response graphs for simulation experiment.

speed(LB)-S/N				
Factor	SS	d.o.f.	mean sq	F
blade friction	0.74	2	0.37	63.1
blade mass	0.47	2	0.24	40.6
error	0.02	4	0.01	

speed(LB)-Mean				
Factor	SS	d.o.f.	mean sq	F
blade friction	126456.00	2	63228.00	18.5
blade mass	81176.00	2	40588.00	11.9
frict torque	1744.00	2	872.00	--
motor res	1224.00	2	612.00	--
error	61592.00	18	3421.78	

Table 6.4 ANOVA table for mean (incorporating error within treatments) and SNR of simulation data

spring' redefined in terms of 'motor resistance' and 'friction torque' respectively for direct comparison with the simulation experiment results.

Run	1 motor res	2 blade friction	3 frict torque	4 blade mass	blade speed ave	blade speed S/N
1	30.30 Ohms	19.1 Ns/m	15.86e-6 Nms/r	0.5 kg	1955.50	65.81 dB
2	30.30 Ohms	6.3 Ns/m	16.06e-6 Nms/r	0.81 kg	1864.00	65.40 dB
3	30.30 Ohms	4.8 Ns/m	16.25e-6 Nms/r	1.12 kg	1572.50	63.93 dB
4	30.26 Ohms	19.1 Ns/m	16.06e-6 Nms/r	1.12 kg	1797.00	65.07 dB
5	30.26 Ohms	6.3 Ns/m	16.25e-6 Nms/r	0.5 kg	1867.50	65.41 dB
6	30.26 Ohms	4.8 Ns/m	15.86e-6 Nms/r	0.81 kg	1737.00	64.72 dB
7	30.25 Ohms	19.1 Ns/m	16.25e-6 Nms/r	0.81 kg	1835.50	65.27 dB
8	30.25 Ohms	6.3 Ns/m	15.86e-6 Nms/r	1.12 kg	1739.00	64.80 dB
9	30.25 Ohms	4.8 Ns/m	16.06e-6 Nms/r	0.5 kg	1911.00	65.61 dB

Table 6.5 L_9 OA and results for physical experiments

Table 6.6 shows the response table for the four design factors and it will be observed that blade mass and blade friction are the most significant factors.

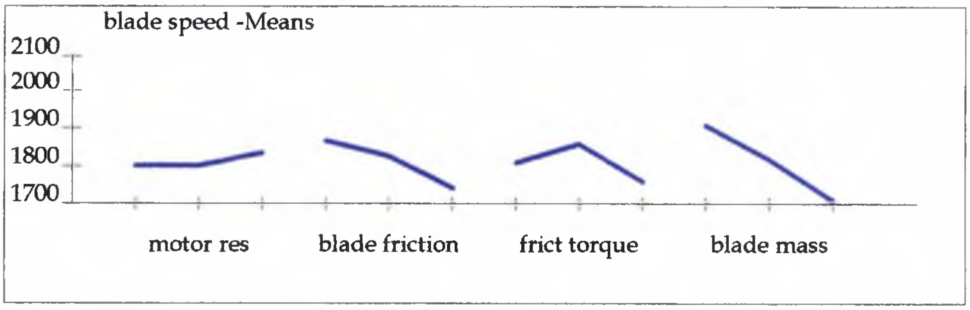
Factor	Level	blade speed (ave)	blade speed (s/n)
motor res	30.30 Ohms	1797.33	65.05
	30.26 Ohms	1800.50	65.07
	30.25 Ohms	1828.50	65.23
blade friction	19.1 Ns/m	1862.67	65.38
	6.3 Ns/m	1823.50	65.20
	4.8 Ns/m	1740.17	64.75
frict torque	15.86e-6 Nms/r	1810.50	65.11
	16.06e-6 Nms/r	1857.33	65.36
	16.25e-6 Nms/r	1758.50	64.87
blade mass	0.5 kg	1911.33	65.61
	0.81 kg	1812.17	65.13
	1.12 kg	1702.83	64.60

Table 6.6 Response table for physical experiments

The response plots in Fig. 6.8 provide further illustration of the factor effects and the ANOVA in Table 6.7 quantifies the contributions. The main difference is that blade friction is the most significant design factor in the simulation whereas here it is blade mass. However, in the physical experiments it was noted (King, 1997) that the setting of friction values was confounded by errors in the clamping bolt torques which could mean that friction was not tested over the same range of levels as for the simulation thus reducing this factor effect for the physical experiments. In both simulation and physical experiments the effects of motor resistance and friction torque investigated are negligible.

6.3.5 Initial estimate of QFD phase 2 parameters

We are now in a position to begin to express some of the output responses of the system (design requirements) in terms of the key design factors (critical part characteristics) identified in the simulation Robust Engineering Design experiments. This initial understanding of the various relationships can be recorded in the QFD phase 2 as indicated in Fig. 6.9 prior to physical experiments.



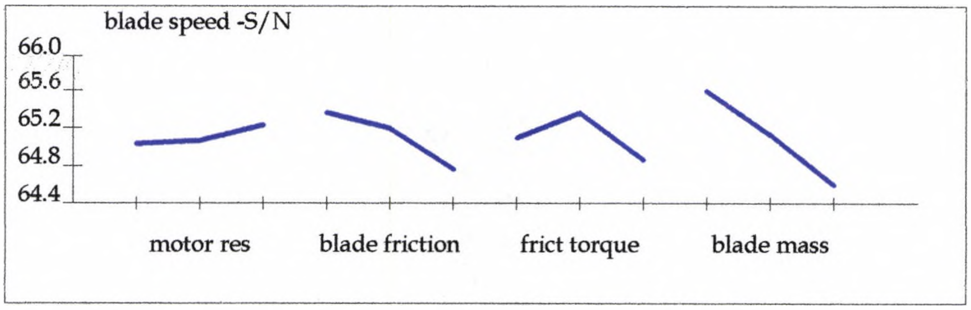


Fig. 6.8 Response graphs for physical experiments.

	blade speed-S/N			
Factor	SS	d.o.f.	mean sq	F
blade mass	1.54	2	0.77	7.3
blade friction	0.63	2	0.32	3.0
error	0.42	4	0.10	

	blade speed-Mean			
Factor	SS	d.o.f.	mean sq	F
blade mass	130516.00	2	65258.00	7.1
blade friction	46964.00	2	23482.00	2.5
frict torque	29324.00	2	14662.00	--
motor res	3524.00	2	1762.00	--
error	83048.00	9	9227.56	

Table 6.7 ANOVA table for mean (incorporating error within treatments) and SNR of physical experiments

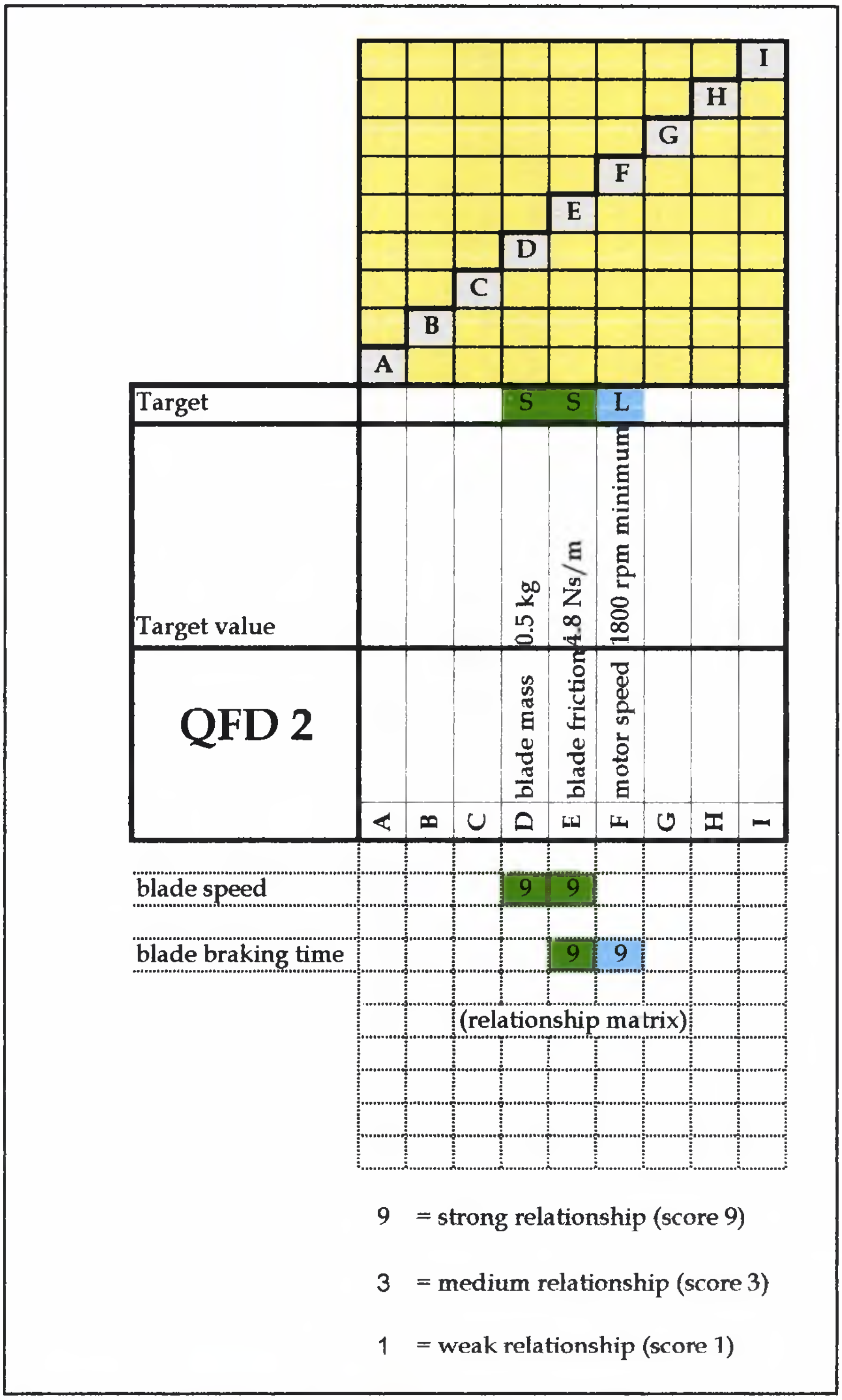


Fig. 6.9 QFD phase 2 entries for motor-blade system

6.4 Summary of Hedgetrimmer Case Study

6.4.1 Discussion

The three-stage approach to developing a bond graph to gain insight into the system has worked well. Challenges lie in accurately estimating parameter values in order to exploit the potential of the state-space equations to provide some insight into the system. Incorporating the scaling method and expected parameter variations have provided valuable enhancement to the engineering insight satisfactorily confirmed by subsequent simulations and physical experiments. Getting the simulation to run has demanded a thorough understanding of bond graph methodology in order to achieve a satisfactory working model. The problems have centred around obtaining the correct dynamic behaviour and correcting errors in constitutive equations. Friction and load behaviour is difficult to estimate for the purposes of simulation. However, simulation has provided a physical insight into the system both in terms of providing a front-end to physical Robust Engineering Design experiments and in providing an estimate of the QFD phase 2 critical part characteristic values before any physical prototypes have been constructed thus contributing to a quicker design process.

6.4.2 Conclusions

A linked Quality Function Deployment-Robust Engineering Design methodology has been demonstrated that starts with a partitioning of the hedgetrimmer design problem. The groups of tasks identified align well with the RED experimental work that has followed and bond graph modelling has provided some valuable insight into the product robustness.

Chapter 7. Diesel Injector Case Study

7.1 Introduction

7.1.1 Overview and purpose of case study

Quality measurements are often multi-valued and therefore should be amenable to multiple objective optimisation. In addition, (i) Taguchi has laid great stress on quality loss functions and loss-to-society in particular, and (ii) a number of techniques are also available from classical statistical decision theory. The prevailing wisdom is that one should separate out the modelling from the optimisation stages and this is carried out, with discussion. This case study clearly shows the trade-off and compromise solutions which are necessary for the optimisation of outputs and the relationship of this trade-off to the design variables and noise factors. The effect of unequal tolerance (unit-to-unit) noise factor distribution on factor effects is also demonstrated.

The concept of *capability mapping* is applied to Robust Engineering Design experiments through taking into account existing production capabilities in the analysis of the results and in selecting optimum design factor level settings. A multiple objective quality model may be optimised using this concept and compared with other methods. *Competitive benchmarking* is shown to be an effective means of calibrating the Quality Loss Function for the purposes of multiple objective optimisation. The argument is supported by this application involving the effect of different diesel injector designs on the emission of pollutants. A model-based Robust Engineering Design methodology is used, that is, the noise factors are modelled alongside the design factors. In this case study the noise is represented by different loads on the system, as dictated by different standard test cycles. This weighted noise approach more closely reflects the non-uniform distribution of noise in reality, whereas Taguchi's (1987)

Signal-to-Noise Ratio has been criticised by Otto and Antonsson (1993) for not achieving this. The model also allows an analysis of the effect of different tolerances on design factors. This approach also shows that the Quality Loss Function can be used to justify the use of out-of-tolerance components in specific product builds. The capability concept is extended to application with the SNR based on a conventional Robust Engineering Design analysis.

7.1.2 Multiple objectives related to energy

7.1.2(a) Engine quality characteristics

It is well known that the automotive internal combustion engine, whilst in existence primarily to provide motive power is also required to satisfy other criteria. For instance it is saddled with objectives for fuel economy and pollutant emissions, and even the notion of motive power can be conveyed in several terms including torque and power characteristics providing multiple quality objectives and constraints.

The emphases of these quality objectives for sub-systems, such as the diesel injector and pump assembly, depend upon the sphere of influence the sub-system exercises on the overall system. For diesel injectors this can translate into a preoccupation with minimising societal loss due to the various pollutants emitted from the engine.

Viewing the fundamental function of an engine in terms of energy conversion (Fig. 7.1) demonstrates the increased likelihood of creating several quality objectives when observing negative effects (e.g. smoke and hydrocarbon emissions) in place of a single positive effect (e.g. specific fuel consumption, torque or power).

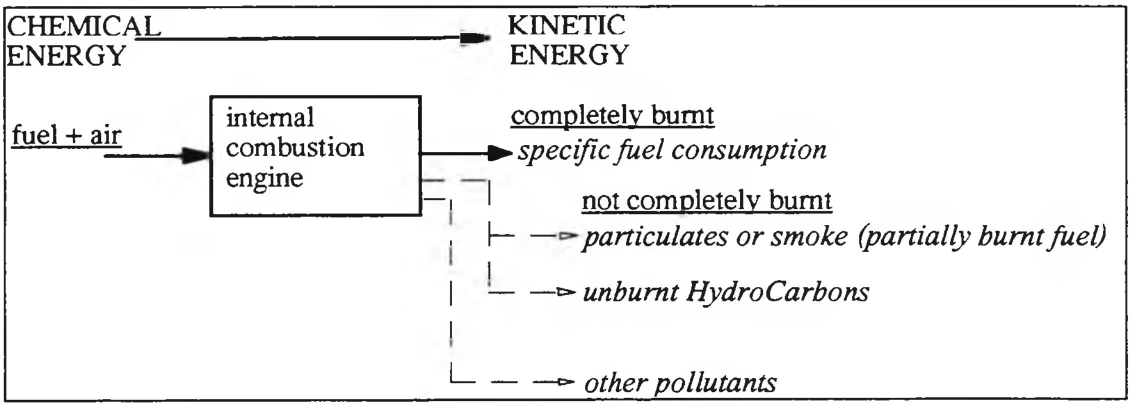


Fig. 7.1 Engine energy conversion

Furthermore, in cascading the primary objective(s) of the engine down to sub-system level, quality objectives of the experiment must relate back to the customer's desired outcome, for example either:

(i) Indirectly through measuring, say, injector spray characteristics when the injector-pump assembly alone forms the basis of the experiment.

or

(ii) Directly through observing the effects of injector configuration on engine outputs.

