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AN INFORMATION THEORETICAL PERSPECTIVE ON DESIGN

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ABSTRACT

Design in general is about increasing the information of the product/system. Therefore it is natural to investigate the design process from an information theoretical point of view. There are basically two (although related) strains of information theory. The first is the information theory of communication. Another strain is the algorithmic theory of information.

In this paper the design process is described as an information transformation process, where an initial set of requirements are transformed to a system specification. Performance and cost are both functions of complexity and refinement, which can be expressed in information theoretical terms. The information theoretical model is demonstrated on examples. The model has practical implications for the balance between number of design parameters, and the degree of convergence in design optimization. Furthermore, the relationship between concept refinement and design space expansion can be viewed in information theoretical terms.

Keywords: Information theory, design optimization, design complexity

1 INTRODUCTION

Information theory of communication was founded in 1948 by C.E. Shannon with his paper "*A Mathematical Theory of Communication*" [1]. Shannon modelled a general communication system.

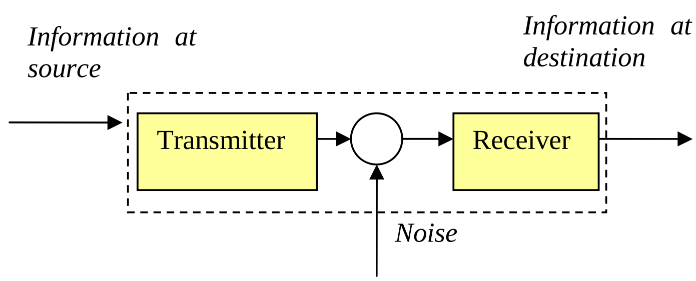

Figure 1. A general communication system (Shannon 1948)

Subsequently it has been recognized that information is a key property of a design, and to describe and analyze the design process. The notion of information theory in design has been introduced by several authors. Notables are N.P. Suh [8], amd Frey and Jahingir [3]. Information theory was used to analyze design optimization in Krus and Andersson [10]. A more recent development is the algorithmic theory of information, ATI, presented in [2] and [3], that although it have interesting implications for measuring system complexity it, is left beyond the scope of this paper.

2 INFORMATON THEORY AND DESIGN

With an information theoretical view, the design process is about transforming the information in the environment of the proposed system into the design specification of the system. This can be viewed as a learning process, as described by D.G.. Ullman [1]. Furthermore, the relationship between the design parameters and the system characteristics can also be viewed as an information transformation process subject to noise in the form of model uncertainty and external disturbances in variables that cannot be controlled by the design. There is also information from the system concept, which might add or remove information, depending on the degree of robustness in the system.

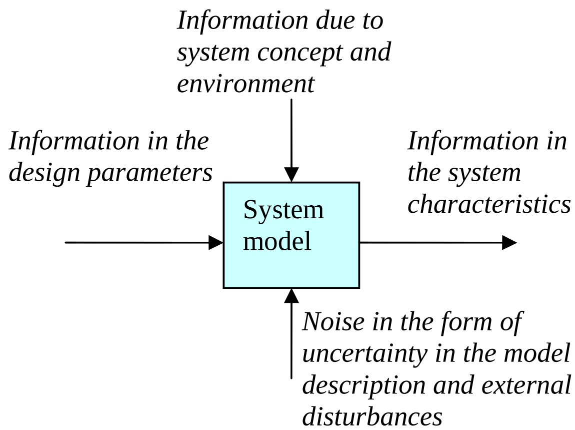

Figure 2. The system model of the designed system as an information transformation system

The notion of information is used in the second axiom of N.P. Suh´s Axiomatic design, which states that the information content in a design should be minimized [9]. This follows common sense in that low information content should mean a simple design, and a design should never be more complicated than necessary. Information theory gives a foundation for formulating this, in strict mathematical terms.

