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Automatic Identification of Critical Design Relationships

by

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Automatic Identification of Critical Design Relationships

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Abstract

As part of the preliminary design, the designer must evaluate the benefits of many alternative design configurations, each of which may depend on a large number of design variables. Even after many alternatives are discarded using qualitative or experiential reasoning, the designer may have to further restrict his alternatives by performing a preliminary quantitative evaluation.

Even very simplified design equations may be puzzling to an inexperienced designer in that a change in any one of the design variables will often influence many functional requirements. As a result, it is difficult to evaluate the merits of the design without more detailed analysis. Experienced designers, on the other hand, are often able to identify important relationships which govern or limit design performance. Identifying important relations, such as a critical ratio or difference, not only contributes to convenience and expediency, but preserves the physical reasoning associated with the design activity and helps focus the designer's creativity toward the governing or limiting aspects of the proposed solutions.

A computer based system has been developed to assist the designer in identifying important design relationships. The system operates on a set of simplified design equations to produce sets of transformed equations in terms of some alternative design variables. The alternative variables are chosen for physical significance and for correspondence to functional behavior. The transformed sets of equations can be thought of as providing an alternative view of the design configuration. They are expected to enhance the physical insight of the designer, to help in identifying governing relationships among design variables and function, and to assist the designer in evaluating performance limitations of alternative design configurations.

Inhaltsangabe

Während des Vorwurfstadiums muss der Konstrukteur die Vor- und Nachteile verschiedener Entwurfsbewerter, jeder dieser Entwürfe hängt von vielen Entwurfsvariablen ab. Sogar nachdem viele Alternativen aus qualitativen oder funktionalen Gründen ausgeschlossen sind, kann der Designer die Alternativwahl durch frühzeitige zahlenmäßige Bewertung weiter beschneiden. Selbst stark vereinfachte Entwurfsregeln können einen unerfahrenen Designer verwirren, dadurch dass eine einzelne Entwurfsvariable viele funktionale Bedingungen beeinflusst. Daher ist es schwierig die Vorteile eines Entwurfs ohne detaillierte Analyse abzuschätzen. Andererseits können erfahrene Konstrukteure wichtige Randbedingungen erkennen, die eine Entwurfsdurchführung unterstützen oder einschränken. Die wichtigen physikalischen Beziehungen, wie Gefügeverhältnisse oder physikalische Messgrößen zu erkennen trägt nicht nur zur Vereinfachung und Zweckmäßigkeit bei, sondern bewahrt auch die physikalischen Beziehungen, die mit dem Entwurf verbunden sind und hilft dem Konstrukteur seine Energie auf die wichtigen Faktoren der angestrebten Lösung zu konzentrieren.

Es wurde ein itchnergestütztes System entwickelt, das den Konstrukteur bei der Erkennung von wichtigen Entwurfsbeziehungen unterstützt. Das System arbeitet mit einem Satz vereinfachter Entwurfsregeln, die funktionale Abhängigkeit zu Entwurfsvariablen in Beziehung setzen, dies sind sowohl die physikalisch wichtigen als auch die direkt in Zusammenhang zu funktionaler Ausführung stehenden Variablen. Das Ergebnis ist ein Satz von Entwurfsregeln. Jeder Satz ist im wesentlichen eine andere Art einen Entwurf zu betrachten. Man erwartet, dass die Regeln das physikalische Verständnis des Konstrukteurs vergrößern, indem sie wichtige Beziehungen zwischen Entwurfsvariablen und Funktion erkennen lassen, und den Konstrukteur in der Beurteilung der Durchführbarkeit alternativer Entwürfe unterstützt.

Introduction

The objective of engineering design is the specification of a process or a product. More specifically, the task is to transform a set of functional requirements for a product into a physical description of the product, including geometric, component and material specifications*. The way in which the designer completes this task is a subject of considerable interest.