7.1.2(b) Injector quality characteristics

With comprehensive understanding of the relationship between injector characteristics and engine behaviour (a) could be considered to be the best approach for optimising the injector design. However, without this comprehensive understanding and in order to be assured that noise factors are represented correctly, (b) will be a more appropriate resolution or level for the experiment (Fig. 7.2).

In this experiment three quality characteristics were measured:

(i) Partially burnt particulates or 'smoke' (in Bosch smoke units).

(ii) Unburnt hydrocarbons or HC (in grammes per hour).

(iii) Specific fuel consumption or SFC (in grammes per kilowatt-hour).

In line with the energetics of the engine's function specific fuel consumption was the best candidate for a single quality objective but for the purposes of studying multiple objective optimisation, hydrocarbons and smoke were investigated. It is recognised that as neither of these two would be considered as positive effects of the system in terms of energy then interactive effects could be expected with a consequent lack of additivity of the main design factor effects.

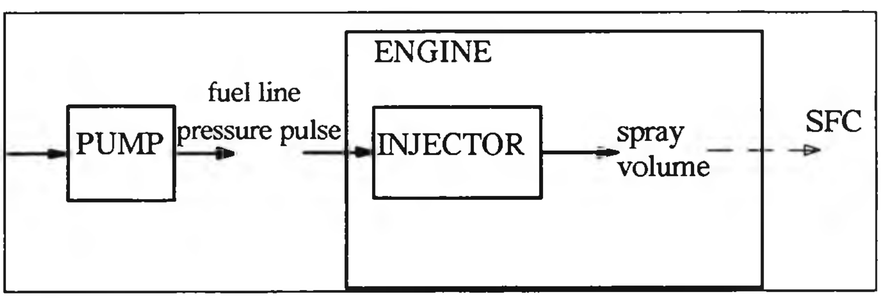


Fig. 7.2 Experiment resolution or level

7.1.3 Defining the quality loss functions

Societal loss due to pollutant emissions can be considered to follow this simple relationship (Fig. 7.3) where:

Loss due to HC emissions, $L_{HC} = k_{HC}y_{HC}^2$ (7.1)

Loss due to smoke emissions, $L_S = k_S y_S^2$ (7.2)

Recalling that whilst the Quality Loss Function is an acceptable model representing the costs associated with this type of product, for a given engine establishing the absolute values of the constants k_{HC} and k_s will be virtually impossible due to the difficulty of determining actual costs. However, relative values of the constants will be derived by setting arbitrary losses (£L) against benchmark products in each category. Thus in Fig. 7.3 the performance of product A on hydrocarbon sets the constant k_{HC} and likewise product B performance sets k_S. The 'common currency' of Loss is then used to compute the Relative Total Loss, $L=L_{HC}+L_S$, any similar product will cause society through the emissions of these pollutants and therefore facilitate identification of a best configuration for minimum overall loss. This is developed further below.

7.1.4 Injector valve and nozzle design factors

Robust Engineering Design attention was focused on the valve-nozzle contact area of the injector (Fig. 7.4). The factors chosen for level setting were of three types, all related to the energy transformation of the system:

(i) Pintle dimensions (x_A, x_B, x_D) related to the flow characteristics of fuel passing through the injector into the engine.

(ii) Other valve features (x_C, x_E) influencing the fuel flow rates at small and maximum valve lifts as measured by an air flow meter.

(iii) Spring characteristics (x_F, x_G) affecting the fuel line pressure pulse required to raise the valve off its seat and allow fuel to flow into the engine.

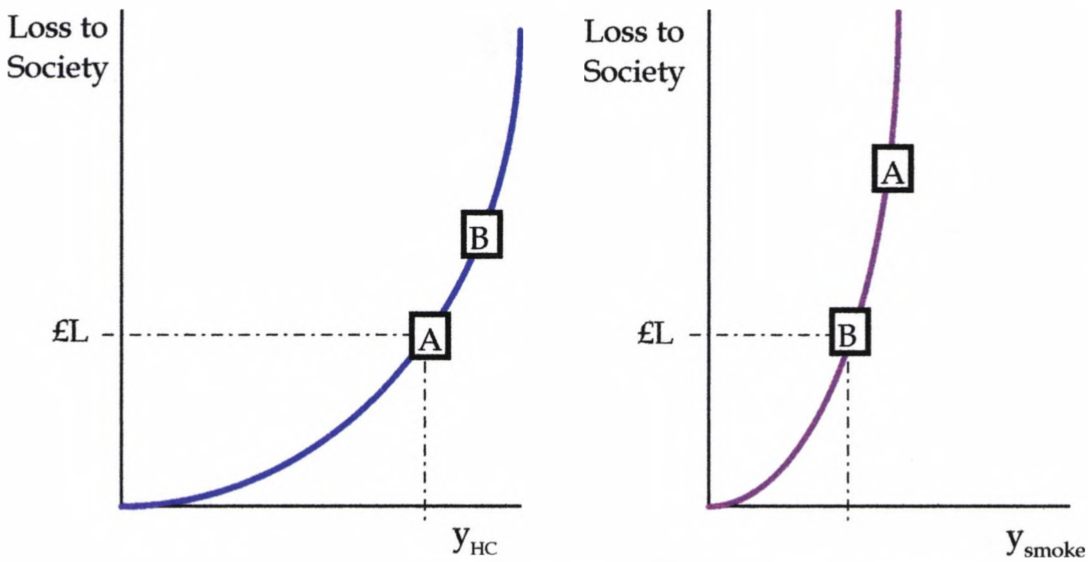


Fig. 7.3 **Loss functions for hydrocarbon and particulate exhaust emissions**

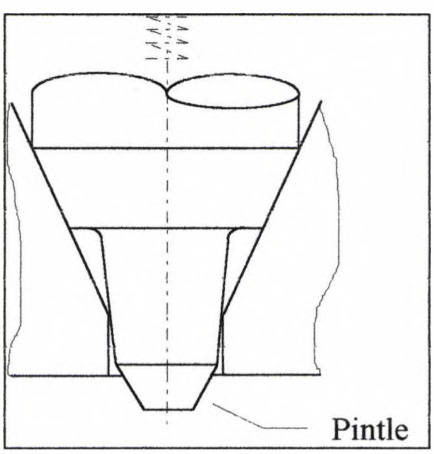


Fig. 7.4 **Schematic diagram showing pintle end of injector valve-nozzle assembly**

x_A -the distance from a gauge diameter on the seat cone of the pintle to the start of a slow taper (not shown) in the region of the nozzle hole.

x_B -the distance from the same gauge diameter to the end of the pintle.

x_C -the axial length of the tapered seat.

x_D -the flow rate of air when the valve is lifted 0.1mm off its seat. This relates to a test conducted on the production line.

x_E -the flow rate of air when the valve is lifted to the maximum extent of its travel. This is also a test conducted on the production line.

x_F -undisclosed spring characteristics.

x_G -setting pressure of the spring (adjusted by shims).

7.2 Experiment

7.2.1 Experiment design and data

This industrial experiment represented a significant resource commitment and therefore it was important to study as many factors as possible. A saturated L_8 Orthogonal Array was used to plan the experimental levels of the seven design factors. The engine was run at a constant 2400rpm, hydrocarbon (HC,) smoke and specific fuel consumption (SFC) data being collected over a cycle of varying engine load. The experiment plan and data collected is shown below (Tables 7.1, 7.2 & 7.3).

2400 rpm represents a high vehicle cruising speed and the engine loads applied were between full-load (800 kPa BMEP) and no-load (20 kPa BMEP).

7.2.2 Building a fitted model of the data

The two main responses Y_{HC} and Y_s represent the hydrocarbon and smoke output in standard units. Separate regressions were carried out with all seven control factors $x_A,...,x_G$ and the load factor modelled x_N. Engine load is a noise factor as it is an environmental fluctuation to the extent that the actual engine load will depend on vehicle use which will vary unpredictably.

Using standard orthogonal contrasts (Montgomery, 1991) scaled to the range –1, 1 the load was extended to second-order polynomial effects: $x_{N,1}$ (linear) and $x_{N,2}$ (quadratic). These contrasts are as follows:

	Design Factors							Engine Load					
	x_A	x_B	x_C	x_D	x_E	x_F	x_G	1	2	3	4	5	6
								no load					full load
								HC (grammes/hr)					
1	−1	−1	−1	−1	−1	−1	−1	4.80	4.80	4.60	3.50	2.70	2.20
2	−1	−1	−1	+1	+1	+1	+1	3.70	3.91	4.54	3.42	3.16	2.89
3	−1	+1	+1	−1	−1	+1	+1	5.30	5.90	6.00	4.40	3.40	2.60
4	−1	+1	+1	+1	+1	−1	−1	5.10	5.90	7.10	4.90	3.60	2.90
5	+1	−1	+1	−1	+1	−1	+1	4.20	4.80	4.20	3.25	2.50	3.30
6	+1	−1	+1	+1	−1	+1	−1	4.10	4.30	5.20	3.30	2.60	2.40
7	+1	+1	−1	−1	+1	+1	−1	4.65	4.60	5.40	3.60	2.80	2.40
8	+1	+1	−1	+1	−1	−1	+1	4.40	4.60	5.70	3.90	2.90	2.70

Table 7.1 OA and engine data for HC under varying load at 2400rpm

	Design Factors							Engine Load					
	x_A	x_B	x_C	x_D	x_E	x_F	x_G	1	2	3	4	5	6
								no load					full load
								Smoke (Bosch smoke units)					
1	−1	−1	−1	−1	−1	−1	−1	2.20	2.10	1.50	1.30	1.50	1.70
2	−1	−1	−1	+1	+1	+1	+1	2.50	2.20	1.60	1.10	1.00	1.40
3	−1	+1	+1	−1	−1	+1	+1	1.90	1.60	1.00	1.00	1.20	1.40
4	−1	+1	+1	+1	+1	−1	−1	1.90	1.70	1.30	1.20	1.20	1.80
5	+1	−1	+1	−1	+1	−1	+1	2.00	2.00	1.50	1.00	1.20	1.50
6	+1	−1	+1	+1	−1	+1	−1	1.90	1.80	1.20	1.00	1.00	1.40
7	+1	+1	−1	−1	+1	+1	−1	1.90	1.60	1.10	1.10	1.30	2.10
8	+1	+1	−1	+1	−1	−1	+1	1.90	1.60	1.10	1.00	1.20	1.80

Table 7.2 OA and engine data for smoke under varying load at 2400rpm

	Design Factors							Engine Load					
	x_A	x_B	x_C	x_D	x_E	x_F	x_G	1	2	3	4	5	6
								no load					full load
								SFC (grammes/kiloWatt-hour)					
1	−1	−1	−1	−1	−1	−1	−1	1920	386	288	263	257	265
2	−1	−1	−1	+1	+1	+1	+1	1221	389	291	263	259	265
3	−1	+1	+1	−1	−1	+1	+1	1293	390	290	263	259	264
4	−1	+1	+1	+1	+1	−1	−1	1759	383	283	259	256	264
5	+1	−1	+1	−1	+1	−1	+1	1400	393	290	262	256	260
6	+1	−1	+1	+1	−1	+1	−1	1206	387	290	260	256	265
7	+1	+1	−1	−1	+1	+1	−1	2214	416	298	267	262	270
8	+1	+1	−1	+1	−1	−1	+1	2316	382	285	262	256	266

Table 7.3 OA and engine data for SFC under varying load at 2400rpm

	Load level					
	1	2	3	4	5	6
$x_{N,1}$	-1	$-\frac{3}{5}$	$-\frac{1}{5}$	$+\frac{1}{5}$	$+\frac{3}{5}$	$+1$
$x_{N,2}$	$+1$	$-\frac{1}{5}$	$-\frac{4}{5}$	$-\frac{4}{5}$	$-\frac{1}{5}$	$+1$

Table 7.4 Standard orthogonal contrasts

Using multiple regression for Y_{HC} and Y_s the fitted models obtained (Minitab) are:

$$\begin{aligned} Y_{HC} &= 4.02 - 0.198x_A + 0.341x_B + 0.195x_C \\ &\quad - 1.18x_{N,1} - 0.493x_{N,2} - 0.213x_B x_{N,2} \end{aligned} \tag{7.3}$$

having a correlation coefficient of approximately 0.88.

$$\begin{aligned} Y_S &= 1.51 - 0.056x_B - 0.0646x_C - 0.287x_{N,1} \\ &\quad + 0.344x_{N,2} + 0.153x_B x_{N,1} \end{aligned} \tag{7.4}$$

having a correlation coefficient of approximately 0.89.

	Load					
x_B	1	2	3	4	5	6
−1	−0.129	−0.384	−0.511	−0.511	−0.384	−0.128
+1	0.129	0.384	0.511	0.511	0.384	0.128

Table 7.5 Effect of x_B on Y_{HC} by load

Table 7.5 shows that $x_B = -1$ has the effect of keeping hydrocarbons down for all load conditions. For smoke the effect is the opposite overall and the main interaction is between x_B and the linear effect of load $x_{N,1}$. The corresponding effects are given in Table 7.6.

	Load					
x_B	1	2	3	4	5	6
−1	0.209	0.148	0.088	0.023	−0.035	−0.096
+1	−0.209	−0.148	−0.088	−0.023	0.035	0.096

Table 7.6 Effect of x_B on Y_s by load

However the increase here is less relative to hydrocarbons and therefore $x_B = -1$ might be suggested as the most robust setting in terms of suppression of maximum combined pollution. The stabilisation against load is also confirmed by the lower standard deviation, shown in Table 7.7.

	HC		smoke	
x_B	mean	std dev	mean	std dev
-1	3.68	0.912	1.56	0.435
+1	4.36	1.056	1.46	0.303

Table 7.7 Effect of x_B on mean and std dev of Y_{HC} and Y_S under varying load conditions

In Fig. 7.5 the plot of Y_{HC} against load level for all experiments it can be seen that $x_B = -1$ (experiments 1,2,5 and 6) forces Y_{HC} to its lower limit.

Conversely, for smoke Fig. 7.6 shows that $x_B = +1$ (experiments 3,4,7 and 8) forces Y_S to its lower limit. This conflict will be resolved using a loss function. In addition, the influence of x_B on specific fuel consumption is small and it was observed that at higher engine loads $x_B = -1$ has a positive effect (i.e. lower sfc).

