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THE EFFECTS OF COUPLING ON PARAMETER DESIGN

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ABSTRACT

Axiomatic Design holds that uncoupled designs are to be preferred over coupled designs. This paper documents an effort to empirically quantify the effects of coupling on the design process and how those effects depend on the scale of the problem (number of design variables). An experiment was conducted with human subjects who solved parameter design tasks through a simple graphical user interface. It is established that, for parameter design tasks with only two inputs and two outputs, coupling had only a moderate effect on the subjects' solution of the problem. As the number of variables increases, the effect of coupling among variables has a drastic effect on the solution procedures and the completion time. The time for a human to solve a coupled parameter design problem rises geometrically as problem size rises from 2X2 to 5X5. These results are discussed in the context of information processing models of human cognition. The implications for Axiomatic Design are discussed.

Keywords: coupling, parameter design, cognitive science, axiomatic design, complexity

1 BACKGROUND AND MOTIVATION

1.1 COUPLING AND AXIOMATIC DESIGN

In Axiomatic Design, the Independence Axiom states: "maintain the independence of the functional requirements" [Suh, 1990]. This axiom can be interpreted using the design matrix, **A**, which represents the mapping between Design Parameters (DPs) and Functional Requirements (FRs)

$$\{\mathbf{FR}\} = [\mathbf{A}]\{\mathbf{DP}\} \tag{1}$$

The elements of this design matrix are defined in terms of partial derivatives

$$\mathbf{A}_{i,j} = \frac{\partial \mathbf{FR}_i}{\partial \mathbf{DP}_j} \tag{2}$$

An uncoupled design is a design whose matrix **A** can be "represented by a diagonal matrix whose diagonal elements are only non-zero elements" [Suh, 1990]. A decoupled design is a design whose matrix **A** can be arranged into a triangular matrix. All designs that are neither uncoupled nor decoupled are coupled designs. The Independence Axiom states that only uncoupled and decoupled designs are acceptable.

Suh holds that the Independence Axiom is among the set of "general principles or self-evident truths that that cannot be derived or proved to be true except that there are no counter-examples or exceptions" [Suh, 1990]. The authors conducted experiments to test the Independence Axiom. This paper will show that human subjects can satisfy functional requirements via parameter design even faced with coupled systems, but that the negative consequences of coupling scale very unfavorably. To make this statement precise, we must now define and discuss the terms "parameter design" and "scale".

1.2 PARAMETER DESIGN AND SCALE

Let us define parameter design as the process of adjusting the values of the DPs in order to achieve desired values of the FRs. Parameter design is therefore distinct from and subsequent to the conceptual design process in which the design parameters are selected and the structure of the design matrix is determined.

The interplay of parameter design and coupling is central to the theory of Axiomatic Design. In fact, Suh restates the Independence Axiom as -- "in an acceptable design, the design parameters and functional requirements are related in such a way that the specific design parameter can be adjusted to satisfy its corresponding functional requirement without affecting other functional requirements" [Suh, 1990]. Based on this quote, one might infer that a coupled design is unacceptable within Axiomatic Design because coupling makes parameter design more difficult.

Some of the design theorems seem make even stronger claims about coupling and parameter design. For example, Theorem 9 (Design for Manufacturability) states -- "For a product to be manufacturable, the design matrix of a product, [A] … times the design matrix for the manufacturing process, [B] … must yield either a diagonal or triangular matrix. Consequently, when … either [A] or [B] represents a coupled design, the product cannot be manufactured." Therefore, one might infer that Axiomatic Design holds that coupling makes parameter design not only difficult, but impossible. It is of significant practical importance whether or not coupling makes parameter design impossible or merely difficult. And if coupling makes parameter design difficult, it is valuable to know approximately *how* difficult.

We posit that the degree of difficulty related to coupling is strongly determined by the scale of the design problem. We define the scale of the design problem as the number of FRs to be satisfied. The purpose of this paper is to quantify the difficulties associated with parameter design of coupled systems and to determine the effect of scale. In particular, this paper focuses on how coupling makes parameter design difficult for *people* as opposed to *computers*. The next section provides some background on human cognition in order to prepare the reader to interpret the results of our experiments.

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1.3 COGNITIVE SCIENCE

Modern cognitive science makes a distinction between the information storage and processing facilities of the human mind. Information storage capabilities of the mind are divided into two distinct categories, short-term memory and long-term memory. The activities of the information storage and processing structures of the human mind are directed by the central executive function, which focuses attention, allocates resources, and directs and controls cognitive processes. Although the evidence for such a supervisory structure in the mind is clear, it is poorly understood in comparison with most other basic cognitive structures [Cowan 1995].