In the early stages of a design, the designer faces the task of evaluating the relative benefits and liabilities of many alternative configurations. The performance of each configuration typically depends on a large number of design variables, which are not yet specified. After evaluating the many alternatives using qualitative reasoning and experiential judgements, the designer eliminates all but the best alternatives for future consideration. Preliminary quantitative evaluations may then be used to further restrict the alternatives. The ease with which quantitative evaluations are made depends, in large part, on the complexity of the design equations involved. Even very simplified design equations may be puzzling to an inexperienced designer because changing the value of one of the design variables may influence many of the functional requirements. As a result, detailed analytical and optimization methods are often applied to the remaining design alternatives. The results of the analysis are used to judge the merits of the design configurations. Experienced designers, on the other hand, often shortcut the detailed analytical work by recognizing important relationships which govern the performance of the design configuration. This is accomplished by identifying important relations among functions and design variables, such as a critical ratio, a nondimensional parameter, or a simple difference; e.g. the column height to diameter ratio in structures, the Reynold's number in fluid mechanics, or the velocity difference across a fluid coupling. This achieves convenience and expediency in quantitative evaluations and enhances the physical reasoning associated with the design activity to better

enable the designer to focus his creativity on the essential deficiencies of the proposed configuration. The discovery of such critical relationships among parameters has been made on an ad hoc basis by experienced designers and engineers. Although certain nondimensional parameters are well known and methods exist for identifying such parameters, there are not, in general, strategies which assist the designer in identifying physically significant relationships which dominate the behavior of a particular design configuration. A computer based system to aid in the identification of critical design relationships would be of value to inexperienced designers in determining better ways of looking at proposed design configurations. It would also be valuable to experienced designers and engineering analysts in determining alternative variables which are better suited for analytical manipulations, optimization, or numerical methods. The results are expected to offer insight into the relationships between design decisions and product characteristics, highlight the underlying physics, and provide increased understanding of the meaning of terms in the governing design equations. In addition to increased understanding and insight, new forms of the governing equations are expected to provide increased efficiency for numerical testing and computations.

Computer Aids in Mechanical Design

The current genre of mechanical CAD systems have impacted the drafting room and the use of computer based analytical methods, notably finite element programs, but have had a negligible effect on most other aspects of the designer's task. Recently a number of researchers have begun to examine design methodologies with the goal of providing additional computer based assistance to the designer. An elaborate, empirical study of human designers by Ullman, Stauffer, and Diettrich [1] is intended to provide a basis for the development of intelligent computer based tools for mechanical designers. Ullman et al have observed that designers tend to follow a single concept in their design configuration rather than to explore alternative conceptual designs. We believe that identifying critical design relationships will encourage designers to explore more alternative configurations by helping them make quicker, more convenient and more focused evaluations of each configuration.

Diettrich and Ullman [2] have also identified what they believe are several basic requirements of software tools for intelligent design aids. Two of these requirements are the ability to conduct a deep search of design spaces to evaluate alternative designs and the ability to infer consequences of a particular design decision on other components of the design. We seek to minimize this difficulty by more directly relating the goals of the design to specific design decisions. We believe that the strategies described herein may be useful, not only to the human designer, but also in computer based design assistance systems.

Other programming environments which aid in the automation of design include languages such as DSPL, created by Brown and Chandrasekaran [3]. They have focused their efforts on an approach to building expert systems for routine design by creating a programming language in which to express routine design problem solving knowledge at the task level [4,5]. This language is geared toward routine design such as the design of air cylinders in which the general configuration is determined beforehand. The system does not explore alternative design configurations and is not intended to provide increased insight on many alternatives.

Dixon has also described a paradigm of design and developed systems to assist designers. His model, based in part on the iterative and recursive nature of design [6], involves decomposition, specification and an iterative redesign procedure. Dixon seeks to construct programs that can produce acceptable designs from a given trial design. He has implemented some of his ideas in computer based AI strategies to solve a limited class of design problems [7]. Dixon's program, Dominic, is similar to a hill-climbing algorithm that

uses the results of analysis to heuristicaUy guide changes in design. The idea is to solve a particular design problem given to Dominic rather than to provide insight on the design configuration to the engineer.