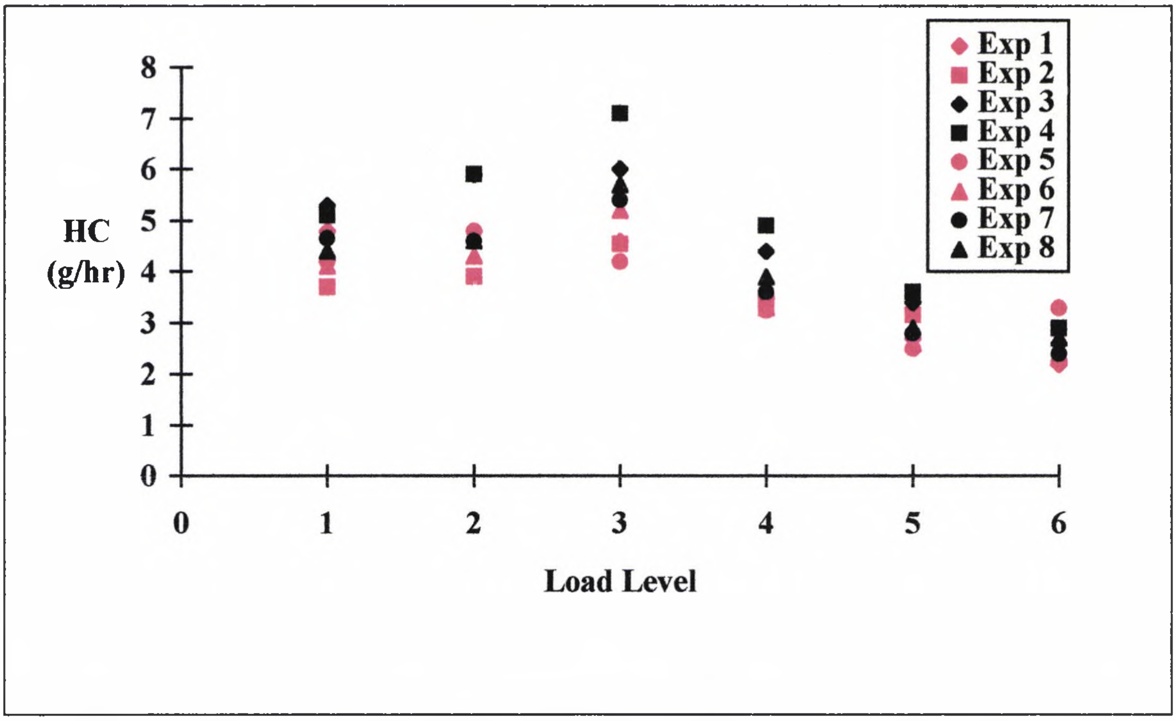


Fig. 7.5 Hydrocarbon emissions vs engine load for 8 experiments

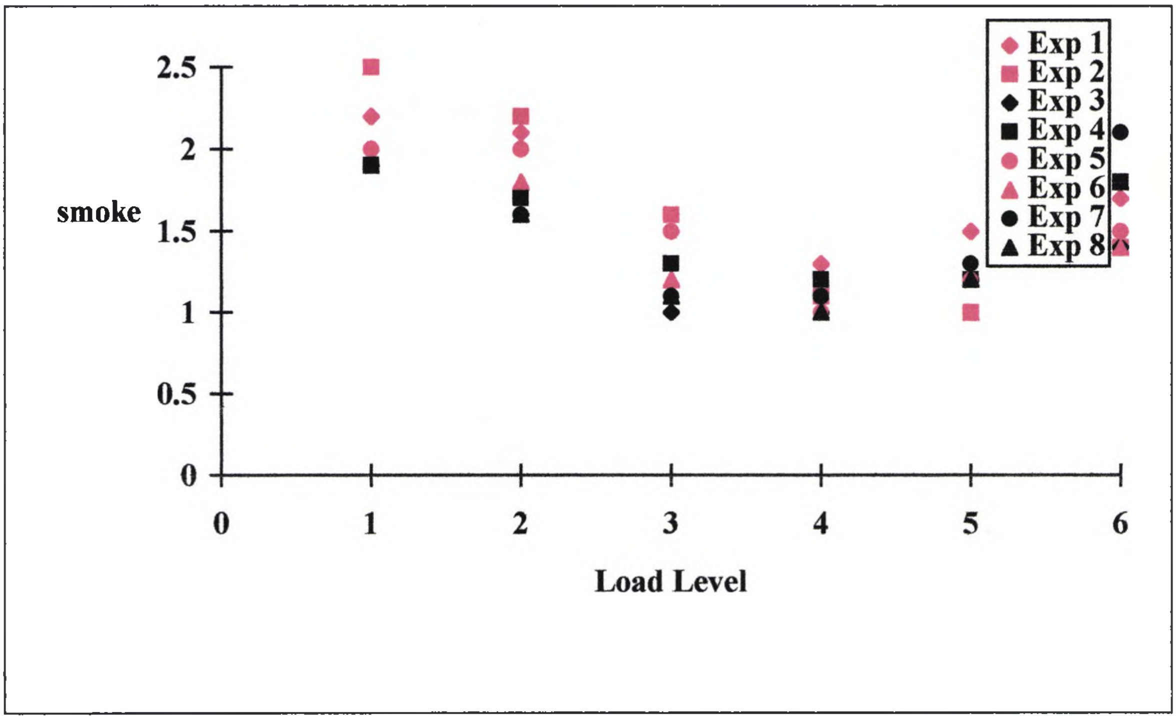


Fig. 7.6 Smoke emissions vs engine load for 8 experiments

7.3 Multiple Objective Optimisation

7.3.1 Defining the Quality Loss Function using competitive benchmarking

The Quality Loss Function will be model-based and of the form $L = k_{HC}Y_{HC}^2 + k_S Y_S^2$ based on the argument above. Inserting the fitted models (Eqs. 7.3 and 7.4) a function is obtained which is quadratic in x_A, x_B and x_C and essentially quartic in x_N. From Chapter 3 a simple exercise is to investigate the behaviour of the average value of L over the load. Thus without loss of generality let:

$$L = (1-\alpha)Y_{HC}^2 + \alpha Y_S^2 \qquad (0 < \alpha < 1) \tag{7.5}$$

Then at the settings $x_A = 0$, $x_B = -1$, $x_C = 0$ and $x_A = 0$, $x_B = 1$, $x_C = 0$ we obtain respectively:

$x_B = -1$: mean total loss, $L = 13.54 - 11.11\alpha$ (7.6)

$x_B = +1$: mean total loss, $L = 19.01 - 16.88\alpha$ (7.7)

Critical value of α, α^*=0.948

Arguments set out in Chapter 3 have led to the judgement that suitable values of the constants use $k = £/y^2$ where y is the best existing performance and £ is an arbitrary loss (= 1, say) at this y value. For hydrocarbon, a competitor's product produced the least average emissions at 2.976 g/hr; and best average smoke emissions were from the client's injectors at 1.672. Thus,

$$k_{HC} = \frac{1}{2.976^2} = 0.113$$

$$k_s = \frac{1}{1.672^2} = 0.358$$

Which in turn leads to an α value of: $\alpha = \dfrac{0.358}{0.113 + 0.358} = 0.760$.

It is interesting to note that α is well within the critical range $[0,\alpha^*]$ for which $x_B = -1$ is the best setting. Inserting this into Eq. 7.6 gives total loss,

$$L = (1-\alpha)Y_{HC}^2 + \alpha Y_S^2 = 5.096$$

Compared with 6.181 at $x_A = 0$, $x_B = 1$, $x_C = 0$.

7.3.2 Incorporating production capability into the Quality Loss Function

In actual manufacture it is likely that the settings can only be met with a certain accuracy due to the capability of the manufacturing process. A tolerance analysis or 'capability mapping' can be performed directly on the average loss function by expanding in δ at the setting $x_A = 0$, $x_B = -1$, $x_C = 0$. This gives the quadratic

$$L = 5.112 + 0.469\delta + 0.030\delta^2 \tag{7.8}$$

In manufacturing the tolerance on x_B is $\pm$ 0.025 and substituting this value into Eq. 7.8 (as a surrogate for process capability) shows that the loss is insensitive to variation about $x_B = -1$ (less than 0.5% about the mean performance).

7.4 Pragmatic Factor Level Selection

7.4.1 Design factor values from production

In Chapter 3 it was shown that an imbalance between the tolerance (unit-to-unit) noise experienced at two levels of a design factor could be dealt with by adjusting the local response variance of interest in proportion to this imbalance and thus reassess the contribution of the design factor. In order to conduct this we need the values of the design factor settings used for each experiment trial. Fig. 7.7 shows the injector nozzle in greater detail.

	L8 OA	A K dim	B M dim	C 0.1 lift	D seat length	E max lift	F spring	G pressure
	1	1.388	2.00	0.193	0.76	4.55	std	114
	2	1.404	2.00	0.204	0.90	5.08	exp	124
	3	1.406	2.43	0.179	0.76	4.67	exp	125
	4	1.426	2.43	0.184	0.90	5.03	std	115
	5	1.433	2.00	0.190	0.76	5.13	std	125
	6	1.447	2.00	0.197	0.90	4.55	exp	115
	7	1.433	2.43	0.190	0.76	5.13	exp	115
	8	1.437	2.43	0.195	0.90	4.57	std	125
level -1 mean		**1.406**	2.00	**0.196**	0.76	**4.59**	n/a	114.75
level -1 std dev		**0.0156**	0.00	**0.0060**	0.00	**0.057**	n/a	0.50
level +1 mean		**1.438**	2.43	**0.188**	0.90	**5.09**	n/a	124.75
level +1 std dev		0.0066	0.00	0.0078	0.00	0.045	n/a	0.50
upper spec limit		1.42 mm	2.46 mm	0.25 l/min	0.90 mm	5.10 l/min	n/a	110 bar
lower spec limit		1.39 mm	2.41 mm	0.13 l/min	0.85 mm	4.75 l/min	n/a	120 bar
est. spec std dev		0.0038		0.0150		0.044		

Table 7.8 Actual factor values used in design experiments

Table 7.8 shows the actual factor values used for the diesel injectors in the L8 Orthogonal Array. The design factors are represented by the mean values assigned to level -1 and level +1 respectively in each of the seven columns (design factors A-G). The variability of the values within the design factor level groupings represents the associated tolerance noise factor.

Note that two design factors, M dimension (Factor B) and seat length (Factor D) effectively have no variability because they are gauge lengths that have been machined to size for every component. Thus they will not

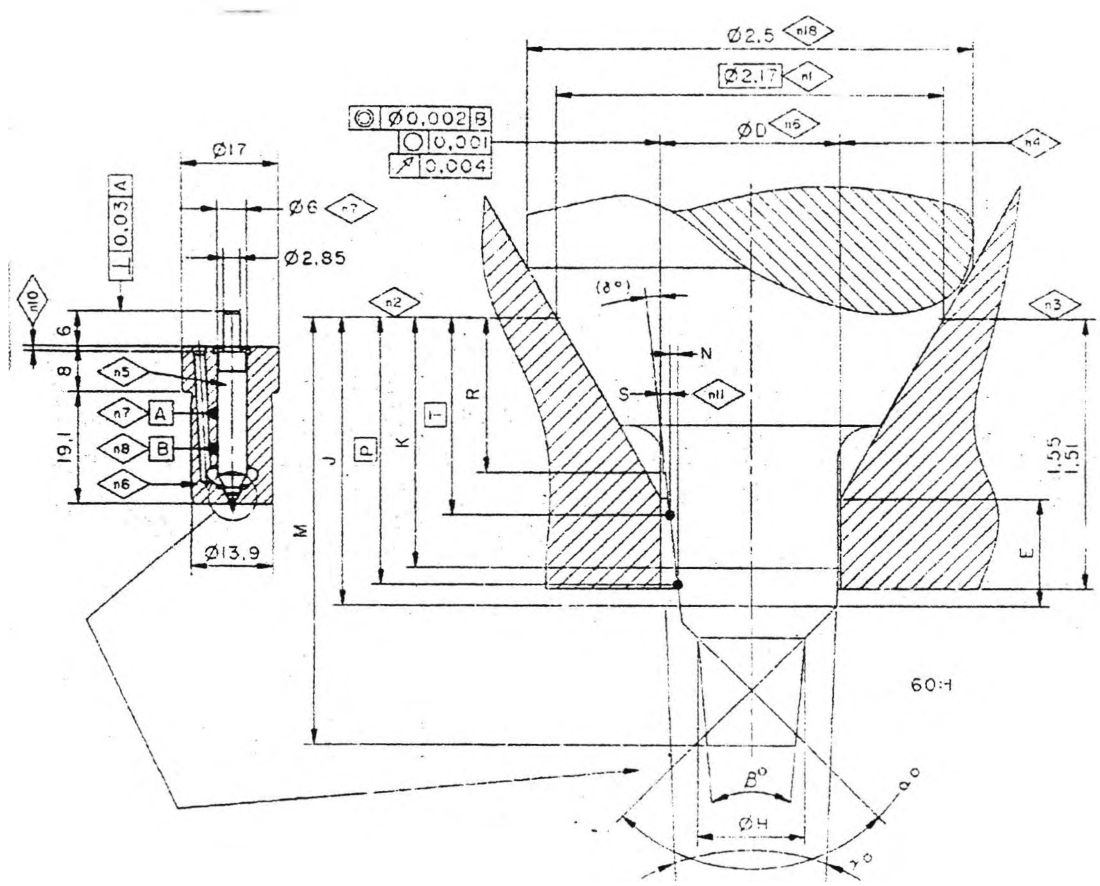


Fig. 7.7 Detail of injector nozzle and pintle

be studied here - even so the significant role of factor B and its interaction with load noise has been the subject of previous sections. Others, namely K dimension (Factor A), air flow at 0.1 lift (Factor C) and airflow at maximum lift (Factor E) are determined more indirectly and exhibit skewed and unequal distributions (see Fig. 7.8). Factor F the spring is not quantified and Factor G has equal noise variance at each design factor level and will be seen below to make very little contribution.

7.4.2 Adjustment of factor effects

Recalling Eq. 3.24 and Eq. 3.25 respectively from Chapter 3, an estimate of SNR_{LB} for design factor A, level -1 is:

$$= -10 * \log_{10}(\frac{1}{3}\sum(\overline{y}_{A-1}, (\overline{y}_{A-1} + \sqrt{\tfrac{3}{2}} * \sigma_{yA-1}), (\overline{y}_{A-1} - \sqrt{\tfrac{3}{2}} * \sigma_{yA-1}))) \qquad (7.9)$$

Adjustment to σ_y for a given factor level:

$$\sigma_{yA-1adj} = \sigma_{yA-1} * \frac{\sigma_{xA+1}}{\sigma_{xA-1}} \qquad (7.10)$$

The factor level standard deviation deemed to be closest to that of production is estimated by comparing with the value obtained from $\sigma_{prod} = \frac{tolerance}{C_{pk} * 6}$. Where C_{pk}, the production capability index is assumed to have a value of 1.33 typically. The factor level standard deviation that is closest to σ_{prod} is then used as the datum to which the other is adjusted according to Eq. 7.10 where the values for y mean and σ_y at each design factor level are shown in Table 7.9 for particulates emissions (smoke) and Table 7.10 for hydrocarbon (HC) emissions.