3 THE CHARATERITICS OF DESIGN INFORMATION/ ENTROPY

3.1 Information theory and optimization

Both design and design optimization is about increasing the information of the product/system. Therefore it is natural to investigate the optimization process from an information theoretical point of view. An interesting aspect is to study the amount of information gained in each evaluation. In general the amount of information to represent a value can be expressed as:

$$S = -\int_{-\infty}^{\infty} p(x)\log_2(p(x))dx \tag{1}$$

This is the information entropy of the signal. If there is a finite range for the variable x and if the range of the variable is divided in equal parts Δx that have the same probability, the information represented by knowing in which part the actual value is, has the following probability distribution:

$$\begin{aligned} p(x) &= \frac{x_R}{\Delta x} : x \in \left[x_{\min}, x_{\max}\right] \\ p(x) &= 0 : x \notin \left[x_{\min}, x_{\max}\right] \end{aligned} \tag{2}$$

where x_R is the design range:

$$x_R = x_{\max} - x_{\min} \tag{3}$$

This yields the information content (in bits) for that variable as:

$$\begin{aligned} I_x &= -\int_{-x_{\min}}^{x_{\max}} \frac{x_R}{\Delta x}\log_2\left(\frac{x_R}{\Delta x}\right)dx = \\ &= \log_2 \frac{x_r}{\Delta x} = \log_2 \frac{1}{\delta_x} = -\log_2 \delta_x \end{aligned} \tag{4}$$

where Δx is the uncertainty of the variable and x_R its design range. δ_x is introduced as the relative spread in parameters.

For direct search optimization methods, such as the Complex method, the increase in information is rather constant. For the Complex method it is about 0.15 bits/evaluation for a benign object function, see ref [10]. This means that the system is gaining 0.15 bits of information at each evaluation. Note that this is independent of the number of optimization variables. However, for more optimization variables, it takes longer time to converge, since more information is needed. This represents an estimate of an upper theoretical limit for the amount of information gained in each function evaluation. It can be used to estimate the number of evaluations needed for an optimization method to converge. If 10 design variables are to be optimized to a tolerance of $\delta_x = 0.01$ the number of evaluations *m* can be estimated from:

$$I_x = 0.15\widehat{m}_{eval} \tag{5}$$

With (4) this yields

$$m_{eval} = -\frac{n}{0.15}\log\delta_x = -\frac{10}{0.15}\log 0.01 = 443 \text{ evaluations} \tag{6}$$

4 PERFORMANCE AND INFORMATION CONTENT

The assumption made here is that performance in a design is a function of the information I_x and size s.

$$p = p(I_x, s) \tag{7}$$

The information content in the sense defined by Shannon represents the size of the design space from which a given system is defined. If a variable with a known design range of x_R is known with the precision Δx , the information content is:

$$I_p = \log_2\frac{x_R}{\Delta x} = \log_2\frac{1}{\delta_x} \tag{8}$$

However, if the design range is increased to x'_R the same amount of information would yield a larger tolerance region $\Delta x'$

$$I_p = \log_2\frac{x_R}{\Delta x} = \log_2\frac{x'_R}{\Delta x'} \tag{9}$$

If the tolerance region is to be brought down to the same area, the information content is increased to:

$$\begin{aligned} I_x &= \log_2\frac{x'_R}{\Delta x} = \log_2\frac{x_R}{\Delta x}\frac{x'_R}{x_R} = \log_2\frac{x_R}{\Delta x} + \log_2\frac{x'_R}{x_R} = \\ &= I_p + I_R \end{aligned} \tag{10}$$

where

$$I_R = \log_2\frac{x'_R}{x_R} \tag{11}$$

This represents the information related to the expansion of the design space. Note that this is also valid if the design space is increased by letting more parameters in a system, to be variable. If *n*-1 parameters are added, the design space will be increased to:

$$\frac{x'_R}{x_R} = \frac{\Delta x\left(\frac{x_R}{\Delta x}\right)^n}{x_R} = \left(\frac{x_R}{\Delta x}\right)^{n-1} \tag{12}$$

This corresponds to an increase in the information content of

$$I_R = \log_2\left(\frac{x_R}{\Delta x}\right)^{n-1} = (n-1)\log_2\frac{x_R}{\Delta x} = (n-1)I_p \tag{13}$$

From this follows that:

$$\frac{I_R}{I_p} = n-1 \tag{14}$$

This is true if all the design ranges of the individual parameters have the same size, that is:

$$\frac{\Delta x_1}{x_{R,1}} = \frac{\Delta x_2}{x_{R,2}} = \ldots \frac{\Delta x_N}{x_{R,N}} \text{ or } \delta_1 = \delta_2 = \ldots \delta_N \tag{15}$$

If, as normally is the case, the different parameters has different influence a more optimal distribution of uncertainty would be to allow for larger uncertainties in the parameters that has low influence. The influence factor is here defined as:

$$\psi(i) = \frac{\Delta p}{\Delta x_i} \tag{16}$$

where Δx_i is an infinitesimal change, or the uncertainty range, or according to some other definition. The important thing is that the same definition is used on all parameters x_i. One suitable assumption is to assume that the influence of design parameters follows a negative power law curve. This is approximately the case if the design parameters are sorted with respect to their influence. This is a rational action, since the parameters with the highest influence should be the ones chosen to be optimized. The negative power law curve is.

$$\psi(i) = c_p i^{-k} \tag{17}$$

In Figure 3. The influences are shown if they follow the relationship in (17) and $k = 1$. Since this is a limiting case, influences that decay faster result in a finite value as the number of parameters goes towards infinity.