The psychologist George A. Miller made an early and influential contribution to the understanding of the limits of humans as information processing agents. In "The Magical Number Seven, Plus or Minus Two," Miller [1956] proposed that human short-term memory capacity was limited by several factors. First, he suggested that what he called the "span of absolute judgment" was somewhere between 2.2 to 3 bits of information, with each bit corresponding to two options in a binary scheme.

This severe short-term memory limitation raises a paradox. How then could one possibly remember an entire sentence if a single word has about 10 bits of information? Miller proposed that people actively engage in the "chunking" of information as it is encoded in their memory to circumvent the span limitation. In this scheme the number of bits of information is constant for "absolute judgment" and the number of "chunks" of information storable within the short-term memory is also constant and both regimes are governed by the rule. Miller suggested that since the short-term memory span is fixed at chunks of information, the amount of data that it actually contains can be increased by creating larger and larger chunks of information, each containing more bits than before. To do this, the information is converted into more efficient representations as it is encoded in the memory. So, as input is received by an individual in a form that consists of many chunks with few bits per chunk, it is re-coded so that it is contained in fewer chunks with more bits per chunk (Miller 1956).

Although there is still debate over the extent and nature of human short-term memory limitations, the facts most can agree upon are that such limitations exist and that they impose a significant bottleneck on the information processing capabilities of the mind. A large body of research has supported the significance of short-term memory limitations with respect to the performance of activities as diverse as game playing, expert system design, and personnel selection (Chase and Simon 1973, Enkawa and Salvendy 1989). Studies have proven short term memory limits be significant in engineering (Christiaans and Dorst 1992, Condoor et al. 1992), the design of CAD systems (Robertson et al. 1991, Waern 1989), finance and economics (Chi and Fan 1997), AI and expert systems (Enkawa and Salvendy 1989), management decision making (Mackay et al. 1992), and operations research (Robinson and Swink 1994)]. The experiment described in the next section is intended to establish the importance of human cognitive limits in yet another area -- parameter design.

2 EXPERIMENTAL METHOD

Our goal was to investigate the effect of problem scale and coupling on human capability to carry out parameter design. To facilitate our investigation, we chose to develop a surrogate for the parameter design process to capture the essential features we wished to study as listed below:

1. The mapping from input to output can be coupled or uncoupled.
2. Problems may differ in scale.
3. The designer can obtain information about the current state and desired state of the outputs only at discrete points in time.

The parameter design surrogate retains these features and strips away any real world context for the design. This simplified representation prevents confounding with the subjects' knowledge of any specific field of engineering.

The parameter design surrogate was embodied in software with a graphical user interface (GUI) as depicted in Figure 1. In order to solve a parameter design problem, human subjects were required to adjust the input variables (design parameters) controlled by slider bars on the GUI until the output variables (functional requirements) indicated by gauges on the GUI fell within specified ranges. The "target range" within which the output had to fall for the design problem to be considered completed, or "solved," was set at 5% of the range of the output variable display gauge range.

Figure 1 depicts a GUI for a 3X3 parameter design task. Other GUIs for 2X2, 4X4, and 5X5 problems were created by adding or removing slider bars and output gauges. In pilot studies, we attempted to present human subjects with 6X6 tasks, but a substantial fraction became frustrated and would not complete the tasks. Therefore, we chose to limit the range of problem sizes in our study.

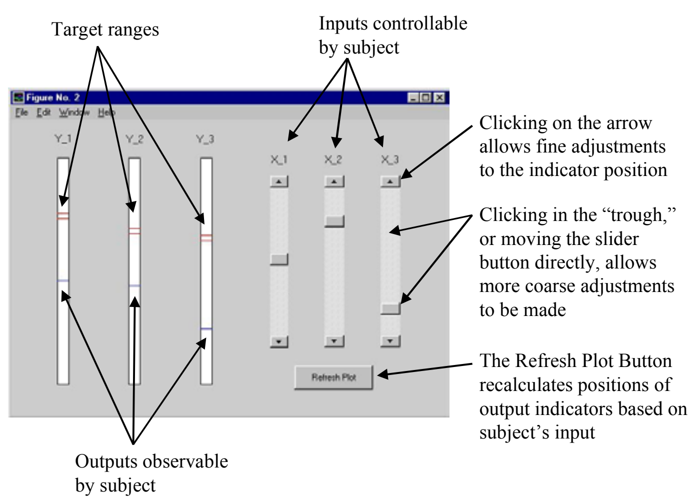

Figure 1. The parameter design surrogate.