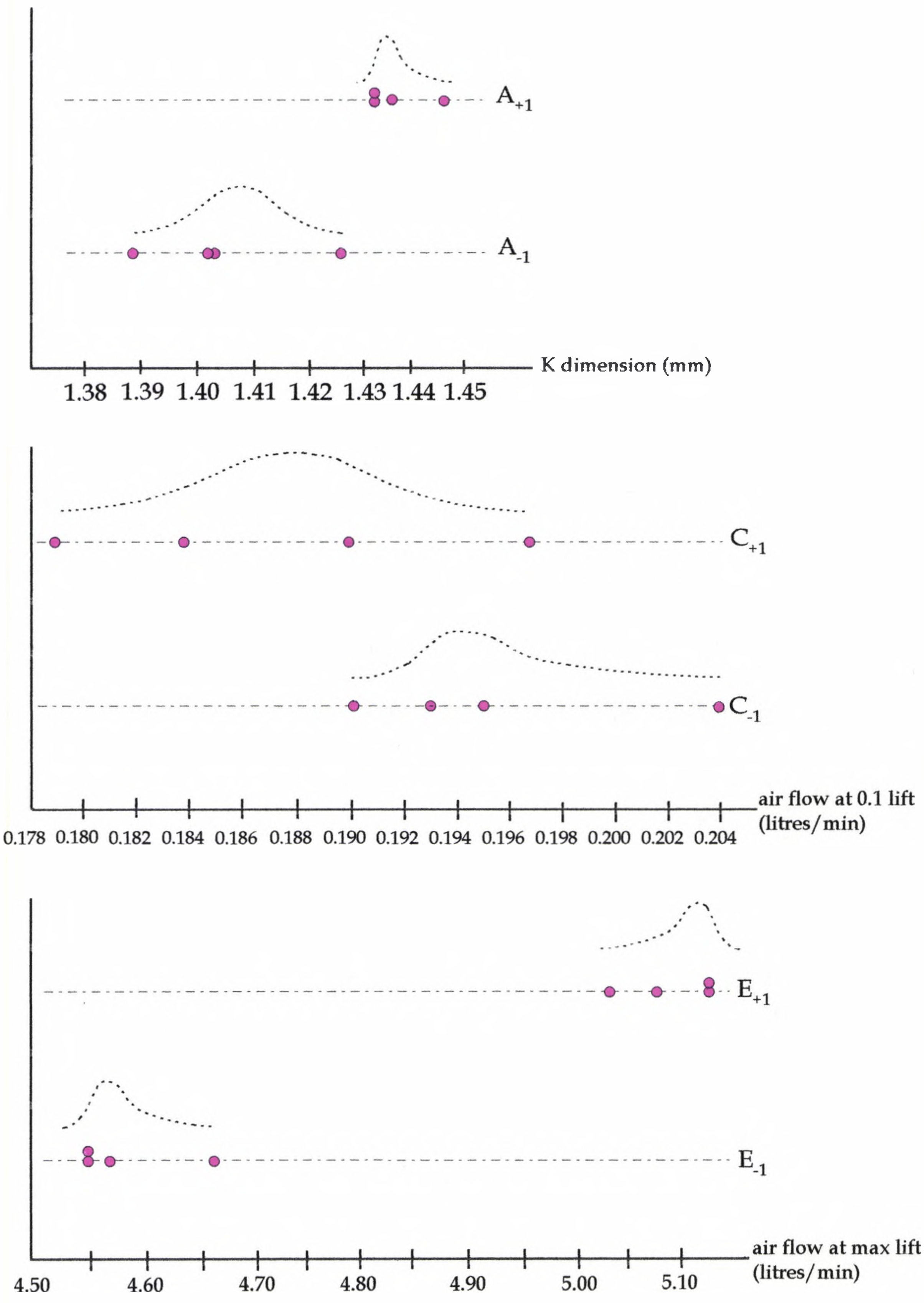


Fig. 7.8 Distribution of factor levels from production

		smoke data versus engine load for 8 experiments						
	1	1.70	1.50	1.30	1.50	2.10	2.20	
	2	1.40	1.00	1.10	1.60	2.20	2.50	
	3	1.40	1.20	1.00	1.00	1.60	1.90	
	4	1.80	1.20	1.20	1.30	1.70	1.90	
	5	1.50	1.20	1.00	1.50	2.00	2.00	
	6	1.40	1.00	1.00	1.20	1.80	1.90	
	7	2.10	1.30	1.10	1.10	1.60	1.90	
	8	1.80	1.20	1.00	1.10	1.60	1.90	
		k dim	M dim	0.1lift	seat length	maxlift	spring	pressure
level -1 mean		**1.554**	1.567	**1.575**	1.529	**1.471**	1.550	1.533
level -1 std dev		**0.420**	0.439	**0.436**	0.385	**0.378**	0.360	0.370
level +1 mean		**1.467**	1.454	**1.446**	1.492	**1.550**	1.471	1.488
level +1 std dev		**0.380**	0.354	**0.355**	0.419	**0.422**	0.438	0.432
estimated SNR-1		**-4.136**		**-4.266**		**-3.629**	best	
estimated SNR+1		-3.608	best	-3.457	best	-4.117		
difference		-0.528		-0.809		0.488		
adj level -1 std dev		**0.178**		**0.561**		**0.298**		
adj SNR+1		**-3.887**	improved	**-4.465**	worsened	**-3.526**	improved	
difference		-0.279		-1.008		0.591		
change in difference		53%		125%		121%		
experiment SNR-1		-4.050		-4.212		-3.545	best	
experiment SNR+1		-3.583	best	-3.420	best	-4.088		
difference		-0.467		-0.792		0.543		
estimated new difference		-0.246		-0.987		0.658		

Table 7.9 Estimates of changes to factor effects for smoke

		HC data versus engine load for 8 experiments						
	1	2.20	2.70	3.50	4.60	4.80	4.80	
	2	2.89	3.16	3.42	4.54	3.91	3.70	
	3	2.60	3.40	4.40	6.00	5.90	5.30	
	4	2.90	3.60	4.90	7.10	5.90	5.10	
	5	3.30	2.50	3.25	4.20	4.80	4.20	
	6	2.40	2.60	3.30	5.20	4.30	4.10	
	7	2.40	2.80	3.60	5.40	4.60	4.65	
	8	2.70	2.90	3.90	5.70	4.60	4.40	
		k dim	M dim	0.1lift	seat length	maxlift	spring	pressure
level -1 mean		**4.222**	3.682	**3.828**	3.996	**4.013**	4.106	4.060
level -1 std dev		**1.263**	0.876	**0.978**	1.133	**1.170**	1.207	1.265
level +1 mean		**3.825**	4.365	**4.219**	4.051	**4.034**	3.940	3.986
level +1 std dev		**1.001**	1.292	**1.282**	1.181	**1.145**	1.100	1.038
estimated SNR-1		**-12.882**		**-11.934**	best	**-12.422**	best	
estimated SNR+1		-11.940	best	-12.887		-12.452		
difference		-0.942		0.954		0.029		
adj level -1 std dev		**0.536**		**1.260**		**0.922**		
adj SNR-1		**-12.579**	improved	**-12.106**	worsened	**-12.292**	improved	
difference		-0.639		0.781		0.160		
change in difference		68%		82%		547%		
experiment SNR-1		-12.702		-11.902	best	-12.337		
experiment SNR+1		-11.913	best	-12.713		-12.278	best	
difference		-0.789		0.811		-0.059		
estimated new difference		-0.535		0.664		0.323	(SNR1 will be > SNR2)	

Table 7.10 Estimates of changes to factor effects for HC

Considering Tables 7.9 and 7.10 the key events should be viewed as:

(i) Calculating the difference between estimated values of SNR.

(ii) Recalculating the difference after one SNR has been adjusted.

(iii) Expressing this change as a percentage change which is then applied to the difference between experiment SNR producing an estimate of the difference under equal tolerance noise conditions between factor levels.

These changes are put into perspective by the Daniel plots of Figs 7.9 to 7.12 where a conventional Robust Engineering Design analysis of the original experiment (Appendix A) is compared with a modified plot incorporating the adjusted experimental data.

For smoke emissions the line of best fit would appear not to pass exactly through the origin suggesting that normality of distribution is suspect. However, the most notable change between Fig. 7.9 and Fig. 7.10 in the diagnosis is that air flow at maximum lift (Factor E) becomes more significant. The change in K dimension means that it could now be considered to be an insignificant influence.

For hydrocarbon emissions the only notable change in Fig. 7.12 is that K dimension again reduces in significance. However, air flow at maximum lift which now is more significant will be seen from Table 7.10 to potentially have its best level changed to level 1 - the same level setting preferred for minimising smoke emissions.

