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Experimental Studies Assessing the Repeatability of a Functional Modeling Derivation Method

Mark A. Kurfman & Robert B. Stone[1]
Department of Basic Engineering
University of Missouri-Rolla
Rolla, MO 65401
rstone@umr.edu

Jagan Rajan & Kristin L. Wood
Department of Mechanical Engineering
The University of Texas at Austin
Austin, TX 78712
wood@mail.utexas.edu

ABSTRACT

As more design methodologies are researched and developed, the question arises as to whether these new methodologies are actually advancing the field of engineering design or instead cluttering the field with more theories. There is a critical need to test new methodologies for their contribution to the field of design engineering. This paper presents the results of research attempts to substantiate repeatability and uniqueness claims of the functional model derivation method. Three experiments are constructed and carried out with a participant pool that possesses a range of engineering design skill levels. The experiments test the utility of the functional model derivation method to produce repeatable functional models for a given product among different designers. Results indicate the method enhances repeatability and leads designers toward a unique functional model of a product. Shortcomings of the method and opportunities for improvement are also identified.

1 INTRODUCTION

Functional modeling is an integral part of the design process. The widespread usage of functional modeling in many contrasting and complementary forms motivates the design community to search for a unified, systematic and formal theory of functional modeling. Many of the current theories lack the scientific data required to substantiate their usefulness. This lack of validation often hinders their acceptance. In this article, we report on efforts to validate our approach to functional modeling (termed the functional model derivation method) as a repeatable method and explore its capacity to generate unique functional representations of products. For repeatability assessment we look at simple frequency of occurrence of sub-functions identified by experiment participants. Concerning uniqueness, we hypothesize that one or very few "correct" functional representations of a product exist given process choices (i.e., choice of input flows such as electrical energy vs. mechanical energy). We term these models "quasi-unique" functional models. Since functional models capture only *what* the product does, there are no form solutions to describe and, thus, a limited set of functions can completely describe the product. Therefore, we assess the uniqueness characteristic of the

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[1] Corresponding author, 102A Basic Engineering Building, University of Missouri-Rolla, Rolla, MO 65409-0210; Phone: 573-341-4086; E-mail: rstone@umr.edu.

method by comparing participant functional models against the quasi-unique functional model that we derive following the functional model derivation method.

If functional modeling can be experimentally proven to be a repeatable design tool, then it would open a world of possible applications. One of the most promising applications is in the area of computer aided design. Just as computer aided design (CAD) has revolutionized the field of engineering over the past twenty years, functional modeling offers an analogous leap. Over the years, CAD has benefited the field of engineering by increasing productivity, reducing a product's time to market, and improving manufacturability. Unfortunately, current CAD applications are only able to capture a product's geometrical feature, but not a product's function or behavior. If a tool is developed that can perform these operations, an engineer would no longer search a database for merely geometric representation, but instead look for products similar in function. In other words, capturing a product's function opens the door for design by analogy techniques (McAdams & Wood 2000; Howe et al., 1986; Goel, 1997; Altshuller, 1984), potentially reducing design time and increasing creativity.

Another area to which a functional modeling derivation method that produces unique (or quasi-unique) functional models could be of great benefit is conceptual product architecture development (Stone *et al.*, 2000a&b). Modular products offer tremendous benefits in terms of interchangeability, using common parts and reducing manufacturing costs (Dahmus *et al.*, 2000; Simpson et al., 1999; Hernandez et al., 2001). Unfortunately, in many instances the benefits of a modular architecture may not be realized until after an initial prototype is produced. By using functional modeling, it is possible to develop product architectures earlier in the product development process. Stone *et al.* use heuristics in order to develop useful architectures. All of this, however, is dependent on a quasi-unique and repeatable functional model. In Section 2 we review current and past function-based design methodologies. Section 3 contains details discussing the procedure of a functional modeling repeatability experiment. The results and data analysis are discussed in Section 4 before conclusions are made in Section 5.