The output variable display gauges were not designed to update themselves smoothly and continuously as the inputs were varied. Instead, the positions of the output variable indicators in

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the displays were only recalculated and updated after the "Refresh Plot" button on the lower right-hand side of the Task GUI was pressed by the subject. Forcing participants to press a "Refresh Plot" button creates some additional difficulties for the subject. If the outputs were dynamically updated as the slider bars moved, it would have been easier to infer the relationship among the variables. However, the "Refresh Plot" feature was a deliberate choice. Design scenarios generally involve making step changes to a prototype or computer model and getting information on the effects of those changes only when a test is run or an analysis is carried out. Designers rarely have the luxury of a dynamic update of the effects of their design changes.

The effects of the slider bars on the outputs was determined by a matrix of derivatives as defined in Equations 1 and 2. The matrices used to represent the design process were carefully selected to facilitate investigation of the effects of coupling and scale. Some of the design matrices were diagonal to provide a baseline of performance with no coupling among design variables. Other design matrices were strongly coupled and orthonormal. An example of one of the matrices used in the experiment is given in Table 1. In all the matrices used in this experiment, there were large off diagonal elements (often as large as the on-diagonal elements). Orthogonality guaranteed that the matrix would be well conditioned. Normalization ensured that all of the input variables would be balanced with respect to one another with none having a disproportionate effect on the output variables. Similarly, all of the output variables are balanced with respect to one another with none being more or less controllable by the input variables.

Table 1. An example of a 3X3 matrix used in the parameter design surrogate.

	Input #1	Input #2	Input #3
Output #1	0.683	-0.658	0.317
Output #2	0.658	0.366	-0.658
Output #3	0.317	0.658	0.683

Twelve human subjects were used in our study. They were paid a small sum for their efforts. The set of experiments was conducted following a uniform protocol. Subjects were seated at a computer in a laboratory and given a scripted presentation on the use of the GUI. During the experiment, subjects were not allowed to use pens, paper, or computational aids. Whenever the subject hit the "Refresh Plot" button, the program recorded the time and the position of the inputs and outputs.

A brief demonstration exercise was required at the outset to teach each subject how to use the software. The software was designed to allow subjects to pause between design problems during the experiment and re-start the program when they were ready to continue, or quit the program if they wished (these features were required by the University's committee on the use of humans as experimental subjects). The software presented the design tasks to the subjects in a randomly selected order that was changed for each participant. This was done to avoid inadvertently training the subjects by progressing from "easy" to "hard" systems and to minimize any other possible effects a consistent design task order might have had on the outcome of the experiments.

In addition, a solution vector with a Euclidean norm of 1 was selected at random for each design problem from a set of twenty-five unique vectors created for each different size of design matrix. Since the solution vectors were normalized, the Euclidean distance between the starting point of the output variables (always at the origin of each gauge on the Task GUI) to the solution position (i.e. the target range) would be the same for each experiment involving a given design matrix. This created a degree consistency among all the solutions. Randomizing the selection of the solution vector also reduced the likelihood of a particularly easy or difficult solution recurring consistently and affecting the experimental results.

To summarize, the parameter design surrogate is a simplified parameter design task embodied in a graphical user interface (GUI). The inputs are represented as slider bars and the outputs are represented as vertical gauges. The mapping from inputs to outputs is determined by a matrix, some of which were entirely uncoupled, some of which were strongly coupled. Twelve human subjects completed a series of tasks presented in randomized order with different numbers of variables (from 2X2 to 5X5). The changes in the inputs and outputs and the times at which they were made were recorded automatically. The next section will present an analysis of the data from this experiment.

3 RESULTS

This section presents the results of our experiments with the parameter design surrogate described in section 2. The data will be examined and discussed in the context of a cognitive science perspective of human information processing and problem solving.

To present examples of subject's behavior in this experiment, we will employ a graphical representations such as in Figures 2 ,3, 4, and 6. The large gray point is the starting value. The black points represent the values returned each time the subject pressed the "Refresh Plot" button. The black lines connect each pair of sequential points as an aid to visualizing the sequence of the changes made. The open gray box represents the target range. It is important to note that the subjects did not have access to such a plot during the experiment.

A typical strategy for subjects solving uncoupled systems was to move one slider bar at a time to adjust the corresponding output onto its target and to repeat the process for each slider in turn. The subject's performance depicted in Figure 2 is an example of this solution strategy for a 3X3 system, but the same pattern was evident in all the systems from 2X2 to 5X5. Because this was an uncoupled system, the effect of moving one slider bar is to move the output value parallel to one of the axes in the graph. Figure 2 reveals that multiple adjustments were needed to get each variable on target and that the subjects sometimes overshot the target.