In general, these approaches seek to solve design problems by developing software that can automatically direct the solution of a given design problem. On the other hand we are concerned with die manner in which the problem is posed and we seek reformulations of the problem that can provide engineering insight and convenience.

Decoupling in Design

Mechanical designs are complex and design decisions are difficult to make, in part, because any one design decision, any single configurational modification, or any parameter change may influence many of *the* required functions of the product To the extent that this occurs, we can say that die desired functions are coupled or simply that the design is coupled. Coupling influences many aspects of designs including modularity and serviceability as well as the methods employed by designers. Simon [8] and Preiss[9] are among those who commented on the nature of coupling in designs. Suh, Bell and Gossard [10] went further in putting forth design axioms which specifically addressed functional independence and design coupling. Rinderle and Suh [11,12] subsequently developed quantitative measures of coupling and demonstrated how the measures could be used to evaluate design alternatives. These measures do not, however, explicitly acknowledge that coupling in design depends, at least in part, on the designer's representation of the product requirements and the design alternatives.

It seems that designers seek, so called, decoupled designs not only because of design efficacy, but also because decoupled designs facilitate reasoning about the design, provide insight into the nature of the design, and permit more convenient and expedient design methods to be employed Toward this end, we seek to reformulate design problems and alternatives in such a way as to promote a greater understanding of the design problem and to focus the creativity of the designer on the most critical aspects of the proposed solutions.

The design of a simple coil spring, although trivial in nature, illustrates some aspects of coupling in design and the potential benefits obtained by refcmnulating the problem into one which is less coupled. The functional requirements (FRs) for the spring might include maximum deflection, δ_{max} and stiffness, k , and the three variables available to complete the design might be *spring* wire diameter, d , coil diameter, D , and the number of coils, N as shown in Figure 1. These last three variables are called design variables or design parameters (DPs). The following two equations give approximate relationships between functional requirements and design parameters for the spring:

$$\begin{aligned} \delta_{max} &= \frac{8\pi\tau_{max}D^2N}{9Gd} &= f_1(d,D,N) \\ k &= \frac{Gd^4}{8ND^3} &= f_2(d,D,N). \end{aligned} \tag{1}$$

Note that G and τ_{max} are material properties and are not design parameters because the material is considered fixed for example purposes.

To obtain the desired stiffness, k , the designer will have to set values for d , D , and N which will leave no independent design parameter with which to set the desired value for maximum deflection, δ_{max} . Thus, the designer must consider both functional requirements when choosing a particular value for any of the three design parameters since it is obvious

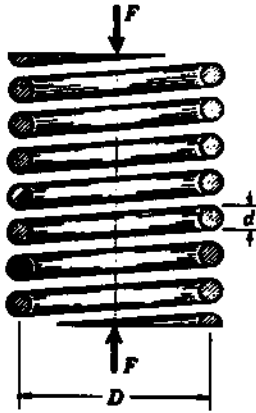


Figure 1: Original helical coil spring design parameters

that changing a single design parameter to achieve either functional requirement will result in an unintended change in the value of the other functional requirement of the spring. This is a coupled system, in contrast to an uncoupled system in which one and only one functional requirement changes in response to a variation in a single design parameter. The fundamental concept of an uncoupled system is that each design decision affects only one function of the product

Uncoupled designs enable the designer to consider required functions independently. In the ideal situation, each design parameter would influence only one functional requirement of the product and therefore relations between functional requirements and design parameters might be of the form:

$$\begin{aligned}
 FR_1 &= f_1(DP_1) \\
 FR_2 &= f_2(DP_2) \\
 &\dots\dots\dots \\
 FR_{n-1} &= f_{n-1}(DP_{n-1}) \\
 FR_n &= f_n(DP_n).
 \end{aligned}
 \tag{2}$$