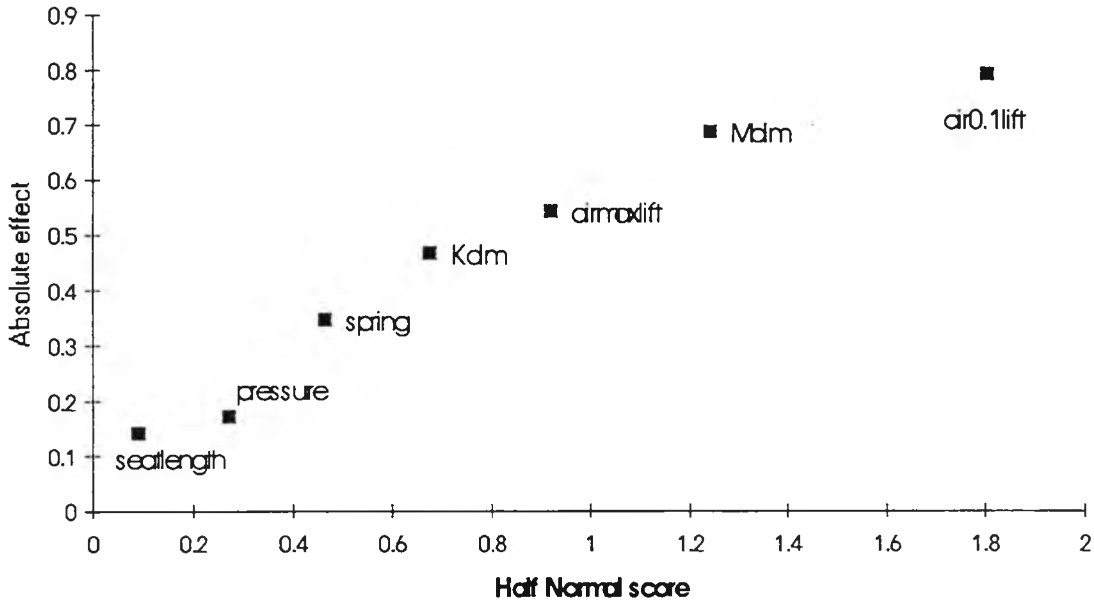


Fig. 7.9 **Daniel plot of smoke emissions data (Appendix A)**

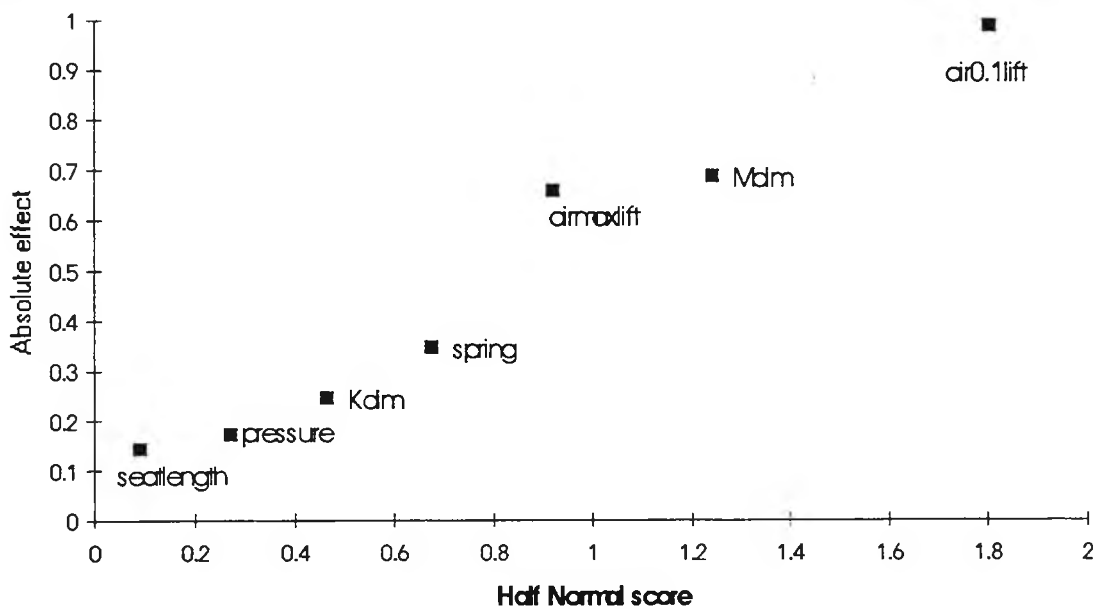


Fig. 7.10 **Daniel plot of adjusted data for smoke emissions**

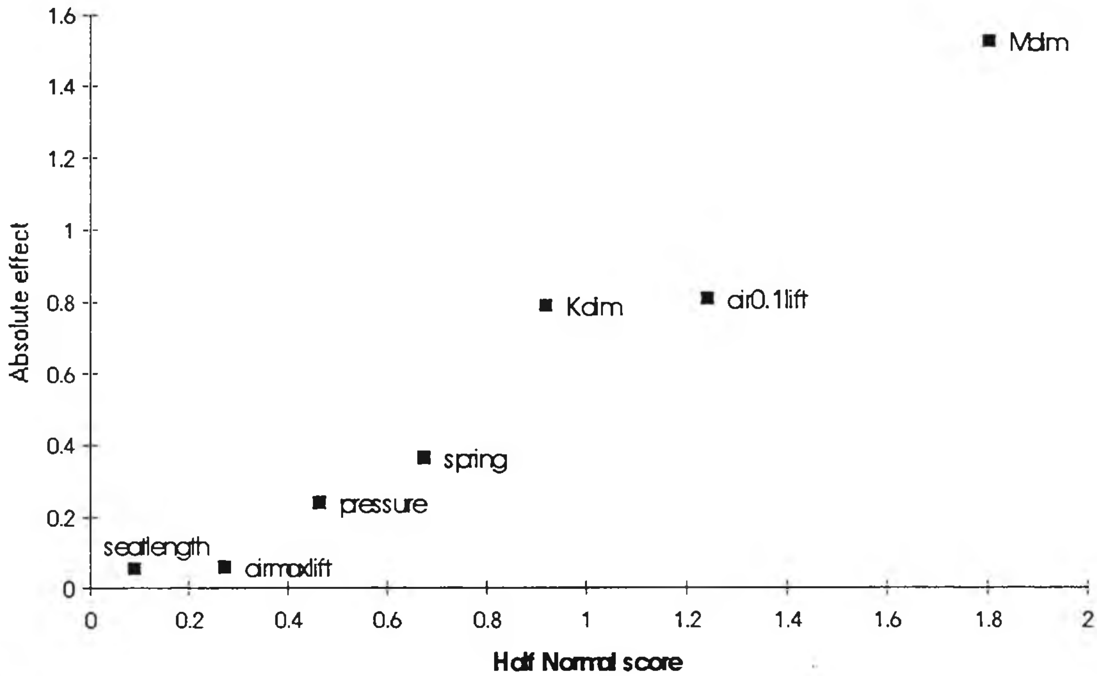


Fig. 7.11 **Daniel plot of HC emissions data (Appendix A)**

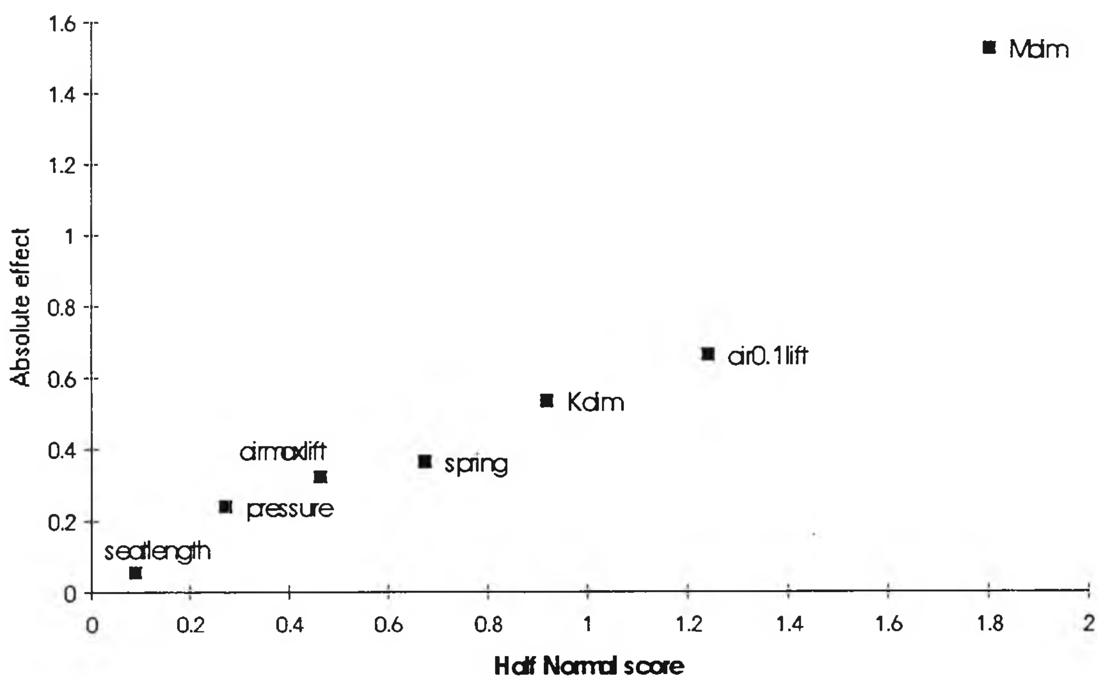


Fig. 7.12 **Daniel plot of adjusted data for HC emissions**

7.5 Summary of Diesel Injector Case Study

7.5.1 Discussion

Using hydrocarbon and smoke emissions as the quality objectives highlights the interdependence that often exists between system responses where a trade-off has to be made. Desirability values are difficult to pitch realistically but determining the loss function constants (weightings) by virtue of the best existing performance available in the market place provides a more dynamic target that will automatically penalise those products that stand still through regularly updating the weightings against the best products. This is a departure from the Taguchi approach which would address the positive features of the design in terms of the energy model of Fig. 7.1. Where competitive benchmarking of real environmental effects can allow measurement of the adverse effects of outputs then these should be incorporated in the modelling; Franklin (1990) quotes Michaelangelo "Removing marble that does not look like David". A further weighting component could be added in this investigation to reflect the client's revised view that, in terms of the measures used, hydrocarbon was twice as undesirable as smoke. This would make $\alpha = \frac{0.358}{2 \times 0.113 + 0.358} = 0.613$ which is further from α^* than the previous value and therefore more supportive of setting x_B = −1 for optimisation of the multiple objectives. Design factor x_B is in fact the pintle length (M dimension) measured from a gauge diameter on the seat and the −1 level is a setting outside the standard specification. Furthermore it should be noted that specific fuel consumption is little affected by the injector design factors considered and more understanding of the system has in fact been gained by studying pollutant emissions. In the subsequent study of tolerance (unit-to-unit) noise factor influence, the departure from Taguchi's approach is continued through focusing on the influence of noise distributions on the results. This provides some fine tuning to experiments conducted within the production constraints.

Fig. 7.13 represents portions of the Quality Function Deployment matrices to highlight the storage of design information generated through the Robust Engineering Design experiments. In any subsequent design modifications the designer will rapidly see the connection between customer requirements (phase 1) through significant design factors (Critical Part Characteristics in phase 2) down to the Critical Process Characteristics (phase 3) that must be maintained to achieve customer satisfaction.

For the valve/nozzle assembly we see that for engineering systems in general, modelling of multiple quality objectives in terms of design factors and noise interactions is important for two reasons:

(i) The manufacture of the fine features is often difficult to keep within tight tolerances. Rejecting a functioning assembly on the basis of dimensional non-conformity is arguably failing to exploit the complex link between product design and the product's performance. An understanding of the effects of non-compliance on the overall loss would enable out-of-specification injector assemblies to be modelled on-line for evaluating conformance with output quality objectives.

(ii) Experimentation with products such as injectors often relies on using design factor levels achievable on the production line rather than those preferred for experimentation (i.e. specifically manufactured). Design factor levels of a wider range can be simulated by mapping the capability of the process through the loss function.

Finally an encouragement to conduct multiple objective experimentation can be sought from Franklin's (1990) strategy of experimentation "independent confirmation using different experiments", suggesting that a hypothesis receives more confirmation from two 'different' experiments than repetitions of the same experiment.

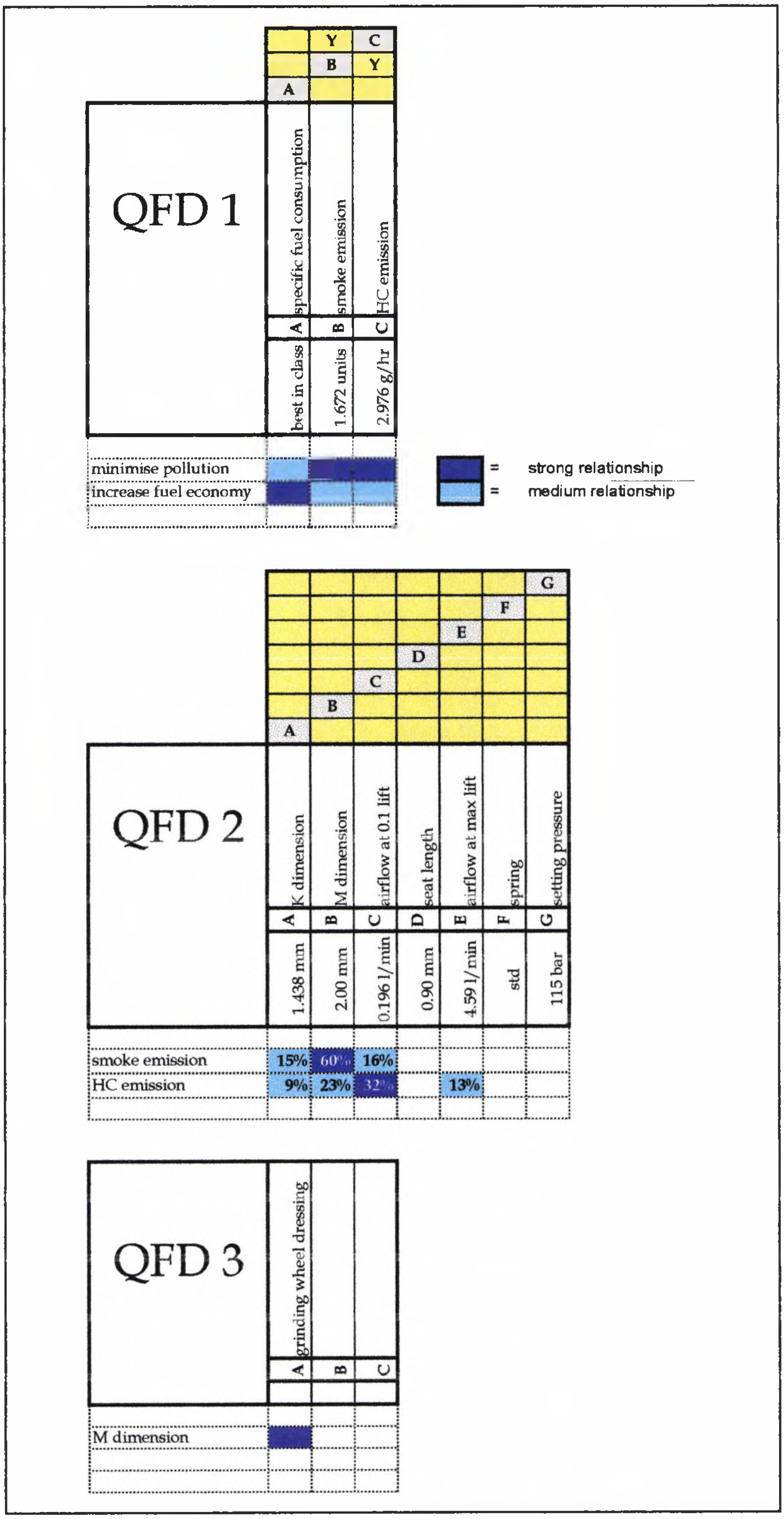


Fig. 7.13 Experiment results in QFD for design retrieval

7.5.2 Conclusions

Model-based methods give considerable flexibility in situations where judgement needs to be made about conflicting outputs. In this case there is a trade-off between hydrocarbons and smoke which is itself a function of design factors and a noise or uncontrollable factor. The noise can be modelled allowing different kinds of performance characteristics (average, peak) to be investigated. Also presentation of models for each output allows different weightings to be studied *after* analysis and in particular sensitivity (tolerance) analysis performed, for example at optimum settings. Differences in noise distribution across factor levels can be accounted for in analysis.

The principal objective is to produce robust designs and the model-based approach can target decision-making more accurately. The critical terms in the model are the design $\times$ noise interactions and these can be used to reinforce the standard parameter design approach.

Chapter 8. Conclusions

8.1 Discussion

The following five sub-sections refer to the five specific project objectives identified in Chapter 3, although there is some inevitable overlap of discussion.

8.1.1 New correlation roof

8.1.1(a) Task partitioning

The existing correlation roof was found to be under utilised due to a perception that its completion is too time-consuming for the return gained. This work has shown that the new QFD phase 1 roof can yield a valuable return in establishing a design procedure by clarifying the dependencies and interdependencies between design functions or tasks represented by the design requirements. Problem decomposition is inherent to the Quality Function Deployment methodology to the extent that it clearly links the market requirements to manufacturing through design. However, new aspects related to decomposition such as task organisation and integration methods (Eppinger, 1997) are currently the focus of much design research. By introducing a task partitioning approach into Quality Function Deployment we have opened up the possibility of incorporating appropriate developments from task organisation research. The correlation roof method described is also mainly intended to provide a simple graphical aid in the form of the correlation chain hierarchy for deepening understanding of the design problem. Processing this phase 1 correlation roof is well suited to an expert system.

Correlation chains in design procedures are applied at the most divergent point in the design process where creative activity has just begun. At this point the interface between intuition and proof calls for readily understood graphical cues about the design problem and its constraints.

The meaning of the term function has been addressed in the literature yielding several taxonomies. For the QFD phase 1 correlation roof the meaning of function in terms of solution-neutral design requirements has been shown to be less important for redesign problems as the general concept design is already decided and thus phase 1 becomes more an issue of embodiment design. Design requirements should therefore be '*embodiment-neutral*'. Generally, the relationships identified in the new correlation roof are in terms of an information source that has a direct and substantial influence between one design requirement and another. This important emphasis on information flow we have termed ***'procedural causality'*** as opposed to ***physical causality*** (phase 2) and the difference is highlighted in the hedgetrimmer case study for the relationship between blade speed and motor specification. In phase 1 therefore procedural causality is concerned with how the blade speed decision informs the motor specification required to achieve it, whereas in phase 2 the physical relationship dictates that the motor specification causes the blade speed. In other words with embodiment will come changes in causality assignments from the procedural to the physical. In QFD phase 2 the link with Robust Engineering Design demonstrated suggests a suitable meaning for function as relating to the transfer or modifying of energy flow through the system.

Clarifying design procedure (decomposition of task) is important in dealing with modularisation (decomposition of product) which is where coupling the correlation chain concept with Modular Function Deployment (Erixon, 1995) would appear to make the sub-division of embodiment design process more complete. This also has important potential for the dynamic approach to Robust Engineering Design (Taguchi, 1993) which encourages a modular approach to experimentation with complex systems. We have shown that the clustering of the design tasks enables grouping of tasks that might be performed simultaneously. Some of these tasks share an interdependence, i.e. they are coupled, which means that iteration is likely before all subjects of these tasks can be assumed to be satisfied. Interdependence also highlights where teamwork is required to be most intensive due to the cross-flow of information required. For example for the solar car design (Chapter 3) there is a high degree of coupling identified between certain aspects which should be addressed by the same team as the best way to process the information flow. If any coupled functions can be estimated within satisfactory limits this would speed up the design process. In the hedgetrimmer case study weight and reach maintain a coupling effect on several design functions which can be reduced by setting target values to work with. There is a balance to be struck on the amount of causation (or interaction) identified in the phase 1 correlation roof. Too few interactions might have an effect on product quality as many views (i.e. information flow) will not be brought to bear on certain functions. Too many interactions if they lead to a high degree of coupling could congest the design process with iterative loops (e.g. solar car).

We will not always minimise coupling between design tasks, which appears to run contrary to the 1st axiom of Suh (1988) that states independence of function requirements. Coupling is an important driver of simultaneous engineering because it is concerned with design issues coming together, typically through teamwork, where a better integrated solution may result. As the early stages of design are complex and unpredictable then iterations seem necessary and preferable in order to reach a solution that is a presentable design which again suggests teamwork for complex products. Further improvement to the design process may come from redefining the tasks thus altering the interdependencies to form preferred groupings (correlation chains). We anticipate that these groupings may not coincide with traditional subsystems. Related to this issue is that the phase 1 correlation roof as currently presented is binary, thus the interactions are identified such that a function either does or does not depend on another. By assigning a value to the interaction (numerical or qualitative) then the strength of coupling is clarified thus enabling selective decoupling if it suits the design procedure. We can consider this interaction strength either in terms of degree of influence where a small value may be decoupled; or in terms of uncertainty of information where a small value, indicating a high degree of confidence in the anticipated accuracy of information, will allow a dependent task to start and thereby effectively decouple it.

The designs tackled with the phase 1 correlation roof have both been redesign problems. One aspect of redesign that could form a barrier to using the new correlation roof in practice is that existing design procedures are likely to be firmly in place preventing a preferred grouping of coupled design functions.