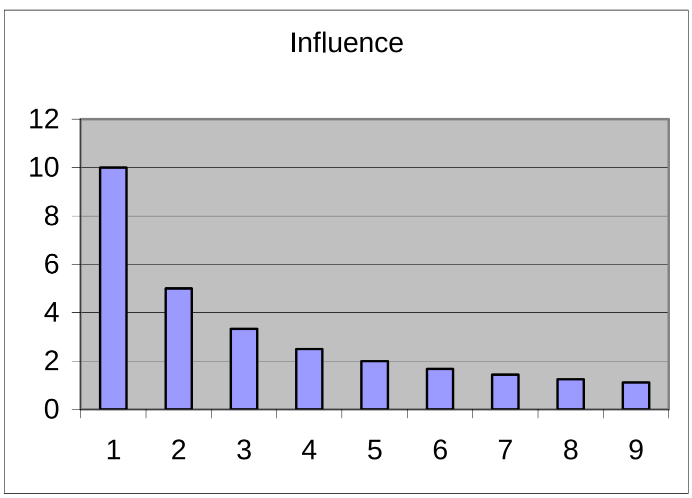

Figure 3. Sorted parameter influences

5 A GENERAL MODEL FOR PERFORMANCE AS A FUNCTION OF INFORMATION CONTENT

Rewriting equation (7) using (10) and (14) yields:

$$p = p(I_x, n, s) \tag{18}$$

or alternatively

$$p = p(I_R, I_p, s) \tag{19}$$

In the following section, only the dependency on information is considered. If optimal values for design parameters x_p are precisely known for a given design range x_R, then

$$x_{p,opt}\left(x_R\right) = x_p : p = \max\left(p\left(x_p \left| x_R\right.\right)\right) \tag{20}$$

Furthermore, if the design range is expanded in the best direction as the design information $I_{R,}$ is increased

$$x_{R,opt}\left(I_R\right) = x_R : p = \max\left(p\left(x_R, x_{p,opt} \left| I_R\right.\right)\right) \tag{21}$$

With “the best direction” is here meant the best direction that can be determined without actually evaluating points in the extended design space, since that belongs to the refinement phase. More generally this can be seen to represent a creative part of design, the concept development. If the number of parameters *n* is used instead to represent the size of the design space (21) instead becomes:

$$x_{R,opt}\left(n\right) = x_R : p = \max\left(p\left(x_R, x_{p,opt} \left| n\right.\right)\right) \tag{22}$$

A simple assumption is then that the performance can be written as a function of the degrees of design freedom (number of design parameters). One reasonable assumption is that the influence of design parameters follows more or less the negative power law curve in equation(17).

Assuming that the total performance is proportional to the sum of the influence of the optimized parameters (independent parameters) yields the total influence of the parameters up to the *n*:th parameter as:

$$\Psi(n) = \sum_{i=1}^{n} \psi(i) = c_p \sum_{i=1}^{n} i^{-\lambda} = c_p H(n,\lambda) \tag{23}$$

where $H(n,\lambda)$ is the harmonic number function. Assuming that the optimal performance that can be achieved with *n* parameters is proportional to the sum of the influences with a possible offset value p_1 yields:

$$\begin{aligned} p_{opt}\left(n\right) &= p\left(n \left| x_{p,opt}\right.\right) = \Psi(n) - p_0 = \\ &= c_p \sum_{i=1}^{n} i^{-k} - p_0 = c_p H(n,\lambda) - p_0 \end{aligned} \tag{24}$$

This function has different asymptotic behaviour depending on the value of the exponent *k*

$$\lim_{n\to\infty} H(n,k) = \varsigma(k) \tag{25}$$

where $\varsigma(k)$ is the Riemann zeta function.