The opposite extreme would be when each functional requirement depends on every design parameter

$$\begin{aligned}
 FR_X &- f_1(DP_1, DP_2, \dots, DP_{m-1}, DP_m) \\
 FR_2 &- f_2(DP_1, DP_2, \dots, DP_{m-1}, DP_m) \\
 &\dots\dots\dots \\
 FR_{n-1} &= f_{n-1}(DP_1, DP_2, \dots, DP_{m-1}, DP_m) \\
 FR_n &= f_n(DP_1, DP_2, \dots, DP_{m-1}, DP_m).
 \end{aligned}
 \tag{3}$$

Most real designs are neither completely coupled nor completely uncoupled. One particularly interesting structure for DP - FR dependencies exists when FRs depend on the DPs as follows:

$$\begin{aligned}
FR_1 &= f_1(DP_1) \\
FR_2 &= f_2(DP_1, DP_2) \\
&\dots\dots\dots \\
FR_{n-1} &= f_{n-1}(DP_1, DP_2, \dots, DP_{m-1}) \\
FR_n &= f_n(DP_1, DP_2, \dots, DP_{m-1}, DP_m).
\end{aligned}
\tag{4}$$

In this case, the FRs can be adjusted without regard to interactions if they are adjusted in the proper sequence. This type of design system is said to be order dependent decoupled. While this system is an improvement over a completely coupled system it may not be the best compromise for many design situations. There are at least two problems. The first is that some functions are much more sensitive to some design parameters than others therefore an order dependent decoupling may require large changes in design parameters to accommodate modest changes in functional requirements. A related difficulty is that a change in a single functional requirement may require changes in many design parameters.

A more realistic system of design equations exists when the equations can be grouped into blocks which are completely decoupled from other blocks. These blocks may in turn be either completely coupled subsystems, uncoupled subsystems, or order dependent decoupled subsystems. By way of example, consider a system with six FRs and seven DPs. The functional dependencies can be shown in matrix format in which the *o* elements represent DPs which do not affect the FR and *x* elements indicate a dependency relationship:

$$\begin{bmatrix} FR_1 \\ FR_2 \\ FR_3 \\ FR_4 \\ FR_5 \\ FR_6 \end{bmatrix} = f \begin{bmatrix} x & x & x & o & o & o & o \\ x & x & x & o & o & o & o \\ o & o & o & x & o & o & o \\ o & o & o & o & x & o & o \\ o & o & o & o & o & x & o \\ o & o & o & o & o & x & x \end{bmatrix} \begin{bmatrix} DP_1 \\ DP_2 \\ DP_3 \\ DP_4 \\ DP_5 \\ DP_6 \\ DP_7 \end{bmatrix} \tag{5}$$

This system consists of three completely decoupled subsystems. The first block represents a completely coupled subsystem, the second block is completely uncoupled, and the third is an order dependent decoupled subsystem. This type of block decoupled system is common in mechanical designs.

The relative merits of uncoupled, block decoupled, and order dependent decoupled systems are discussed elsewhere [11,12]. The rest of this paper will focus on order dependent decoupled systems, not because they are the most beneficial or the most important, but because they are conceptually simple and convenient in describing issues related to obtaining less coupled design representations.

There are two methods to avoid coupled designs. The first method is to change some feature of the design configuration to eliminate the coupling. Another possibility is to select an alternative set of design parameters (DPs). Changing design parameters does not change the design itself, only the representation of the design. Consider the helical coil spring example. If the functional requirements are recast as functions of new design parameters, for

example, the ratio of coil diameter to the wire diameter, (R^D/d) , wire length, (L) , and the wire cross section area, $(A=JU^2/4)$, then the spring design equations are transformed as follows [13]:

$$\begin{aligned} \delta_{max} &= \frac{8\tau_{max}RL}{9G} &= g_1(R,L) \\ k &= \frac{GA}{2LR^2} &= g_2(R,L,A). \end{aligned} \quad (6)$$

These equations are now order dependent decoupled in the form of equations(4) and the design of the spring can be carried out without simultaneously considering both of the functional requirements. If a reasonable value for the diameter ratio, R , is chosen then the **maximum** spring deflection, $S^{\wedge}t$ is proportional to the wire length, L , and the stiffness, K is proportional to the wire cross section area, A . Wire length and cross section area are themselves physically significant, however, this representation may lead to the more important observation that spring weight, being proportional to the product of wire length and area, must also be proportional to the product of spring stiffness and the square of allowable deflection.