Comincini (1994) proposed that the correlation roof could be replaced by correlation chains implanted in the main relationship matrix but we have shown that the benefits of a new correlation roof override this move:

(i) The resultant correlation network helps to document design procedures and speed design.

(ii) Clarifying information flow deepens understanding of the design problem.

(iii) Identifying dependencies stimulates sharing of data and facilitates appropriate teamwork interaction therefore improving design quality.

8.1.1(b) Link with RED

The partitioning of the design problem described above suggests boundaries within which to confine Robust Engineering Design experiments for the benefit of procedure or team allocation. However, the loudspeaker driver unit experiment has shown that in confining the Robust Engineering Design experiment to a particular subsystem, there is a risk of leaving out some significant design factors. This constraint reflects the industrial imperative of balancing experiment effectiveness with design efficiency. The link between Robust Engineering Design and the correlation roof of Quality Function Deployment phase 2 has been approached on two fronts. Firstly, the use of simulation techniques in the loudspeaker voice-coil and hedgetrimmer cases to estimate the correlation roof and Robust Engineering Design interactions, and secondly, subsequent physical RED experiments to establish actual values. In particular the loudspeaker example has demonstrated the introduction of numerical values to the correlation roof as an enhancement which is similar to the numerical correlation chains proposed by Comincini (1994). Furthermore in quantifying the relationships in the main relationship matrix we could consider this as establishing of a design quality metric for comparing and improving design performance. However it is likely that an entirely numerical approach may prove difficult to complete and in practice a mixture of quantitative and qualitative relationships will be used.

8.1.1(c) Design retrieval

The role of the correlation roof in design retrieval has been discussed in the literature. Comincini's (1994) proposal to replace the correlation roof with correlation chains has already been challenged above on the grounds of design procedure; and for design retrieval we have seen that the new correlation roof presents information on causality not shown by the Comincini correlation chain approach. For the loudspeaker driver unit it was shown that quantifying the correlation roof relationships provides valuable information for subsequent redesign activity. As part of linking Quality Function Deployment and Robust Engineering Design the results of physical experiments may be used to revise the relevant critical part characteristic values and in particular their correlation values.

8.1.2 Energy-based Robust Engineering Design

8.1.2(a) Bond graphs

The use of bond graphs as a front-end to Robust Engineering Design has been demonstrated via a three-step process. The graphical insight of bond graphs is a skill acquired with practice and the voice-coil example has demonstrated that causality identified in the bond graph confirms correlations found in experimentation. Moreover, design synthesis using bond graphs has been demonstrated by several researchers (e.g. Ulrich & Seering, 1989; Redfield, 1992) to be able to generate novel solutions to given problem specifications. However determining the significance of model parameters requires numerical values to be used with a bond graph simulation or visualisation/analysis of the state-space equations. Either of these approaches requires significant knowledge of bond graph methodology for effective Robust Engineering Design use.

We have encountered limitations in the method in terms of the ease of modelling the kind of non-linear complexity associated with Robust Engineering Design. For example in the hedgetrimmer, correctly modelling the motor torque-speed characteristics has proved to be at the limit of novice capability. Enhancing this model further by representing the blade stick-slip friction (Karnopp, 1985) is desirable yet friction generally is a difficult parameter to represent accurately. Another limitation of the bond graph method applied to Robust Engineering Design is that only parameters expressed in energy terms are included, thus some important parameters that can only be expressed in non-energy or pseudo terms will not be represented in the model. Several other advanced aspects of bond graphs for use in Robust Engineering Design development include:

(i) Using distributed parameters in place of lumped parameters, e.g. to represent the loudspeaker diaphragm (rather like Finite Element Analysis).

(ii) Modulating certain elements to accurately reflect dynamic component behaviour such as the yoke/crank mechanism used in the hedgetrimmer bond graph.

(iii) Non-linear constitutive equations describing the relationship between effort and flow of, for example, motor torque-speed curves.

(iv) Libraries of bond graphs components to be accumulated so that they can be utilised more effectively as a front-end to Robust Engineering Design for large complex systems, particularly in mechatronics.

(v) Like all graphical techniques conveying complexity is cumbersome therefore hierarchical models need to be produced.

Recently Bleakely et al (1997) have proposed a link between Design Function Deployment and Activities-Channels-Pools diagrams for the concept/embodiment interface of Quality Function Deployment methodology. ACP diagrams are a mechatronic modelling tool. However, bond graphs have a number of distinct advantages over ACP diagrams. The first is the rapid causal information inherent in the graphical notation. Secondly, the efforts and flows of bond graphs are not separated therefore the geometric topology of the physical system is preserved. Thirdly, the system equations are quickly and easily generated from the graph.

8.1.2(b) Dimensional analysis

Dimensional analysis provides a more general and abstract view of the underlying system of equations describing the physical system than bond graphs. Therefore there is a distinct risk that aliasing of parameters, especially geometry, will occur where there is a lack of system knowledge. The link between dimensional analysis and Robust Engineering Design and its relevance to sliding factor levels was described in Chapter 3. Additivity is an important Robust Engineering Design issue and we have shown a way of identifying the non-transformable interaction relationships between design factor levels. Thus the Hamada & Wu (1995) equation is unnecessary when sliding levels are determined from engineering science as scaling and centering are automatically dealt with by the physics.

Dimensional analysis of the loudspeaker voice-coils has confirmed that experimental groups can be identified for an Robust Engineering Design experiment using dynamic similarity. However setting sliding levels was frustrated primarily by the random nature of the design factor levels used from production. In addition, *Bl* (known as 'shove factor') the non-transformable interaction identified in the π_1 group is one compound parameter and therefore can only be slid if an experiment of greater resolution is configured that addresses *B* and *l* separately. In this case for π_1 *l* will be slid against *B* according to $l = shove\ factor\ value\#1/B$ and so on. For the mixing system a more practicable arrangement of sliding factor levels has been identified.

A generalisation of dimensional analysis in Robust Engineering Design is that the more restrictions that are placed on the model in the form of $\pi=C_i$ the more the restrictions that are placed on the degrees of freedom for the Signal-to-Noise Ratio. This was touched upon in matching the voice-coils by virtue of each π group being interrelated via shared parameters.

8.1.2(c) Noise factor categories

Our survey of noise factors has revealed that energy-based noise factors account for approximately half (27% direct- and 19% indirect-energy) of all influential noise factors. With such a high proportion we have argued that the conventional internal/external/unit-to-unit categories should be enhanced with energy sub-categories in order to stimulate an appropriate view of the system under investigation. This development is of course compatible with using the bond graph front-end. The survey also revealed that the use of load noise factors is a relative small proportion. In the diesel injector experiment we demonstrated a representative weighted approach to using load as a noise factor where the loading pattern is known. Load was also effectively used as a noise factor in the hedgetrimmer case study.

8.1.3 Factor levels in production

8.1.3(a) Design factors

The use of design factor levels off the production line is attractive in terms of convenience and economy particularly for high value-added and precision products. The diesel injector experiment used actual production values to achieve design factor levels that had detectable effects on performance even though the levels were relatively close. We agree that wide levels are ideal, Phadke (1989) states, from an electronics standpoint, that "sensitivity does not change with small level differences". Refraining from pondering what is 'small', we have seen a familiar and contradictory phenomenon confirmed for narrow levels in mechanical engineering production - fine features can have big influences.

8.1.3(b) Noise factor distribution effects

The effect of noise factor level distribution on the design factor effects has been addressed and a method for taking into account the unit-to-unit noise factor bias between design factor levels has been introduced. For the diesel injector experiment the apparent effect of one design factor was reduced for both quality characteristics and for another the optimum level was shifted from being opposite to being the same in both cases subsequent to adjustment. This highlights the importance of paying due attention to the actual distribution of noise factor values in practice. In this thesis the *consistency* of noise factor levels across design factor levels has been shown to be of comparable importance to their *width* particularly for a production-based Robust Engineering Design experiment. It's another aspect of the design factor -noise factor (DxN) interaction central to the Robust Engineering Design philosophy.

8.1.4 Noise factor level weightings

This a departure from the Taguchi approach which samples noise space with equal probability. We have shown how noise (load on the diesel injector engine) can be weighted in the analysis and furthermore in the Signal-to-Noise Ratio. In fact the weighted sampling of noise space was a representation of the noise space to be experienced by the actual product as depicted by emissions legislation. Further work on the method of adjustment to the local response based upon equalising noise variance would be valuable. The link between noise weighting and both the effect of - and the effect on - the environment is hinted at in the injector experiment. Here we might suggest that the environment (ambient conditions) affects the noise factor distributions (unit-to-unit noise), which affects the response variability (pollutant emissions) which in turn has a varying effect on the environment (ambient conditions) and so on.

8.1.5 Multiple objective optimisation in RED

8.1.5(a) Multiple objectives

Multiple objectives are inevitable in engineering design - a fact graphically illustrated by the many-to-many mapping of Quality Function Deployment and yet ignored in the Robust Engineering Design literature.

We have presented and demonstrated a multiple objective approach for Robust Engineering Design based on the quality loss function and also demonstrated a stochastic-to-deterministic approach using design factor - noise factor modelling. This consideration of multiple objectives has also unveiled an interesting aspect of the energy-based view of systems in terms of the choice of quality characteristics. From the diesel injector experiment we learn that whilst a single quality characteristic based on the ideal positive energy transfer of the system, e.g. specific fuel consumption, might be best used during the parameter selection stage; for the analysis stage we should use energy-related quality characteristics required by the customer, e.g. hydrocarbons and smoke and be prepared for trade-off. This shows that in certain cases if a negative output characteristic is of primary concern then there is a likelihood that in this negative domain energy can be manifested and traded in many forms. Therefore measuring the positive domain is not necessarily the reverse image of what we are interested in (apart from when there is 100% efficiency) from the negative domain. Thus relying on an energy view of the system in order to manifest a single objective, as correctly advocated by Fowlkes & Creveling (1995), Grove & Davies (1992), Phadke (1989), and Taguchi (1987), is not always a practical option.

Changes in the relative weighting of objectives has a bearing on the choice of optimum design factor level setting. We have shown that dealing with this benefits from checking the sensitivity of the decision to this weighting to be reassured that the optimum level is not close to switching. Dealing with multiple objective optimisation in Robust Engineering Design provides a last statement on linking with Quality Function Deployment where the design factor levels (critical part characteristics) are often related to two or more responses (design requirements) and found to be in conflict. Recording such conflicts in target values of critical part characteristics are not adequately catered for in Quality Function

Deployment. Changes to the presentation of the relationship matrix are all that is required.

There are situations where engineering understanding of the relationship between the output of a subsystem and that of the entire system is insufficient. For example, greater technological understanding between diesel injector spray characteristics and the engine emissions was required in order for the experiment to be conducted at a greater resolution and therefore enabling a much clearer link with factor effects on the injector performance. For the loudspeaker voice-coil/driver-unit outputs the link was more tenuous and constrained the simulation. Inevitably then multivariate problems encountered have to be reduced to univariate ones and the quality loss function has been shown to be well-suited to this task.

8.1.5(b) Competitive benchmarking

Competitive benchmarking has been shown to be a pragmatic way of establishing a dynamic quality loss function that promotes continuous improvement. The justification for using the quality loss function is in terms of its link with robustness and its customer orientation whereas alternatives like the desirability function have weighting values that are difficult to pitch. For the injector experiment it was shown that differences in the significance (e.g. hydrocarbons emission twice as dangerous as smoke) of the objectives could be superimposed on this loss function approach. In this case it consolidated the initial decision. Furthermore we established a critical range akin to a confidence interval on these decisions.

8.1.5(c) Capability mapping

The effect of noise factor distribution on the multiple objective decision-making process was an additional consideration of the modelling approach that makes it feasible to avoid rejecting product on the basis of geometric non-conformance when the desired performance can still be achieved. The diesel injector experiment demonstrated that selective assembly of out-of-tolerance injectors could match the emissions performance of conforming product by virtue of a multiple objective approach that incorporates production capability.

8.1.6 Future work

Some future developments are addressed in the above discussion but they can be summarised as:

(i) The new Quality Function Deployment phase 1 correlation roof can be developed to include the significant amount of current research into task decomposition. In addition the applicability of the methods to original design problems requires investigation.

(ii) Applying the bond graph to a more complex system in preparation for a large experiment would fully demonstrate the power of the new Robust Engineering Design method for complex systems. Furthermore, the modelling of non-linear constitutive equations should be attempted in order to identify more complex robustness enhancing opportunities. Dimensional analysis should be further investigated in terms of scale effects on robustness.

(iii) Extensive production trials to determine noise factor distributions would enable more accurate simulation of the effects of unit-to-unit noise on proposed designs.

(iv) The orthogonal contrasts used in the injector experiment assumed equal spacing between noise factor (load) levels. A method of accommodating unequal spacing would appear a useful development.

(v) Expanding the multiple objective optimisation to more than two quality characteristics would perhaps present new challenges in terms of defining the quality loss functions and making trade-offs between conflicting design factor levels

8.2 Conclusions

8.2.1 Hypothesis #1

This thesis has dealt with practical enhancements to Robust Engineering Design in terms of strengthening the links with the design process (Quality Function Deployment) and production constraints. Pragmatic approaches to Robust Engineering Design described herein that involve engineering science and production capability in parameter selection and level setting can yield effective results efficiently. It has been shown that for parameter selection in dynamic systems energy-based considerations of the system yield some valuable insights into causal relationships and non-transformable interactions. Dealing with the effects of noise factors on the analysis in a production environment has been demonstrated, together with weighted noise sampling. A strategy for dealing with multiple objectives in Robust Engineering Design has emerged.

8.2.1 Hypothesis #2

Through the case studies we have shown a clear link between Robust Engineering Design and Quality Function Deployment phase 1 to phase 3 in terms of multiple objectives. The link between Robust Engineering Design and Quality Function Deployment has also been addressed via a new correlation roof that provides a general contribution to design procedure and design retrieval. The new phase 1 correlation roof promotes deeper understanding of the design problem in terms of the flow of design information. Therefore it is reasonable to assume that better design solutions will follow.

Glossary

additivity is a desirable superposition property of Robust Engineering Design where the estimated effects of individual features or parameters of a product can be assumed to be independent and therefore added in order to make a reliable prediction of performance.

Analysis of Variance (ANOVA) is a statistical data analysis method that decomposes the variability inherent in data into its component parts.

compound noise factors are uncontrollable disturbance parameters of a product whose settings are grouped with others according to having the same effect on directionality of the measured response. (see noise factors).

confounding - where the effects of product features are numerically "mixed up" with interaction effects between product features by the experimental plan being used in a Robust Engineering Design experiment. This makes it difficult to determine the actual effects of the confounded product features if the interaction effects are strong.

control factor - see design factor.

Critical Part Characteristics are the main product features relating to design requirements in Quality Function Deployment.

Critical Process Characteristics are the important process features that determine whether critical part characteristics will be achieved in Quality Function Deployment.

degrees of freedom (dof) Used to describe the size of an experiment and how much information can be extracted.