2 BACKGROUND

Functional modeling in engineering design research theory is a well-researched and active field of engineering study. There are numerous functional modeling methodologies, all of which follow a similar procedure. They begin with an overall product function and then break that function down into sub-functions. The most well-known approach to creating a functional modeling of a product is that of Pahl and Beitz (1996). They model the overall function and decompose it into sub-functions operating on the flows of energy, material, and signals. Their functional approach was a great advance for engineering design, but their methodology did not provide an all-encompassing list of sub-functions to describe all possible engineering systems or produce repeatable function structures. Since then, many researchers have sought to fill in the missing portions of Pahl and Beitz's work (Kirschman and Fadel, 1998; Hundal, 1990; Hubka 1984; Murdock et al., 1997; Lai and Wilson, 1989; Iwasaki et al., 1995; Umeda and Tomiyama, 1997).

A problem with many of the reviewed function based design methodologies is their inability to produce repeatable functional models of a particular product. Two engineers can be given the same product, customer needs, and process choices, but the likelihood of them producing similar function structures is low. Some designers have suggested that this is the essential flaw with functional modeling and therefore disregard its significance. We have attempted to resolve this problem by developing a common language to create functional models that enhances repeatability. The reason we believe some level of repeatability is needed for functional modeling goes back to the motivating factors in Section 1. To reuse existing design knowledge, there first must be a way to consistently archive the knowledge. While many solutions exist for essentially the same product, we contend that truly similar products perform largely the same set of functions. It is at this level of commonality, i.e., the functional model, that automated design approaches may be applied to generate possible product solutions, pulling from the archived design knowledge.

Developing a common language for functional modeling can trace its beginnings back to the study of value analysis (Miles, 1972; Akiyama, 1991; VAI, 1993). In this work, they define all of their functions using a verb and a noun, but they go one step further than the previously mentioned design methodologies by developing suggested verbs-noun lists. Their lists, however, are not complete and cannot begin to describe all of the possibilities that one might encounter in engineering. Collins *et al.* (1976) used over 500 individual failed parts from helicopters to propose a list of elemental mechanical functions to classify their failure. Their investigation resulted in a list of 105 elemental mechanical functions that can be used to classify helicopter failure data. While very useful, its scope is limited to helicopter applications.

Modarres (1997) uses conservation principles to develop a common vocabulary for functional modeling. Using his methodology, an engineering system can be described using input and output flows of mass, energy, and signals, which he terms *main commodities*. His methods are very similar to Pahl and Bietz's (1996) function based method, but Modarres goes on to further describe the system by defining *support commodities*. These *support commodities* enter the systems boundaries and make the energy conversion possible. His functional classification system has seven main categories and these are further decomposed into 24 major forms. He also classifies six *functional primitives* that are used in the processing of commodities. Modarres does not specify a format to create functions such as the *verb-object* format described in Pahl and Beitz (1996) which leaves room for variability between different users. His classification system is more appropriate for mechanical systems and is lacking in appropriate *functional primitives* for the processing of signals.

Another example of a function classification system is the TROPOS functional modeling language (Amoussous *et al.* 1997; Vicarini 1995). Developed for the modeling of industrial maintenance problems. Using two classes of words, *role class* and *form class*, the TROPOS vocabulary identifies different industrial plant activities. The application of TROPOS is limited to industrial plant applications.

Szykman *et al.* (1999) has developed a functional vocabulary that is used to represent a product's function and its link to product form. This form dependence hinders its use during the conceptual design phase, but is a great advance towards a repeatable functional model. Stone and Wood (2000) develop a function and flow vocabulary they call the functional basis. This work sought to identify functions and flows describing the entire mechanical design space and selected the name functional basis to imply the mathematical characteristics of a basis - spanning the space and exhibiting linear independence. Recently, these two works have been integrated to form the reconciled functional basis (Hirtz et al., 2001). The two highest level classifications of the reconciled flow and function sets, called the *class* and *secondary* or *basic* levels, are shown in Tables 1 and 2. In practice, a functional description uses a verb-object format where the verb is chosen as a function word (from Table 2) and the object is chosen as a flow word (from Table 1). The different levels of classification allow discrete levels of detail to be specified for functional descriptions, i.e., product functionality may be described at either the class or secondary level.

Table 1 Flow classes and their basic categorizations.

Class	Material	Signal	Energy		
Secondary (or Basic)	Human Gas Liquid Solid Plasma Mixture	Status Signal	Human Acoustic Biological Chemical	Electrical Electromagnetic Hydraulic Magnetic	Mechanical Pneumatic Radioactive Thermal

Table 2 Function classes and their basic categorizations.