As can be seen, decoupled representations of designs, even for the simple spring example are useful to the design engineer because they reduce the complexity of the task at hand. This is the immediate result of a more decoupled set of design equations. A more important result is that the new DPS (the variables of the design) may clarify some important or critical relationship which governs or limits the product performance and which the designer had not previously observed or considered. There are two reasons why a transformation to more decoupled design equations is useful in discovering parameters which may be critical. First, there is more of a one to one relationship between functional requirements and design parameters which emphasizes the importance of each new variable. Secondly, in order to achieve decoupling new variables are formed as combinations of the old variables which tends to reduce the total number of new design variables. As an example, consider that many fluid dynamics problems have been greatly simplified by the identification of critical nondimensional parameters, such as the Reynold's number. Thinking in terms of one important variable such as the value of the Reynold's number rather than considering flow rate, length, density, and viscosity is a great simplification from four variables to one.

Dimensional Analysis and Critical Design Variables

The use of Reynold's number in the previous section raises questions regarding the relationship between dimensional analysis and the identification of important, alternative sets of design parameters. Dimensional analysis, more specifically, the Buckingham pi theorem is used to transform a function expressed in terms of dimensional parameters to a related function in terms of nondimensional parameters. If a physical problem is described by an equation with n parameters which involve m fundamental dimensions, then the pi theorem [14] states that an equivalent function can be expressed in terms of $(n-m)$ nondimensional parameters. The reduction of variables is of prime importance, however, the method of determining the pi parameters is not contained in the pi theorem and in fact there are an infinite number of sets of pi parameters. Furthermore, the pi theorem says nothing about which sets of nondimensional variables will result in simple and useful transformations and says nothing at all about dimensional variables [15]. We, on the other hand, seek to transform design equations from one set of dimensional variables to a more useful and insightful set of dimensional or nondimensional variables.

Methods for Identifying Transformations

Consider a class of simple cases where a set of design equations is of the form where each FR is proportional to a product of DPs raised to arbitrary powers:

$$FR_i = m \cdot KDP_1^{a1} DP_2^{a2} \dots DP_n^{a_n} \quad (7)$$

The helical spring equations are of this form. By taking the logarithm of both sides of each design equation the entire system can be put into matrix form as shown using the original equations for the helical coil spring:

$$\log \begin{bmatrix} \delta_{max} \\ k \end{bmatrix} = \begin{bmatrix} -1 & 2 & 1 & 1 & 0 \\ 4 & -3 & -1 & 0 & 1 \end{bmatrix} \log \begin{bmatrix} d \\ D \\ N \\ \frac{8\tau_{max}}{9G} \\ \frac{G}{8} \end{bmatrix} \quad (8)$$

or ignoring the constant terms for example purposes only:

$$\log \begin{bmatrix} \delta_{max} \\ k \end{bmatrix} = \begin{bmatrix} -1 & 2 & 1 \\ 4 & -3 & -1 \end{bmatrix} \log \begin{bmatrix} d \\ D \\ N \end{bmatrix} \quad (9)$$

In matrix notation the general case can be represented as:

$$\log F = M \log D_0 \quad (10)$$

where F is Ac FR column vector, M is the system exponent matrix, and D₀ is the column vector of original DPs. As can be seen, the original spring design equations are completely coupled in that both of the functional requirements depend on all three of the design parameters.