Design of Experiments (DoE) This is an established approach to planned design experimentation that utilises mathematically-based matrices in order to methodically gather response data and efficiently evaluate the effects of design features.

design factor is a product feature or parameter set (or controlled) by the designer. and more generally known as a control factor. The settings chosen for the design factor are known as levels.

dynamic characteristic - a powerful approach to Robust Engineering Design in which the functional intent of a product (its "signal") and its output are studied and optimised in terms of linearity, sensitivity and variability over a signal range.

experimental trial - any particular combination of design factor level settings (see Orthogonal Array).

factor effect - see main effects.

factor level an integer representing a common setting or value of a factor used in the experiment.

fractional factorial is an Orthogonal Array that searches all possible design factor combinations using only a subset of combinations.

full factorial relates to all the possible combinations of factor levels being tested.

function decomposition is the dividing of the main function of a product into subfunctions as part of a design methodology.

interaction is where the effect of one design factor level setting depends upon that of another.

main effects - the net mean contribution a factor makes to the measured change in response independent of interaction effects and experimental error.

noise factor is a parameter that is uncontrollable and acts as a disturbance to the system robustness. Reducing its effect is the object of RED.

Orthogonal Array (OA) - a matrix that sets out a plan for a series of experiment trials in a balanced way such that more than one design factor at a time can be changed between trials and yet the independent effects of the factors can be established.

Quality Characteristic (QC) is a quantified measure of the product output or function, ideally in energy terms, that directly affects the customer's satisfaction.

Quality Loss Function is a function used in Robust Engineering Design to represent the idealised cost to society 'beyond the factory gates' of a product deviating from its intended performance and incurring costs due to personal injury, lost time, inconvenience and many other losses.

robustness is a desirable property of a product where it is insensitive to the effects of noise factors without the noise factors being removed.

saturated orthogonal array is an orthogonal array in which all the columns are allocated a design factor. Thus confounding is inevitable.

signal factor is a parameter often representing an intent or demand by the user which changes the average response of the product. In conventional *static* experiments the signal is assumed to be constant.

Signal-to-Noise Ratio (SNR) is a transformation of the response data which relates the mean (useful part) to the standard deviation (nonuseful part) as an objective function for improving additivity.

trial - see experimental trial.

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Appendix A Diesel Injector Experiment Data

A Robust Design experiment was conducted on diesel fuel injectors to investigate the performance of injectors falling outside the specified limits on a critical dimension.

In the manufacture of these nozzles the nozzle hole is a particularly difficult feature of the design to keep within the specified limits due to the capability of the process used and the fact that it has a negative taper, i.e. it has a larger diameter inside than at the exit. Consequently up to 15% of the nozzle holes are produced oversize - termed 'B' size. Those within specification being termed 'A' size. The 'B' size nozzles can have pintles matched to them in order to achieve the specified flow-lift characteristics. However, ultimately engine tests are required to verify the performance of the injectors, particularly as the effect of the difference between 'A' size and 'B' size on pollutant emissions is not nearly as well understood as for the effect on engine characteristics such as torque and power. For this reason the effect of design parameters on pollutant emissions was investigated.

Several types of engine test were conducted but the experiment data considered here is from the 2400 rpm loop tests which represent high vehicle cruising speed. The engine was held at a constant speed of 2400 rpm and subjected to various loads between full-load (800 kPa BMEP) and no-load (20 kPa BMEP).

The smoke values are obtained by taking a one litre sample of the exhaust and passing it through filter paper. A light source is then shone through the resultant deposits onto a photosensor which assigns a value to the intensity of light between 0 (clear) and 9 (total blackening). HC is measured more directly with special sensors.

The responses recorded are the lower-the-better signal-to-noise values based upon six data points using the equation $\mathrm{SNR}_{\mathrm{LB}} = -10 * \log_{10}(\frac{1}{n}\sum_{i=1}^{n} y_i^2)$.

Analysis of Variance (ANOVA) on the data revealed the following:

		smoke	HC	SFC
x_A	K dimension	15.0%	9.1%	-
x_B	M dimension	59.9%	23.2%	-
x_C	air flow @0.1 lift	16.1%	31.7%	7.1%
x_D	seat length	-	-	20.8%
x_E	air flow @max lift	-	13.3%	7.0%
x_F	spring	-	-	25%
x_G	setting pressure	-	-	-
	(error)	(9%)	(22.7%)	(40.1%)

Analysis of a designed experiment using an L8 array

1. Experiment title

Title	HC

2. Design factors assigned to OA columns.
Response values are lower-the-better SNR for HC emissions.

Row no.	Kdim	Mdim	air0.1lift	seatlength	airmaxlift	spring	pressure	Response	Actual run order
1	−	−	+	−	+	+	−	-12.39	8
2	+	−	−	−	−	+	+	-14.17	4
3	−	+	−	−	+	−	+	-11.55	6
4	+	+	+	−	−	−	−	-11.23	2
5	−	−	+	+	−	−	+	-12.15	7
6	+	−	−	+	+	−	−	-13.57	3
7	−	+	−	+	−	+	−	-11.56	5
8	+	+	+	+	+	+	+	-11.84	1
							Average	-12.308	

3. Factor names and descriptions of the levels

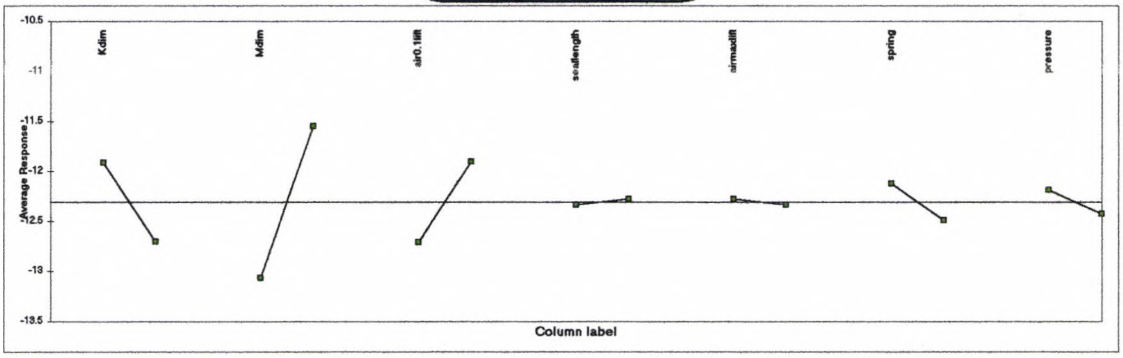
Factor name	Abbrev-iation	Description of (-) level	Description of (+) level
K dimension	Kdim	av1.438	av1.406
M dimension	Mdim	2.43	2.00
air flow @ 0.1mm lift	air0.1lift	av0.188	av0.196
seat length	seatlength	0.90	0.76
air flow @ max lift	airmaxlift	av5.09	av4.59
spring	spring	exp	std
setting pressure	pressure	126	115

Response table

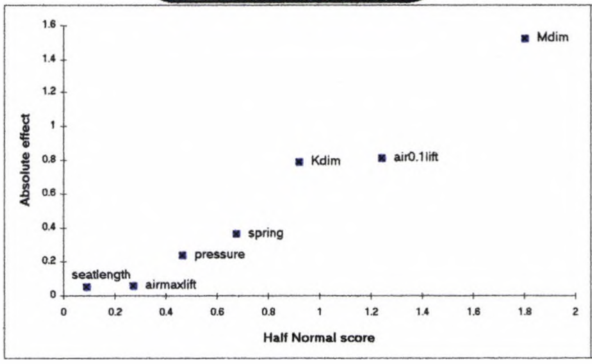
	Kdim	Mdim	air0.1lift	seatlength	airmaxlift	spring	pressure
Average at (+)	-12.702	-11.545	-11.902	-12.280	-12.337	-12.490	-12.427
Average at (–)	-11.913	-13.070	-12.713	-12.335	-12.278	-12.125	-12.188
Effects	-0.790	1.525	0.810	0.055	-0.060	-0.365	-0.240

4. Analysis of effects:

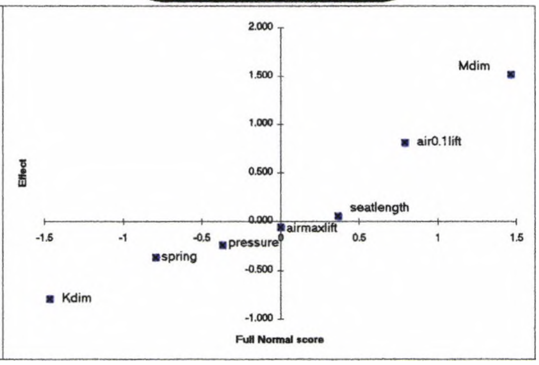
Effects plot



Daniel plot



Full Normal plot



Analysis of a designed experiment using an L8 array

1. Experiment title

Title	smoke

2. Design factors assigned to OA columns. Response values are lower-the-better SNR for smoke emissions

Row no.	Kdim	Mdim	air0.1lift	seatlength	airmaxlift	spring	pressure	Response	Actual run order
1	–	–	+	–	+	+	–	-3.38	8
2	+	–	–	–	–	+	+	-3.77	4
3	–	+	–	–	+	–	+	-3.10	6
4	+	+	+	–	–	–	–	-4.73	2
5	–	–	+	+	–	–	+	-3.89	7
6	+	–	–	+	+	–	–	-2.85	3
7	–	+	–	+	–	+	–	-3.96	5
8	+	+	+	+	+	+	+	-4.85	1
							Average	-3.816	

3. Factor names and descriptions of the levels

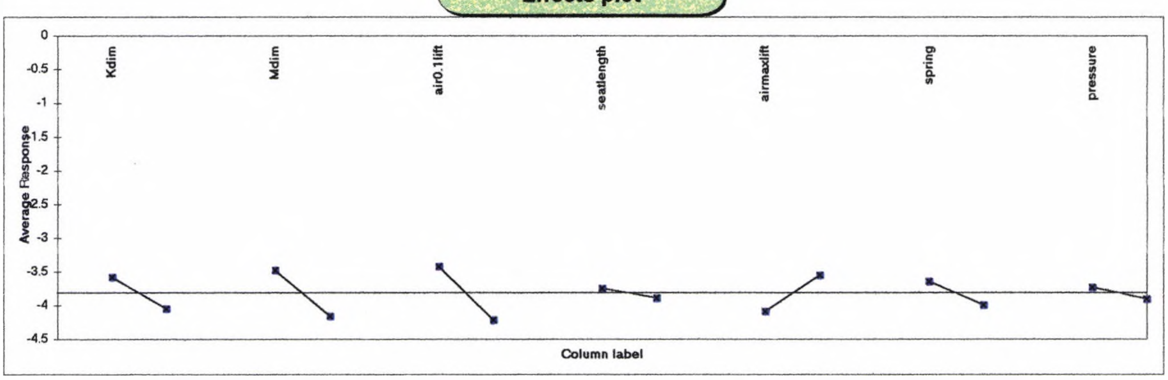
Factor name	Abbrev-iation	Description of (-) level	Description of (+) level
K dimension	Kdim	av1.438	av1.406
M dimension	Mdim	2.43	2.00
air flow @ 0.1mm lift	air0.1lift	av0.188	av0.196
seat length	seatlength	0.90	0.76
air flow @ max lift	airmaxlift	av5.09	av4.59
spring	spring	exp	std
setting pressure	pressure	125	115

Response table

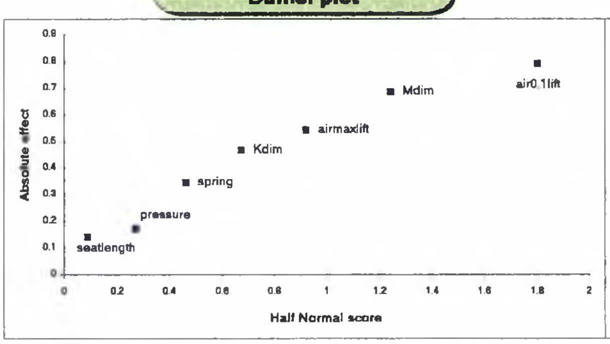
	Kdim	Mdim	air0.1lift	seatlength	airmaxlift	spring	pressure
Average at (+)	-4.050	-4.160	-4.212	-3.887	-3.545	-3.990	-3.902
Average at (–)	-3.583	-3.473	-3.420	-3.745	-4.088	-3.643	-3.730
Effects	-0.467	-0.687	-0.792	-0.142	0.543	-0.347	-0.172

4. Analysis of effects:

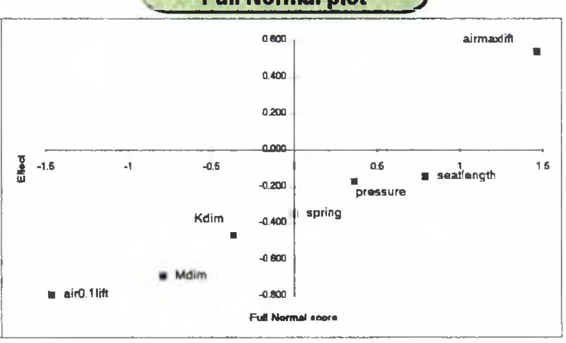
Effects plot



Daniel plot



Full Normal plot



Analysis of a designed experiment using an L8 array

1. Experiment title

Title	SFC

2. Design factors assigned to OA columns.

Response values are lower-the-better SNR for Specific Fuel Consumption

Row no.	Kdim	Mdim	air0.1lift	seatlength	airmaxlift	spring	pressure	Response	Actual run order
1	–	–	+	–	+	+	–	-9.37	8
2	+	–	–	–	–	+	+	-9.34	4
3	–	+	–	–	+	–	+	-9.42	6
4	+	+	+	–	–	–	–	-9.47	2
5	–	–	+	+	–	–	+	-9.77	7
6	+	–	–	+	+	–	–	-9.47	3
7	–	+	–	+	–	+	–	-9.45	5
8	+	+	+	+	+	+	+	-9.42	1
							Average	-9.464	

3. Factor names and descriptions of the levels

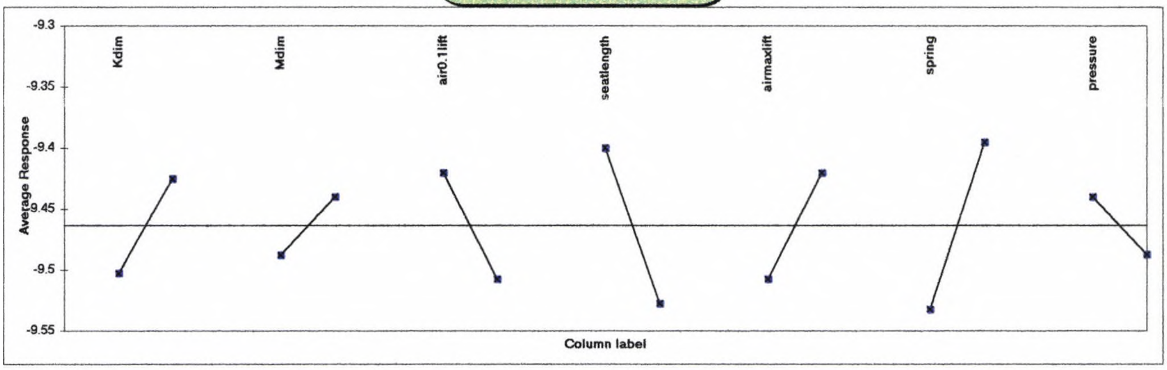
Factor name	Abbrev-iation	Description of (-) level	Description of (+) level
K dimension	Kdim	av1.438	av1.406
M dimension	Mdim	2.43	2.00
air flow @ 0.1mm lift	air0.1lift	av0.188	av0.196
seat length	seatlength	0.90	0.76
air flow @ max lift	airmaxlift	av5.09	av4.59
spring	spring	exp	std
setting pressure	pressure	125	115