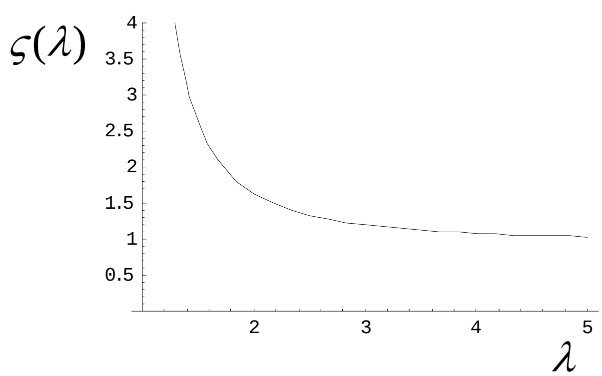

Figure 4. The Rieman Zeta function

$$\lim_{n\to\infty} H(n,\lambda) = \varsigma(\lambda) = \begin{cases} \infty \text{ when } \lambda \le 1 \\ \text{finite value} > 1 \end{cases} \tag{26}$$

For the first case the performance is unbounded, any performance can be obtained as long as the number of design parameters is sufficiently large. For the second case, the performance is bounded. This is true for a wide range of systems where there is an upper limit related to efficiency. In any case, however, the performance is monotonously increasing. As a consequence, the performance is always higher for a more complex product, which should be true. (For a product of a certain complexity, there always exists another product with more complexity (as defined in terms of design freedom, but with at least the same performance, i.e an identical product but with an extra null component).

The total information content in all the design parameters can be written as:

$$I_x = -\sum_{i=1}^{n} \log_2 \delta_{x,i} = -n \log_2 \delta_x \tag{27}$$

under the assumption that all $\delta_{x,i} = \delta_x$. For small uncertainties and close to constraints a reasonable assumption is that, the larger the uncertainty, the larger the margin to constraints has to be, and assuming a linear relationship between performance and uncertainty, this yields.

$$p_{opt}\left(\delta_x\right) + p_1 \sim \left(1-\delta_x\right) \tag{28}$$

The difference between this optimal performance, and the optimal performance with no uncertainty in the design variables, is then:

$$p_{opt}(n) - p_{opt}(n,\delta_x) = c_p H(n,k)\delta_x \tag{29}$$

Since δ_x represents the uncertainty in all variables, this can be calculated from the total information content I_x using equation (27) as:

$$\delta_x = 2^{-\frac{I_x}{n}} \tag{30}$$

This means that the performance can be written as:

$$p_{opt}(n,I_x) = c_p H(n,k)(1-2^{\frac{I_x}{n}}) - p_0 \tag{31}$$

So far the design problem has been viewed as an optimization problem. However, if the objective is to model how the refinement and complexity affect the performance of a complex product, the equation also provides some clues. However, since the number of parameter is hard to establish in absolute terms the number *n* can be seen as a measure of expansion of the design space in relative terms, from a reference state. Furthermore, if the number of parameters is large the Harmonic number function can be approximated by a continuous function:

$$H(n,\lambda) \approx c(\lambda) + \frac{1}{\lambda-1}\left(1-\frac{1}{n^{\lambda-1}}\right) \tag{32}$$

where $c(\lambda)$ is a constant. The performance can then be written as:

$$p_{opt}(n,I_x) = k_p\left(c(\lambda) + \frac{1}{\lambda-1}\left(1-\frac{1}{n^{\lambda-1}}\right)\right)(1-2^{\frac{I_x}{n}}) - p_0 \tag{33}$$

For the special case where $\lambda = 1$, we have:

$$p_{opt}(n,I_x) = k_p\left(c(1) + \gamma + \ln n\right)(1-2^{\frac{I_x}{n}}) - p_0 \tag{34}$$

The design cost should be a function of information content. Another aspect of importance associated with a design is its logical depth, suggested by Charles Bennet [7]. In design, the logical depth could be the smallest number of steps needed to design the system from the initial requirements.

$$T(x) \ = \ \text{Number of computational steps after which } U \text{ halts on input } x \tag{35}$$

The logical depth can then be expressed as:

$$D(x) = \min(\mathrm{T}(x)) : \mathrm{U}(p) = x \tag{36}$$

This can be viewed as a measure of the computational cost and in design this could be used as one measure of design cost. A simple assumption is:

$$C(D) = k_{CD} D\left(I_x\right) = k_{CD} k_D I_x^{\ \gamma_{I,x}} = k_{CI} I_x^{\ \gamma_{I,x}} \tag{37}$$