If any one element of M is zero then the equations can be written in an order dependent decoupled form, such as:

$$\log \begin{bmatrix} \delta_{max} \\ k \end{bmatrix} \text{ or } \begin{bmatrix} \sim k \\ \&max \end{bmatrix} = \begin{bmatrix} a & b & c \\ 0 & d & e \end{bmatrix} \log \begin{bmatrix} V_1 \\ V_2 \\ V_3 \end{bmatrix} \quad (11)$$

The new design parameters V₁, V₂ and V₃ are functions of the old design parameters d, D, and N. The letters a, b, c, d, and e represent the exponents of the new DPs. Note that if b and c are equal to zero then the spring system would be completely decoupled

Assume for convenience that the new variables will be a product of the original variables raised to arbitrary powers such as:

$$V_i = K DP_1^{\beta_1} DP_2^{\beta_2} \dots DP_n^{\beta_n} \quad (12)$$

where V_j is a new design variable, DP_1, DP_2, \dots, DP_n are the original design variables and K is a constant. Restricting new variables to this form may preclude the use of some important variables, such as a pressure difference, however, for the time being we will consider only variables of this form.

The transformation between the original and new design parameters is represented in matrix notation as:

$$\log D_o = T \log D_B \quad (13)$$

where D_n is the column of new DPs and T is the variable transformation matrix. So that new design parameters can be uniquely determined from the old design parameters and vice versa, it is necessary that the determinant of the transformation matrix, T , be non-zero. This cannot be the case when the number of new design parameters which appear in the design equations is less than the number of original design parameters. In these instances the new design parameters are supplemented with auxiliary variables which preserve the number of degrees of freedom of the design.

For example purposes, consider a set of new design parameters to be at least order dependent decoupled in terms of the original design parameters. This results in an upper triangular T matrix. This requirement is often imposed for convenience in transforming the design variables and design equations and because it greatly reduces the number of candidate sets of design variables¹.

Combining the design equation transformation with the design variable transformation we have:

$$\log F = MT \log D_n \quad (14)$$

In order for the transformed design equations to be at least order dependent decoupled the matrix product MT must contain enough zero elements in positions such that some rearrangement of elements in the columns F and D_B will produce an upper triangular matrix relating the two.

This generalization might be better understood using the spring example with real numbers. The spring design parameters, d , D , and N , can be transformed to L , R , and A with wire length, ($L = nDN$), wire cross section area, ($A = nd^2/4$), and ratio of coil diameter to the wire diameter, ($R = D/d$)^m.

¹This requirement may, however, be too restrictive* resulting in a missed reformulation of the design equations that may have physical significance or may be particularly convenient. If the design equations can be more greatly decoupled, or decoupled in some more useful form by relaxing this objective, then the benefits of doing so would have to be considered in a complete implementation.

$$\log \begin{bmatrix} N \\ D \\ d \end{bmatrix} = \begin{bmatrix} 1 & -1 & -0.5 \\ 0 & 1 & 0.5 \\ 0 & 0 & 0.5 \end{bmatrix} \log \begin{bmatrix} L \\ R \\ A \end{bmatrix} \quad (15)$$

which is obviously an order dependent decoupled transformation. Applying this transformation and rearranging rows and columns we obtain the upper triangular form for the design equations:

$$\log \begin{bmatrix} k \\ \xi_{r_{max}} \end{bmatrix} = \begin{bmatrix} 1 & -1 & 2 \\ 0 & 1 & -1 \end{bmatrix} \log \begin{bmatrix} A \\ L \\ R \end{bmatrix} \quad (16)$$

The matrix-logarithm representation discussed so far only applies to design equations in which each FR depends on a product of DPs raised to arbitrary exponents. This technique can be extended to equations of many terms separated by additions and subtractions. The extension requires taking a separate logarithm for each term, performing the same design parameter transformation on each term, and then reconverting the equations back to a nonlogarithmic format by taking the antilog on each term.

The transformation process is simple to implement and evaluating whether or not a particular transformation produces more decoupled design equations is relatively straightforward. The difficult task is to generate candidate sets of new design parameters which span the old design parameters, and most importantly are useful and insightful to the designer. What is needed is an approach to generate candidate new design parameters, evaluate them for usefulness and physical significance and then arrange them into groups which can be used as an alternative set of design parameters.

There are several ways to generate candidate new design parameters. The first method, and the one we have implemented and experimented with the most, can be called the common combinations technique. This involves searching through all the given design equations for groupings of the original variables that also appear in other design equations. The reason that common groupings may be important is precisely because they are common. The problem with this technique is that it runs counter to the idea that new variables that are common to many equations are not what are needed to produce more decoupled equations. Less common new variables are desired. The ideal situation is to have a unique and physically significant design variable for each equation.