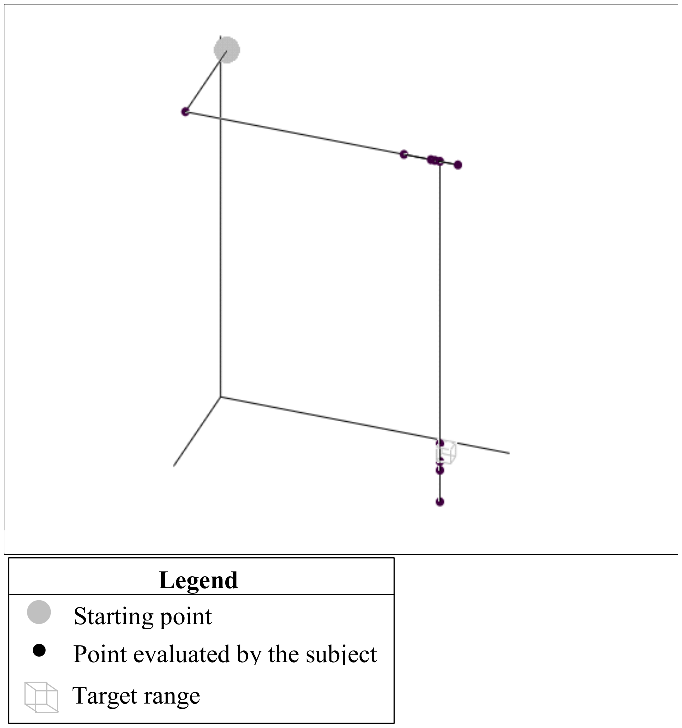

Figure 2. A typical solution strategy employed by a human subject solving an uncoupled 3X3 system.

The behavior of subjects solving coupled 2X2 systems was qualitatively similar to the their approach to solving uncoupled systems. An example of a subject's performance is shown in Figure 3. Again, the input slider bars were moved one at a time, but in the coupled system, this resulted in changes along lines skew to the axes. The main similarity between the approach to the coupled system (in Figure 3) and approach to the uncoupled system (in Figure 2) is the directness of the solution. The changes made by the subjects tended to move the state of the outputs closer to the solution (in the Euclidean sense). There were some exceptions to this. Some non-converging moves are seen early in the solution process as the subject works to discover the dependencies of outputs on inputs. But after each slider bar had been moved once, the state of the outputs generally moved consistently closer to the target.

The fact that 2X2 coupled systems could be solved in a direct manner is generally consistent with the results of cognitive scientists' investigations of human limitations on information processing. A fully coupled 2X2 linear system requires only four scalar values to completely characterize its behavior. Since our targets cover 5% of the available range, one digit of precision would provide almost enough information to solve the problem. Given Miller's "Magical Number Seven, Plus or Minus Two", one would expect that an approximate model of these 2X2 systems to be within the "span of absolute judgment" of most humans. We conjecture that once the four parameters governing the behavior of the coupled systems were learned, the subject was able to proceed with the solution of coupled 2X2 systems almost as if they were uncoupled.

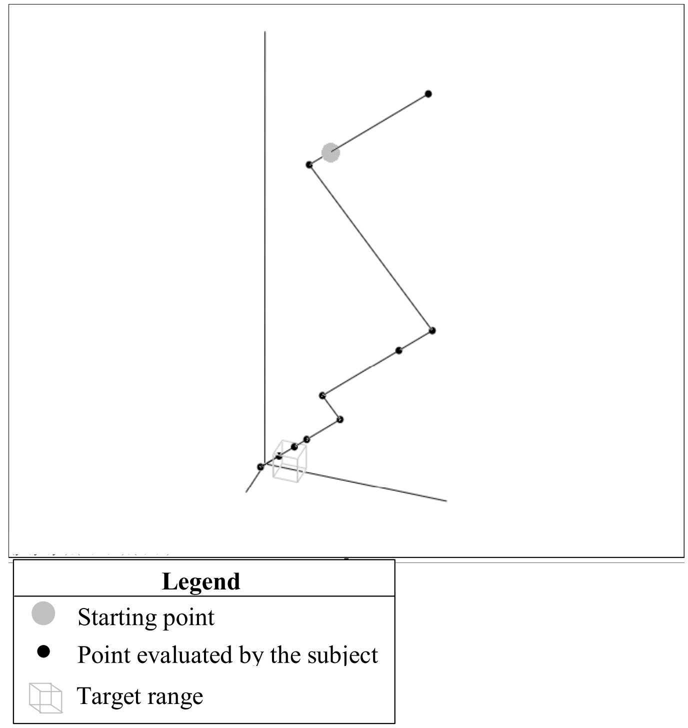

Figure 3. A typical solution strategy employed by a human subject solving a coupled 2X2 system.