The simplest assumption is that relationship is linear, hence:

$$C = k_{CI} I_x \tag{38}$$

Furthermore, manufacturing cost can also be assumed to be proportional to the information content. The performance can then be calculated as a function of cost as:

$$\boxed{p_{opt}(n,C) = c_p H(n,\lambda)(1-2^{\frac{C}{k_{CI} n}}) - p_0} \tag{39}$$

An interesting example is the performance of micro processors. Figure 5 shows the processor performance as a function of price for the Intel Pentium 4 and the Celeron processors in 2004. The low end is covered by the low cost Celeron processor whiles the medium to high end is covered by the more complex Pentium 4 processor. The main difference between different processors of the same category is the processor speed, which in turn is a function of the quality (tolerances), hence information of the processor. (In the diagram different buss speed and cache memory has been converted to performance and are included in the equivalent processor speed). This was done using the following formula:

$$\omega_e = \omega_p + k_b \omega_b + k_c m_c \tag{40}$$

Here ω_e is the equivalent processor speed. ω_p is the actual processor speed. ω_b is the buss speed, and m_c is the cache memory size. The coefficients k_b and k_c are selected solely on the criteria to make the curve as smooth as possible (all the Celeron processors does, however, only have the same combinations of buss speed and cache memory, so it is not affected). In Figure 5 two models based on eq. (63) has been adapted to fit the data. Interestingly $p_1 = 0$.

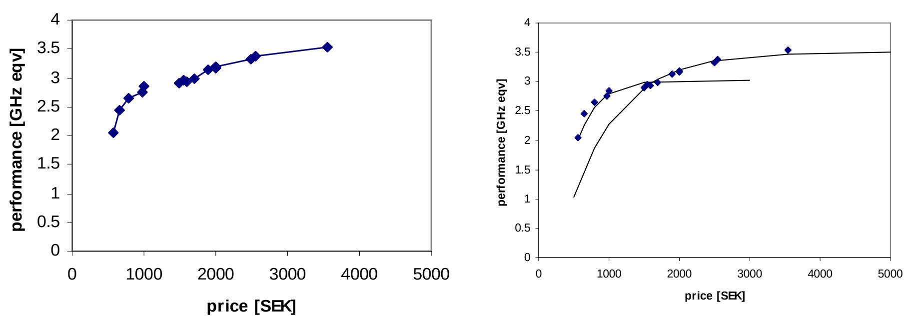

Figure 5. Processor performance as a function of price for Intel Pentium and Celeron processors, with fitted models (right).

4.1 Example: optimization of a beam

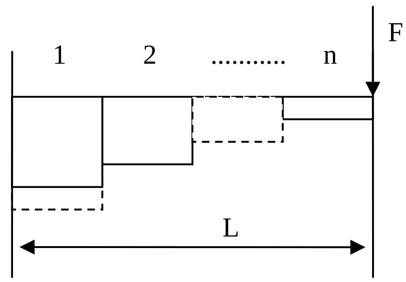

Figure 6. Beam with a point load, divided in n segments.

The performance in this case is the maximum load it can handle without exceeding maximum stress. An efficiency measure can be introduced as the quotient between the minimum mass the beam can have if it had a continuously variable shape with absolute accuracy, and the mass needed with the given amount of segments and a given uncertainty in of the height of each segment. The required mass of the beam can be calculated as:

$$m = \frac{FL}{\eta k \sigma_{\max}} \tag{41}$$

Here k is a constant σ_{max} the highest permissible stress. η is an efficiency factor such that:
$\eta \in \left]0,1\right]$

An infinite number of segments with absolute accuracy would give an efficiency of 1. The beam can be optimized both by increasing the information content in the geometric dimensions of the segments and by increasing the number of segments.
Figure 7 shows the relative performance of the structure as a function of information. The different curves show different behaviour for different numbers of segments. In each case the height of each segment is optimized (the width is constant, so the problem can be regarded as two dimensional). In this case 1,2, 3, 4 and 5 segments respectively. Interestingly, a lower number of segments give a faster convergence (fewer parameters) but a lower final value; therefore there are intersections between the points where it is a rational choice is to increase the number of sections. Therefore, for a certain amount of information there is an optimum number of segments (design parameters).