The second method is similar to the first. New variables are chosen from groupings that appear in the equations but the variables are not evaluated on the basis of repetition. This results in a greater number of new variables to consider but it does not suffer from the problem of the first technique. This technique does, however, suffer from the fact that the new design parameters with the most significance might not appear as a combination of the original variables in the given form of the original design equations. Premanipulation of the equations into other formats before identifying the groupings can often eliminate this problem. This mathematical manipulation might include expanding terms, rationalizing, factoring, or transforming to an approximate relationship. Nevertheless, there is still no assurance of producing the best new design parameters.

An alternative is a more systematic and computationally more expensive technique. The idea behind systematic generation is to choose new design parameters of the form:

$$V = KDP_1^j DP_2^k \dots DP_n^m \quad (17)$$

where the new variable, V , is composed of a limited number of the original variables, taken to arbitrary (but reasonable) powers. A large number of candidate design parameters will be generated, in part, because this technique does not take advantage of the information contained in the format of the original design equations. Some balance between blind identification of candidate design parameters and a design equation driven identification will likely be superior to either extreme. Incremental identification and transformation may be advantageous.

No matter how design parameters are generated, an evaluation of the utility and physical significance of each design parameter must be made. A first evaluation may be based on the dimensions of each variable. The designer may have some idea which units are physically significant for the particular design problem. This information can be used to reduce the number of candidate design parameters.

A second method for eliminating design parameters is to evaluate each on a level higher than the basic units. Additional information which could be used might include, for example, whether a unit of length represents a diameter, height, width, or thickness. Nondimensional numbers can be identified as a ratio of lengths or forces. It is also simple and useful to tag a variable having units of a force-length as being either energy or torque as appropriate. One method for using such information is to establish a set of rules ranked according to importance. For instance, areas can be formed from diameters squared but not from a thickness squared even though both have units of length. The notion that area may be important is more useful and fundamental than the notion of length squared being significant. We have not developed or implemented an extensive list of rules based on such information, but we consider it an important area of research for the future.

A third criterion for evaluating the significance of each newly generated design parameter is to employ the concept of spatial proximity. A mechanical system generally consists of many components. For instance, the helical coil spring is a single component but if it is used in a suspension system it would be one of several components. Figure 2 shows an example of a simple suspension system with two basic components, a spring and a beam.

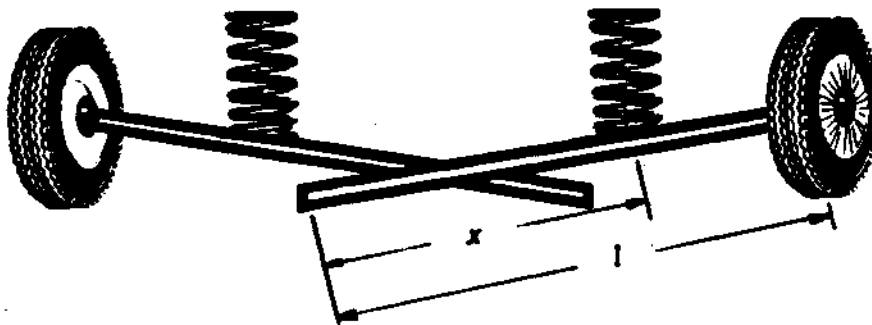


Figure 2: A simple suspension system

The proximity with which components are connected often indicates the "associative" importance of the design parameters measured on each component. Design parameters measured or indicated on the same component may form, when grouped among themselves, new design parameters with the greatest likelihood of being important. The second most important groupings might be the design parameters measured on two adjacent components

and so on. Using the suspension example consider, designing for wheel deflection and stiffness, S_{max} and k_w :

$$\begin{aligned} \delta_{max} &= \frac{8\pi r_{max} D^2 N l}{9Gdx} &= h_1(d, D, N, x, l) \\ k_w &= \frac{Gd^4 x^3}{8ND^3 l^3} &= h_2(d, D, N, x, l). \end{aligned} \quad (18)$$