Response table

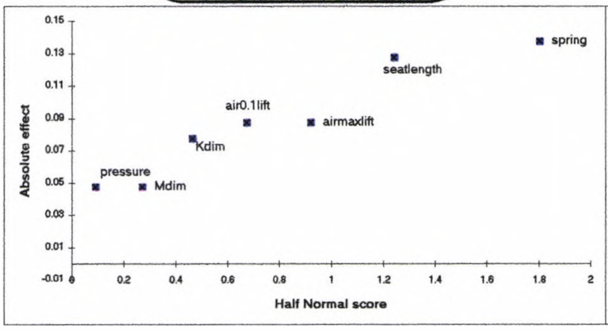
	Kdim	Mdim	air0.1lift	seatlength	airmaxlift	spring	pressure
Average at (+)	-9.425	-9.440	-9.507	-9.527	-9.420	-9.395	-9.487
Average at (–)	-9.503	-9.488	-9.420	-9.400	-9.508	-9.533	-9.440
Effects	0.078	0.048	-0.087	-0.127	0.088	0.138	-0.047

4. Analysis of effects:

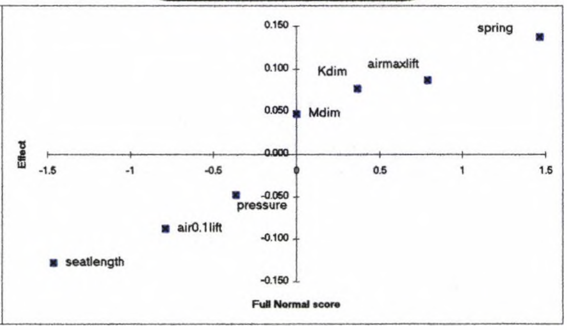
Effects plot



Daniel plot



Full Normal plot



Appendix B Hedgetrimmer Teamwork

This appendix contains samples of work produced by two teams applying the QFD and Robust Design methodologies to the design of a hedgetrimmer for a major garden tool manufacturer.

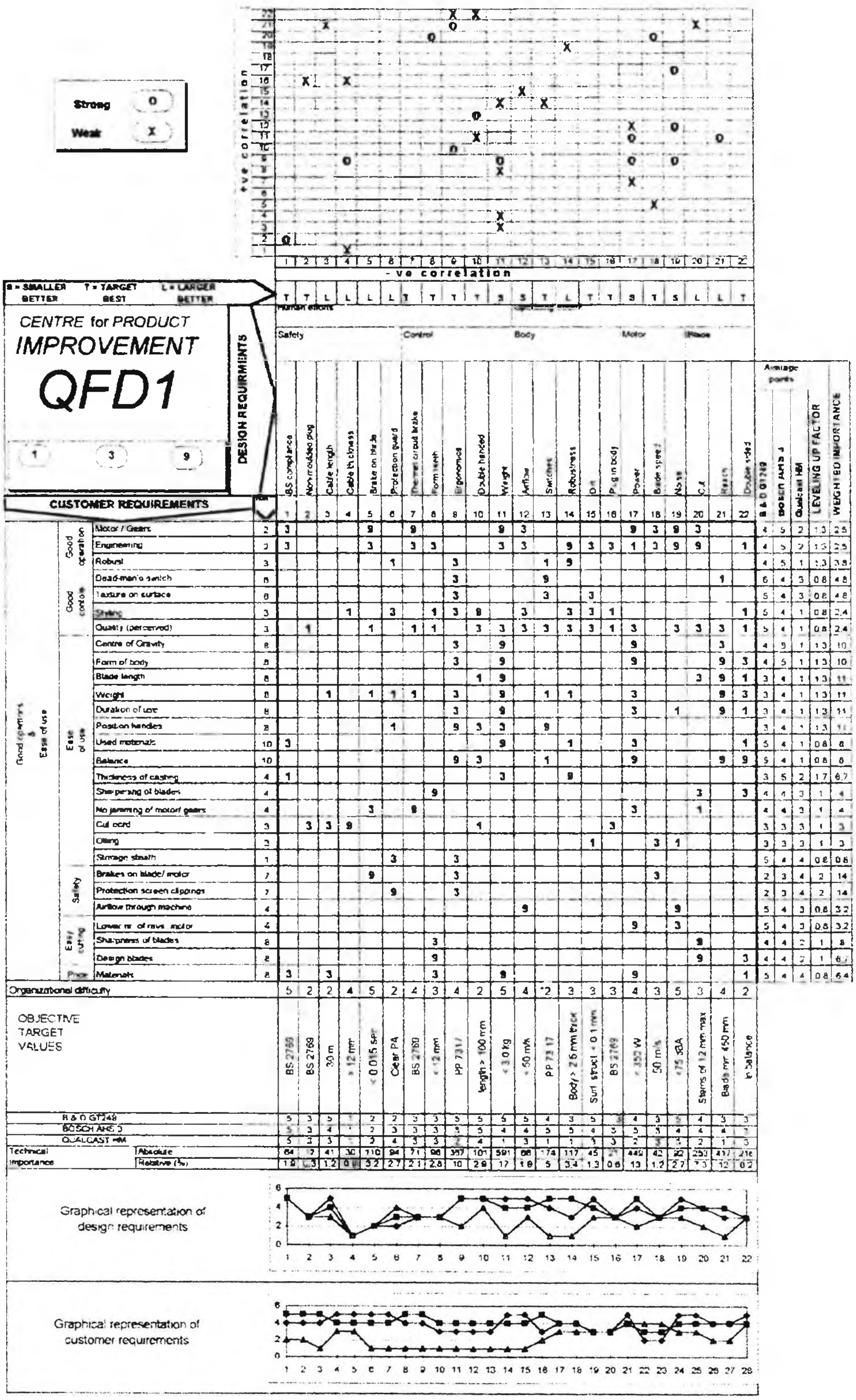


Fig. B.1 Team A QFD phase 1 output (de Wildt, 1996)

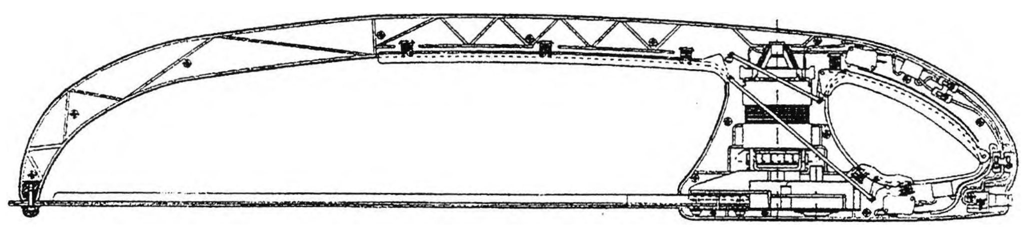


Fig. B.2 Team A concept design (de Wildt, 1996)

L8 OA	brush material	blade lubrication	brush spring	blade friction	motor speed	blade mass	motor ventilation	stop time (seconds)										mean	stdev	SNR(SB)
1	Carbon	none	std	std	std	std(500g)	std	2.59	2.56	2.98	2.62	2.22	2.59	2.59	2.86	2.37	2.31	2.57	0.234	-8.23
2	Carbon	none	std	lower	slower	+620g	none	0.02	0.08	0.07	0.07	0.16	0.05	0.04	0.1	0.06	0.07	0.07	0.038	21.88
3	Carbon	oiled	inc. force	std	std	+620g	none	1.37	1.88	2.05	1.96	1.99	1.44	1.69	1.82	1.88	1.96	1.80	0.233	-5.19
4	Carbon	oiled	inc. force	lower	slower	std(500g)	std	0.86	0.59	0.68	0.76	0.4	0.72	0.74	0.72	0.77	0.86	0.71	0.135	2.88
5	Copper	none	inc. force	std	slower	std(500g)	none	0.006	0.03	0.02	0.06	0.08	0.02	0.03	0.04	0.04	0.04	0.04	0.021	27.59
6	Copper	none	inc. force	lower	std	+620g	std	0.04	0.04	0.04	0.03	0.04	0.03	0.03	0.04	0.03	0.03	0.04	0.005	29.03
7	Copper	oiled	std	std	slower	+620g	std	0.03	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.05	0.04	0.006	27.67
8	Copper	oiled	std	lower	std	std(500g)	none	0.11	0.19	0.24	0.24	0.14	0.12	0.16	0.2	0.2	0.18	0.18	0.045	14.74

Fig. B.3 Team A robust design experiment (de Wildt, 1997)

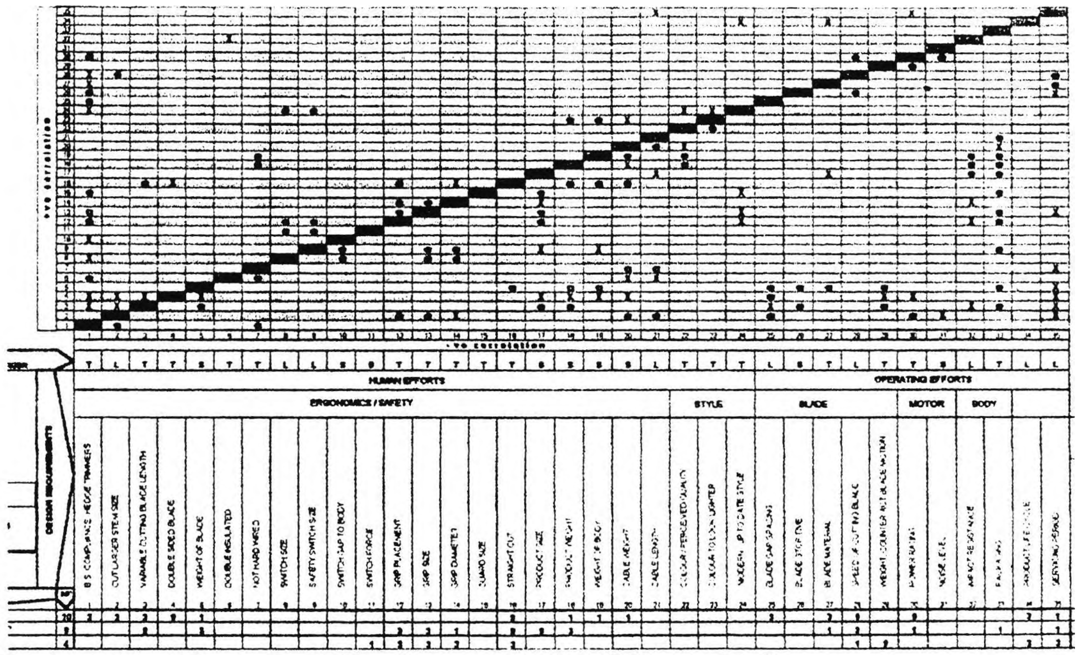


Fig. B.4 Team B QFD phase 1 output (King, 1996)

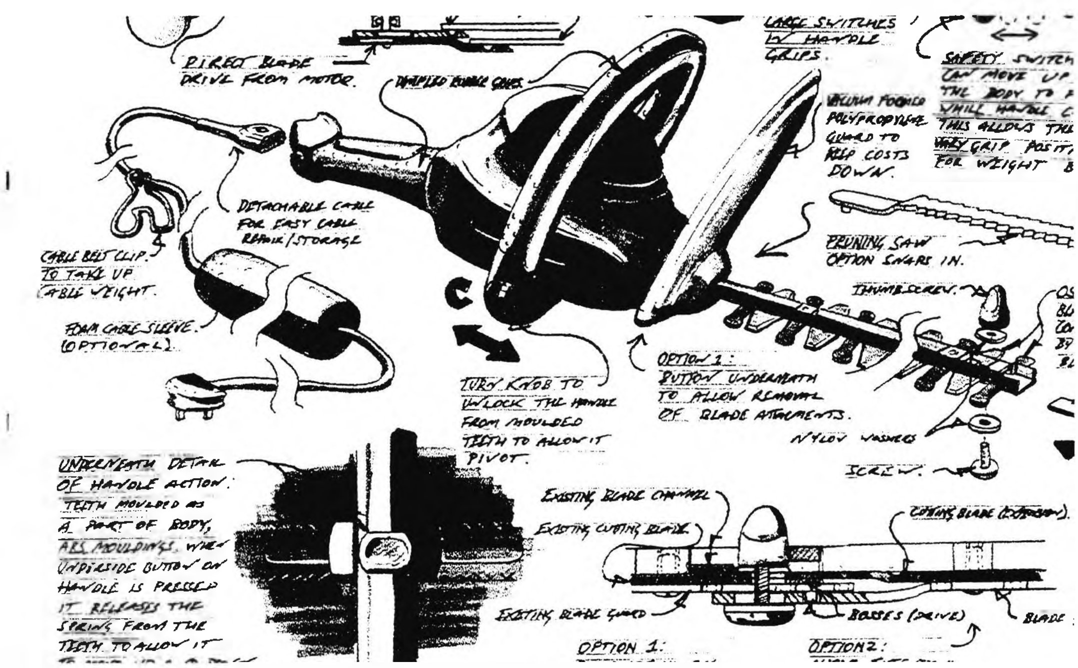


Fig. B.5 Team B concept design (King, 1996)

L9 OA	internal wire CSA	blade friction	brush spring	blade mass	blade speed (measured in stroboscope flashes per sec)										mean	stdev	SNR(LB)
1	std 0.5mm dia	std contact area	std 22mm length	std 500g	2010	2020	2010	2020	2015	1850	1900	1910	1910	1910	1956	65.2	65.81
2	std 0.5mm dia	33% of std	26 mm length	810g	1900	1920	1920	1915	1910	1795	1820	1820	1820	1820	1864	52.5	65.40
3	std 0.5mm dia	25% of std	30mm length	1120g	1620	1600	1600	1605	1600	1540	1535	1540	1545	1540	1573	34.8	63.93
4	2mm dia	std contact area	26mm length	1120g	1890	1850	1890	1870	1880	1715	1720	1720	1720	1715	1797	84.0	65.07
5	2mm dia	33% of std	30mm length	std 500g	1910	1940	1935	1930	1925	1780	1830	1800	1810	1815	1868	65.4	65.41
6	2mm dia	25% of std	std 22mm length	810g	1875	1890	1850	1870	1860	1600	1600	1600	1610	1615	1737	139.6	64.72
7	3mm dia	std contact area	30mm length	810g	1885	1855	1890	1895	1890	1790	1795	1760	1800	1795	1836	52.3	65.27
8	3mm dia	33% of std	std 22mm length	1120g	1780	1765	1765	1765	1765	1700	1710	1715	1715	1710	1739	31.2	64.80
9	3mm dia	25% of std	26mm length	std 500g	1950	1945	1990	2000	1990	1840	1850	1850	1850	1845	1911	69.6	65.61

Fig. B.6 Team B robust design experiment (King, 1997)