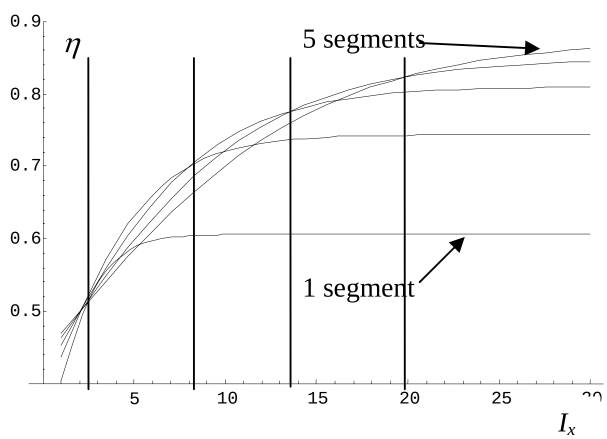

Figure 7. The efficiency of the structure as a function of information I_x

It can be observed that the amount of information where there is a transition, for that one more segment yield a better result than one without, is only few times higher than the number of parameters.

The beam can be described as a sequence of segments with the height of each segment as a variable. If all heights are known with the same accuracy I_p, the following information content is achieved:

$$I_x = nI_p = -n\log_2 \delta_x \tag{42}$$

This means that the relative influence of the n:th parameter (relative to the first parameter) can be written as

$$\psi_{0,n} = n^{-\lambda} \tag{43}$$

The uncertainty represented by the uncertainty in parameters is

$$\delta_x = 2^{-I_p} = 2^{-\frac{I_x}{n}} \tag{44}$$

For a sufficiently high number of n the uncertainty in the influence of the first parameter will be larger than the influence of the n:th parameter. Clearly there is no point in increasing the number of parameters beyond this point. This can be expressed as (assuming linear relationship between uncertainty and performance):

$$\begin{aligned} \delta_x &= n^{-\lambda} \\ 2^{-\frac{I_x}{n}} &= n^{-\lambda} \end{aligned} \tag{45}$$

This can be solved for n as:

$$n = \frac{\left(\dfrac{I_x \log(2)}{\lambda}\right)}{W\left(\dfrac{I_x \log(2)}{\lambda}\right)} \tag{46}$$

Here $W(z)$ is the product log function that gives the solution for w in:

$$z = we^w \tag{47}$$

Equation (46) can also be written as:

$$n = \frac{0.693\dfrac{I_x}{\lambda}}{W(0.693\dfrac{I_x}{\lambda})} \tag{48}$$

This function is shown in Figure 9. Alternatively, this function can be viewed as function for how the design space should be expanded as a function of design cost. For the beam example the behaviour can be approximated with a model with $\lambda = 2$ which can be seen in Figure 8. This means that the transition from 4 to 5 elements should occur at 20 bits of information, which is consistent with Figure 7.

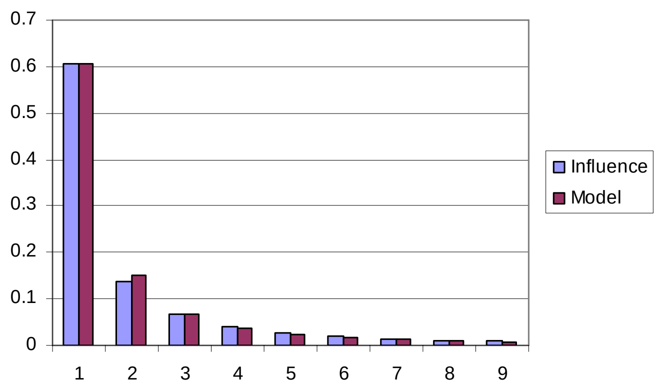

Figure 8. Influence of increasing the number of elements in the beam model. Exact solution and a model based on a negative power law relationship with λ=2.

It can be concluded that the efficiency/performance that can be achieved, is determined by the number of parameters, and there is little point in increasing the information content in the parameters more than a few times more than the number of parameters. This is to say, just a few bits per parameters.

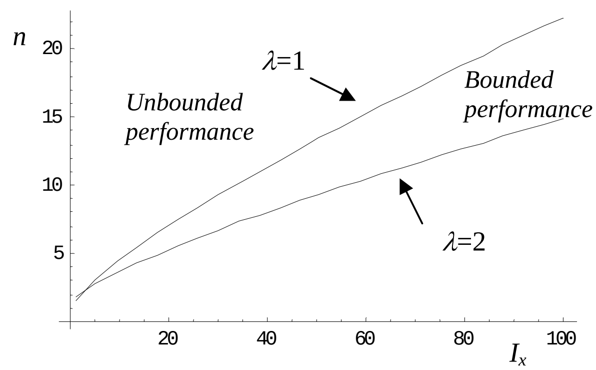

Figure 9. The optimal number of design parameters as a function of design information.