The original design parameters N, d, D, x, l can be transformed to A, L (as before) as well as one additional new variable, $X_r = x/l$ to result in order dependent decoupled equations. The parameters N, d, D are all spring only design parameters, l is a beam only design parameter, and x is shared between spring and beam. In a discrete implementation the following table indicates which design parameters belong to which components:

DP	spring	beam
N	P	0
d	P	0
D	P	0
x	s	5
l	0	P

where p indicates primary ownership, s secondary ownership and 0 no ownership. If we mix all design parameters despite ownership then the set used to generate new DPs is $\{N, d, D, x, l\}$. If only primary relationships are used we have two sets $\{N, d, D, d\}$ and $\{l\}$ and mixing between the two is not permitted. Finally, if both primary and secondary considerations are permitted then we have two different sets $\{N, d, D, d, x\}$ and $\{l\}$ where x is common to both. The useful result can be found using the first or third groupings, however, the third grouping is more directed, hence quicker, and produces fewer alternative reformulations for the designer to consider.

All three methods of evaluating new design parameters, namely using units, using rules based on additional information, or using spatial proximity, will involve a tradeoff between speed on the one hand, and the risk of eliminating potentially good answers from consideration on the other. From the simple problems experimented with, it is clear that these ideas and perhaps others, will have to be implemented if any automatic routine is to be genuinely useful.

To summarize, it appears that more useful and physically significant design equations can often be obtained by transforming the original design equations. There are at least four tasks involved in making such transformations:

1. Generate candidate new design parameters by using one or more of the methods:
 - a. Common combinations in equations
 - b. Existing variable groupings in the equations
 - c. A systematic generation technique.
2. Evaluate candidate new design parameters and prune the list using:
 - a. Units of the new design parameters

- b. Rules involving additional information about each original variable
 - c. Spatial proximity rules.
3. Form spanning sets of design parameters by forming and testing transformation relationships between the old and new design parameters.
 4. Transform the design equations and test for increased decoupling.

In practice, these four tasks need not be performed serially. In fact, certain economies are obtained, for example, by using tests of transformations to focus the generation of candidate design parameters.

Results

A computer based system, written in Lisp, implements some of the techniques discussed. The design equations are limited to simple algebraic equations. Important units as indicated by the user are the main criterion, at present, in choosing potentially significant new design parameters. The implementation has produced some useful results. For example, the helical coil spring design equations were reformulated by the program into only four new sets of design equations. One set, seen earlier in equations (6), appears to be a useful way of looking at the spring problem because the equations are decoupled and the new design parameters, diameter ratio, D/d , wire length, L , and wire cross sectional area, A provide some insight to the designer. The results for other sets of design equations have not been as successful. This is due in large part to the lack of implementing a more complete criterion for choosing potentially useful new design parameters. For instance, the suspension system shown in Figure 2, has design equations very similar to those for the helical coil spring alone, except for the addition of the term x/JL . When units were the sole criterion for selecting design parameters, solving the suspension problem required excessive computer time and produced extraneous results in the search for a worthwhile design parameter transformation. The addition of spatial proximity rules alleviated these problems.

Conclusion

A greater understanding of the many alternative design configurations a designer has to consider can be achieved, at times, by a transformation from the original design parameters to an alternative set of design parameters. To achieve this goal, the alternative set of design parameters must be physically significant and critical to the design situation. Methods were presented for identifying and evaluating critical design parameters. Systematic methods were also presented for the formation of sets of new design parameters that can be used in a transformation of the original design equations. A major criterion for ranking the potential usefulness of the new sets of parameters is a test for increased decoupling in the reformulated design equations. Decoupled design equations generally result in reduced complexity and more convenience for the designer. The transformed equations are expected to enhance the physical insight of the designer, to help in identifying governing relationships among design variables and function and to assist the designer in evaluating performance limitations of alternative design configurations.

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