As a result of the directness of the solution of 2X2 coupled systems, the times were only modestly affected as compared with uncoupled 2X2 systems. The 31 coupled 2X2 systems solved by the subjects took on average 40 seconds to solve. By comparison, the uncoupled systems required 24 seconds (about 40% less time). This difference in the means was statistically significant (α=0.05), but the practical significance seems very small compared with the differences for the larger systems studied (3X3, 4X4, and 5X5).

On the basis of cognitive parameters, one may construct an approximate explanation of the modest increase in completion times for 2X2 coupled systems compared to uncoupled 2X2 uncoupled systems. The coupled 2X2 systems have require two more scalar values to characterize them. If the two extra scalars were stored as digits in long-term memory, then approximately 10 extra seconds should be required. Also, the mental arithmetic or graphical manipulations required for solution are more complex for coupled systems. The 16 second increase revealed in this study seems reasonably consistent with what is known of human cognitive parameters. To more precisely determine the causes of the increase will likely require additional experiments. For the present, the authors prefer to focus on the much larger effects that are revealed as the number of variables increases beyond 2X2.

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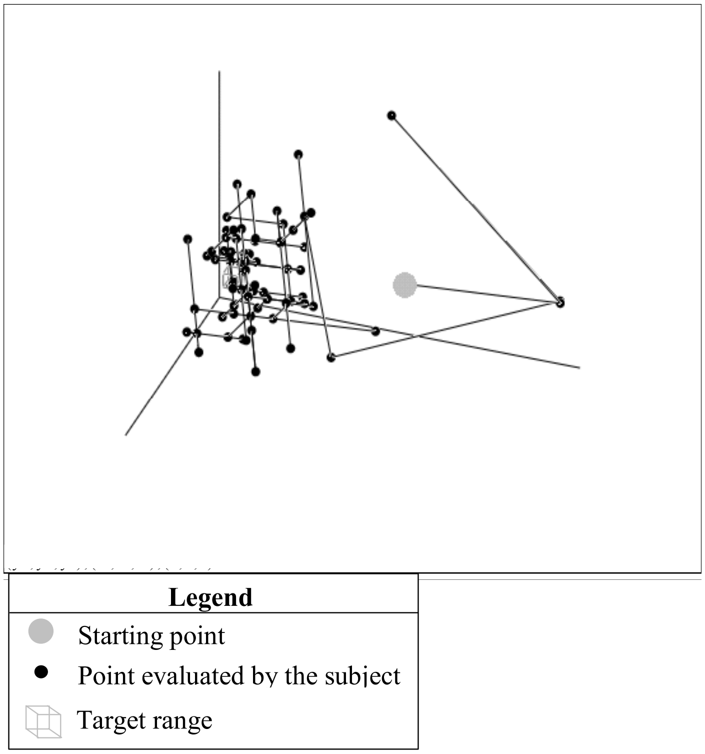

Figure 4. A typical solution strategy employed by a human subject solving a coupled 3X3 system.

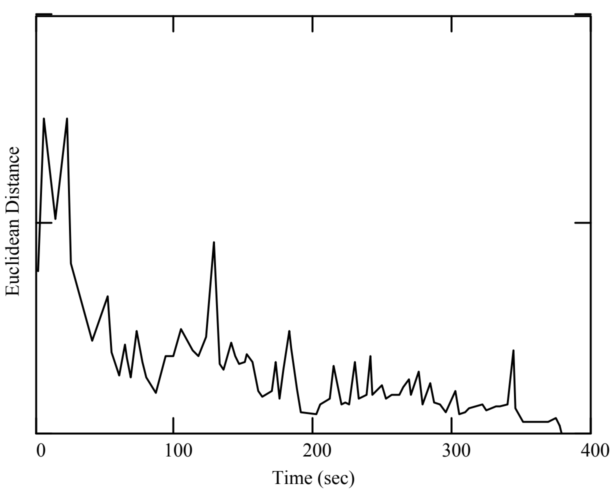

Figure 5. The convergence of the strategy used for the coupled 3X3 system in Figure 4.