The implication is that when few design parameters are at hand, the number of parameters to some extent represents a measure of the modelling accuracy. In the beam example it represents a spatial resolution. Even in a more general design problem, the number of design parameters can give a first indication of the accuracy of the solution, or how close to optima it is possible to come. Furthermore, all problems that have bounded performance/efficiency can be found in the lower region of the diagram in Figure 9, where $\lambda > 1$. The curve $\lambda = 1$ form an upper bound to the number of design parameters for a given amount of information for systems with bounded performance. Careful design modelling, where one design parameter controls several system parameters through similarity relationships, can also be used to increase the exponent λ further. Conversely, a less suitable choice of design parameters can yield a situation where several parameters have more or less the same influence, which gives a distribution that deviates considerably from the negative power law model.

Nevertheless, the results are interesting, and points in the direction that sometimes it may be more efficient to increase the number of design parameters, rather then let the optimization run for a long time (or to further pursue refinement of a static concept).

Another aspect of interest is the cost of the beam. A simple model for the cost of the beam is.:

$$c = mk_c + k_I I_x \tag{49}$$

where k_c is the material price and k_I a price associated with refinement/information. Since m is a function of refinement/information this function can be shown to have an optimum level of refinement. Another example is in the modelling of efficiency, i.e. in a motor or engine, where it is known that the efficiency can never go above unity or some other (lower) limit, no matter how refined the machine is. It is there more appropriate to express efficiency in an auxiliary variable connected to refinement.

$$\eta = 1 - e^{-\gamma_\eta} \tag{50}$$

This equation has the property that for small values:

$$\eta \approx \gamma_\eta \tag{51}$$

and for large values

$$\lim_{\gamma_\eta \to \infty} \eta = 1 \tag{52}$$

This makes it more useful to express, for example uncertainty in the efficiency, as an uncertainty in γ_η instead of directly in η, since that could yield values above one (unless special care is taken when selecting a distribution). γ_η can here be seen as a direct measure of design refinement/design information.

PARAMETER INFLUENCE IN AN AIRCRAFT DESIGN EXAMPLE

An aircraft design was optimized and analyzed using sensitivity analysis. This was done to obtain the influence of various parameters on the design objective. In this case it is a combination of design characteristics for such things as, takeoff weight, fuel consumption, cruise speed etc, for a given mission. This is an example of a problem where there are a mixture of design parameters, both geometrical and others. In Figure 10 the design sensitivities for a transport aircraft is shown together with an adjusted model of the parameter influence. For this case the exponent $k = 1.3$ which is indicative that the performance is bounded. From Figure 9 it can be seen that $n = 10$ and $k = 1.3$ yields $I_x \approx 45$. Alternatively, using equation (45) directly yields that a suitable cut-off criterion for optimization should be:

$$\delta_x = n^{-k} = 10^{-1.3} = 0.05 \tag{53}$$

Of course, in this example where the actual parameter influences has been calculated, the actual values can be used instead, such that the value of the parameter with the lowest influence is taken as the reference:

$$\delta_x = \frac{\psi_n}{\psi_1} = \frac{\psi_B}{\psi_{tc}} = \frac{0.04}{7.9} = 0.0056 \tag{54}$$

Since the influence of the variable *tc* (thickness to cord ratio of the wing) is so small compared to the wing span B, this suggests that it should be dropped. However, in reality, the small value is due to a non-linear effect. If the thickness ratio is increased its influence will dramatically increase as well. Another thing that should be taken into consideration is that modelling error due to uncertainty in parameters that cannot be controlled, ultimately place a limit to what degree of refinement it is meaningful to go.

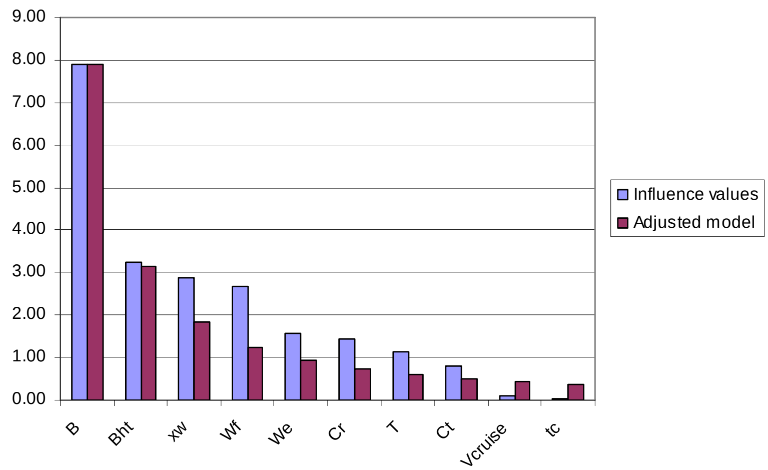

Figure 10. Sorted influences for different design parameters of a transport aircraft.

DISCUSSION

The fact that the micro processors, as well as the loaded beam example, follow the behaviour in equation (31) is a indication that this is a fundamental relationship. For a concept, a set of parameters (or more generally, objects, features etc) are selected for the design. A rational choice is to choose a set of parameters in the lower end of a spectrum of sorted parameters. This means that the contribution of introducing another parameter is monotonously diminishing. Strictly, this is true only in a linear design, but in reality it is still a rather effective explanation model. The C-K theory Hatchuel [12], describes the design process as a process alternating between concept expansion, and knowledge expansion. As knowledge is gained, it can be used to create and expand more of concept space.

In Figure 11. The design (or concept) domain is a subset of the knowledge domain. The design domain includes all objects/parameters that are included in the optimization of a particular design. The knowledge domain represents all objects/parameters that could have been included into the design with our present state of knowledge. It includes all factors that we can compute the influence of. This is a subset of the total object domain, which represents all possible objects.

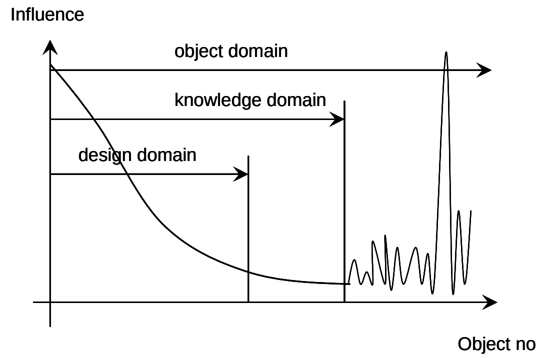

Figure 11. If previously unknown design parameters enter the knowledge domain the optimal solution might shift into an entirely different optimum, a disruptive design

In information theoretical terms that would correspond to a creating a concept, parameter convergence (optimization), hence concept refinement, followed by an expansion of the concept, adding more dimensions to the design (concept) space, adding more parameters, that are then optimized further. If the most influential parameters are chosen there will in the end only be parameters with little influence to include in the concept space. As knowledge is expanded new parameters are entered into the knowledge domain. Their successive influence can be regarded as random, since they have not been sorted prior to entering the knowledge domain. Therefore new knowledge can be disruptive and shift the optimal design into a totally different location of the concept space. In nonlinear design, also an addition of an element to the design can be disruptive, since it might tip the balance to the favour of another alternative concept. This corresponds to an innovation, and it does not involve an expansion of knowledge but primarily an expansion of concept.

The concept of design information provides a sound base for defining creativity as the process of selecting areas for expanding the design space, to think “outside the box”. While the automated activity of design optimisation, corresponds to refinement. Furthermore, the results here points out that the value of adding more design parameters as optimization variables is rapidly diminishing in the general case. Consequently, rather than using a simultaneous optimization of all design parameters, it is usually sufficient to use optimization for a few parameters (seldom more than 10-20) at the same time and then use design rules for the others, connecting them to the optimization variables.

CONCLUSIONS

In this paper it is demonstrated that introducing information as a state, simplifies the models of various aspects of design. This is consistent with the view that the design process is a learning process. A general model is presented that links information to optimization, refinement, performance and cost. Design information can be changed in basically two ways, design space expansion and parameter refinement. This corresponds to concept generation and expansion, and design optimization.

The results points out that there is a balance between the number of design parameters and the degree of uncertainty in these parameters. Therefore, there is an optimal level of refinement for a certain number of parameters, or system complexity. Beyond that, it is better to expand the design space by adding additional degrees of freedom. This shed some light on the relationship between design optimization and concept development. This is an indication that design information entropy describes a fundamental underlying state in design.

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