In the 3X3, 4X4 and 5X5 coupled systems, the solution procedures employed by subjects appeared qualitatively different than that observed in the 2X2 coupled systems. A typical example of solution behavior for 3X3 systems is shown in Figure 4. It appears to include random steps in 3D space with the step size decreasing as the distance to the target decreases. The convergence of the solution method of Figure 4 is graphed in Figure 5. The Euclidean distance from the target generally

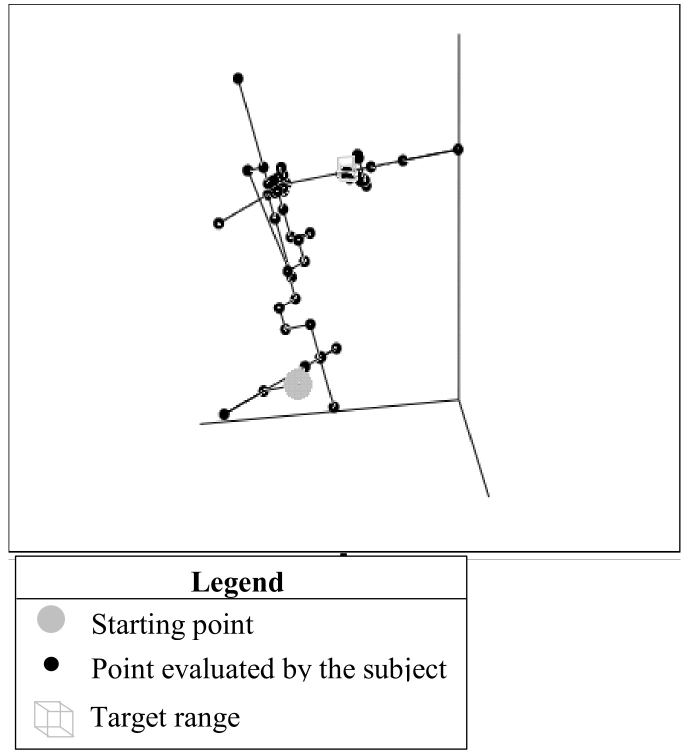

Figure 6. An alternative solution strategy employed by a human subject solving a coupled 3X3 system.

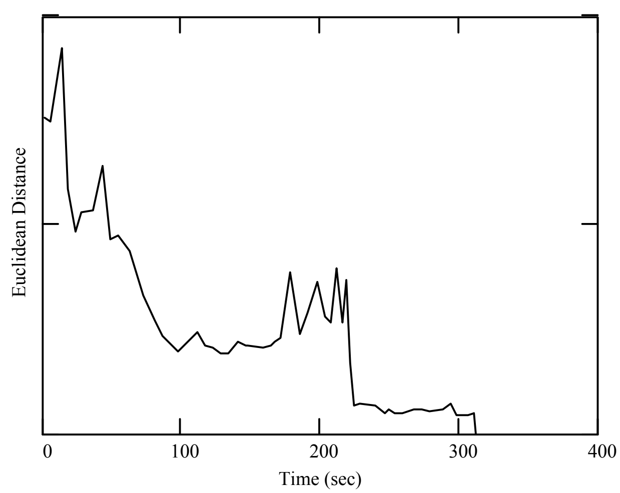

Figure 7. The convergence of the strategy used for the coupled 3X3 system in Figure 6.

decreases over time despite the fact that almost half of the moves result in movement away from the target. The subjects may be moving slider bars in sequence in an attempt to get "closer" to the target (perhaps in the Euclidean sense). To determine whether a move is "closer" to the target requires only that the previous state of the outputs be retained in memory. The current state is available on the screen (a form of external memory). A difference can therefore be computed and processed. At any given point, one or more of the bars will allow some degree of

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movement toward the target. The subjects seem to cycle through the slider bars in different sequences seeking sliders that will allow them to move closer to the target.

In some cases, the subjects seem to employ a different approach that includes very extensive sampling in areas of space not containing the target (see Figure 6). In these cases, it appears that the subject is focused on only two output variables and two input variables. The subject works to place those variables within their target range while the remaining variables are substantially off of their target values. Following this extensive search within an area of space that does not include the solution, large moves are made with the remaining variables and the process is repeated with a different selective focus on the output variables. Figure 7 shows the convergence over time of the solution approach in Figure 6. The convergence includes plateaus with little change followed by large changes leading to new, lower plateaus. With this approach, the subjects may be attempting to bring the problem back within their "span of absolute judgment". By selecting a 2X2 subset of the larger problem, the subject is able to make a sequence of moves that take them monotonically to a region of space in which two outputs are on target. After some local search confirms that the complete solution is not available, larger moves in an orthogonal direction are made and the process is repeated.

Despite the fact that at least two distinct approaches were employed in solving coupled problems, there was no clear bi-modality in the distribution of completion times. The distributions were not normal (as verified by Anderson-Darling and Kolmogorov-Smirnov tests). There was significant skew towards long completion times.

To summarize the results of this section, the subjects completed the uncoupled tasks in a sequential process, placing each output on target using its corresponding slider bar. The subjects completed coupled 2X2 tasks in a fairly direct manner with few missteps after the underlying dependencies among inputs and outputs were determined. There was a modest but statistically significant increase in time required to complete the coupled 2X2 tasks as compared to uncoupled 2X2 tasks. The solution procedures employed by subjects for coupled 3X3, 4X4 and 5X5 tasks seemed qualitatively different than those for 2X2 systems. Solution of these larger systems involved more iteration, a greater fraction of non-converging moves, and much more time. The next section will quantify that time penalty for coupling more precisely by proposing scaling laws for time versus problem size.

4 PRPOSED SCALING LAW

This section will propose scaling laws for the growth of completion time versus number of variables in the problem. Such scaling laws are commonly used to characterize the "complexity" of algorithms. Uncoupled and coupled systems are analyzed to provide separate scaling laws due to the significant differences in the effects of scale on coupled systems versus uncoupled systems.

Figure 8 presents the normalized task completion times for fully coupled matrices and for uncoupled matrices. The graph indicates that completion time increased much more rapidly with matrix size for coupled matrices than for diagonal matrices. The error bars on the data points indicate standard deviation of the normalized completion time. The standard deviation of the time rises with the completion time.

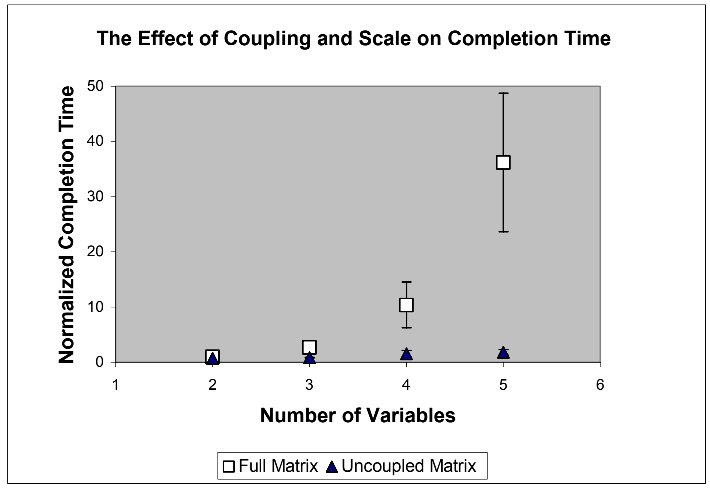

Figure 8. Normalized completion times versus scale.

The normalization procedure for the data in Figure 8 warrants some explanation. There was a great deal of variation in how long it took individuals to complete the set of tasks. Some were able to complete all of the design problems included in the experiment within about 45 minutes, while other subjects took nearly three times longer. To better reveal the way that completion time is affected by scale and coupling, we normalized the task completion time for each subject by the time to complete one particular 2X2 fully coupled matrix that each subject solved at some random point after the training period. This normalization procedure allowed us to correct for such inter-subject variations as facility in manipulating a mouse.

For uncoupled systems, normalized task completion times scale linearly with matrix size. Linear regression of the normalized completion time data versus problem size, n, fit a standard linear model with an adjusted R-square of 0.71. The regression model's residuals indicated that they were randomly distributed. Virtually none of the residual error in the regression model was due to lack of fit -- a regression of the average normalized completion times fit a standard linear model with an adjusted R-square of 0.90.

The linear scaling law for uncoupled problems is consistent with the observations made in Section 4. Given the sequential nature of the solution process observed, the subjects had only to store a single scalar parameter at a time. The number of times a parameter had to be learned and the time for iterative adjustments should grow linearly with n given the solution procedure we observed.

For fully coupled systems, normalized task completion time scales geometrically with matrix size (there is roughly a factor of three increase with each increment of problem size, n). Linear regression of the log of normalized completion time data versus problem size, n, fit a standard linear model with an adjusted R-square of 0.70. The regression model's residuals indicated that they were randomly distributed. Virtually none of the residual

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error in the regression model was due to lack of fit -- a regression of the average log of normalized completion times fit a standard linear model with an adjusted R-square of 0.99. Based on the slope of the best fit line of the log transformed data, the normalized completion time for fully coupled matrices was found to be proportional to 3.4 raised to the power of the problem size n.

The geometric form of the scaling law may be explained in an approximate sense on the basis of the observations in section 3. The subjects tended to use a solution process that resembled a random sampling within a limited region of n dimensional space. The target was a hyper cube with the length of the side constant with n. Let us model the human search procedure as random sampling within a space of fixed linear dimension with a target of fixed linear dimension. Let us assume that the time required for each sample is constant. Based on this model, the average number of samples required to hit the target should grow geometrically with n. The observations in section 3 show that the subjects' performance was more complex and varied than the simple model described above. The model is not offered as a complete explanation of the scaling law, but this simple model may provide some insight into the reason that geometric growth was observed.

The observations of section 4 suggest that the subjects' performance was qualitatively different for 2X2 coupled systems as compared with 3X3 and larger coupled systems. Therefore, one would not expect the same scaling law to fit the data at n =2 that fits the data at n =3, 4, and 5. Nevertheless, the data from this experiment show both that the solution procedure was different and that the scaling law fits. We do not have an adequate explanation for this fact, and suspect that it is merely coincidental.

The unfavorable scaling of problem completion time with problem size is supported by other research on human performance of mental calculations. Completion time for mental arithmetic tasks correlates well with the product of the digits or square of the largest digit involved in the calculation (Dehaene 1997, Simon 1974). This scaling law appears to be valid whether the mathematical operation in question is multiplication, division, addition, or subtraction, and is likely to be due to both short- and long-term memory constraints and the degree and type of domain-related training received by the subject (Ashcraft 1992).

Geometric scaling of human performance in solving coupled linear systems is in contrast to that required for solution by formal algorithms. An LU factorization of an n by n linear system followed by Gaussian elimination to find the solution to the problem requires $\frac{2}{3}n^3 + \frac{5}{2}n^2 - \frac{7}{6}n$ mathematical operations. Therefore, formal solution of linear systems is $O(n^3)$ while human performance in this study was $O(3.4^n)$. The difference in these scaling laws is significant even in the small range of n tested in these experiments (from two to five). The predictions of these scaling laws differ by over a factor of two as n rises from two to five.

To summarize the results of this section, time for the human subjects to complete uncoupled parameter design tasks scales linearly with problem size. In contrast, time for the human subjects to complete coupled parameter design tasks scales geometrically with problem size; a roughly three-fold increase in time is required for each additional variable as problems grow from 2X2 to 5X5. This is very different from the polynomial scaling law for computers to solve similar systems. The poor scaling of human solution on coupled parameter design problems seems to arise from the stochastic features of the iterative process humans employ.

5 RELATIONSHIP TO AXIOMATIC DESIGN

Great care should be taken in applying the results of this paper to authentic design scenarios. The simplified parameter design task investigated here neglects a host of considerations that are present in engineering design. The difficulty of a parameter design problem can depend many factors including the designer's experience and skill in the given domain or the presence of external problem solving aids (i.e. CAD and other tools). Nevertheless, this study provides some insights that may have significant bearing for engineering design in general and Axiomatic Design in particular.

In one sense, the results of this experiment may provide an empirical justification for the Independence Axiom. This paper experimentally demonstrates the strong effects of coupling on human performance in design tasks.

Although this paper reinforces Axiomatic Design's caution against coupling, some aspects of Axiomatic Design theory should perhaps be reinterpreted in light of these new experimental results. The wording in The Principles of Design [Suh, 1990] sometimes suggests that coupled designs are unacceptable and that they cannot meet the stated functional requirements. For example, Theorem #9 states that a design with a coupled mapping from either FRs to DPs or from DPs to PVs cannot be manufactured. Theorem #15 states that when the FRs are not independent, the design must be modified. This sort of strong language might be interpreted as a call to avoid functional coupling at all costs. The experimental results in this paper suggest that such an extreme interpretation of Axiomatic Design should not be adopted. When only two functional requirements are to be satisfied, the designer should be able to satisfy the functional requirements even if the design is coupled. The paper also suggests that, for 2X2 coupled systems, the added difficulty of executing the design may be modest. In some cases, modest increases in difficulty should be quantified and traded off against other considerations before discarding a coupled alternative. In some cases, the coupled alternative will have advantages that mitigate the disadvantage of a more difficult parameter design process. For example, there are some cases in which coupling provides an improved probability of success due to the correlation induced among functional requirements [Frey et al., 2000]. In other cases, coupled designs may have advantages in cost or physical simplicity.

This investigation suggests the possibility of an anthropocentric reinterpretation of the Independence Axiom. Indeed, coupling should be avoided when practicable through careful system design, especially when the subsystem in question appears to be coupled across more than two variables. In the opinion of the authors, the need to avoid coupling is not self-

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evident and is not a general principle without counterexamples. Rather, the need to avoid coupling arises from practical necessity due to human cognitive limitations. If a design is to be implemented successfully, its human designers must be capable of understanding the design despite their limited capacity to cope with functional coupling.

6 ACKNOWLEDGMENTS

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