Class	Branch	Channel	Connect	Control	Convert	Provision	Signal	Support
Secondary (or Basic)	Separate Distribute	Import Export Transfer Guide	Couple Mix	Actuate Regulate Change Stop	Convert	Store Supply	Sense Indicate Process	Stabilize Secure Position

One common thread of these function-based design methodologies is the lack of testing and validation. As suggested by Antonsson (1987) there is a need for hypothesis generation and testing related to engineering design theories. He goes on to detail a possible procedure to follow. Antonsson's experimental procedure is adopted for the work reported here. This paper is a significant extension of previous functional modeling research and offers statistical measures of the repeatability of our functional modeling methodology (Otto, 1996; Stone *et al.*, 1999& 2000; Otto & Wood, 2000; Stone & Wood, 2000; Kurfman *et al.*, 2000).

3 FUNCTIONAL MODELING REPEATABILITY EXPERIMENT

To begin, we define the process of deriving a functional model as consisting of five steps. These steps, shown schematically in Figure 1, are: 1) identify flows that address customer needs, 2) generate a black box model, 3) create function chains for each input flow, 4) aggregate function chains into a functional model, and 5) verify the functional model with customer needs (Kurfman *et. al.*, 2000; Bryant et al., 2001).

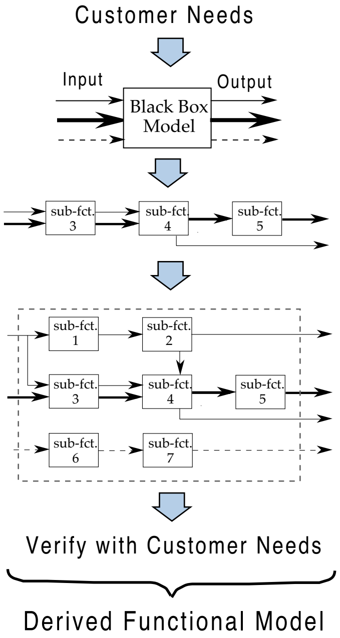

Figure 1. Steps of the functional model derivation method.

Our hypothesis is that using the functional model derivation method, as described above, will produce repeatable functional models among different designers, given the same customer needs and process choices and lead to a quasi-unique functional model. In order to test this hypothesis we develop a functional modeling repeatability experiment. This experiment builds on previous efforts (Kurfman *et. al.*, 2000) at measuring the functional model derivation method's repeatability. Here we propose and follow a more rigorous experimental procedure. Our experiment is designed to identify if repeatability gains may be made when designers use the functional model derivation method vs. no formal method. Additionally, we explore any differences that exist between redesign and original design cases. In constructing the repeatability experiment, we develop the following experimental plan,

1. Have designers create a functional model of an existing product prior to being exposed to our formal approach.
2. Prepare a functional model derivation methodology that can be used to create functional models.
3. Have designers learn the functional model derivation methodology.
4. Have designers apply the methodology on the same existing product as in Step 1 and to an original design.
5. Compare the functional models, and either validate or disprove our hypothesis.

Implementation of this experimental plan consists of three different experiments. Test subjects consist of academic and industrial designers and mechanical engineering design students at The University of Texas at Austin and the University of Missouri-Rolla, with a final sample size of twenty-one persons. The repeatability experiment is administered as three separate components. The details of each experimental component are given in the following sections.

3.1 Experiment #1

Experiment 1 is designed to provide a baseline of each subject's functional modeling capability. The first experiment consists of giving the test subjects a Nerf® Ball Blaster and a set of customer needs. A picture of the Nerf® Ball Blaster is shown in Figure 2, and a list of the customer needs is given in Table 3. The test subject is asked to create a functional model for the Nerf® Ball Blaster using any functional modeling method that they prefer. Additionally, a brief questionnaire is given to identify each subject's experience with functional modeling and design work.

Figure 2: Nerf® Ball Blaster

Table 3: Nerf® Ball Blaster Customer Needs List (5 = most important)

Customer Need	Importance
Shoot balls a long distance	5
Easy to hold	4
Reliably hold a large number of balls	5
Shoots accurately	5
Human powered with minimum exertion	5
Lightweight	3
Colorful	3

3.2 Experiment #2

Experiment 2 introduces the functional model derivation method to the subjects and captures any improvement that occurs in their functional model. The second experiment asks the subject to once again develop a functional model for the Nerf® Ball Blaster using the product and the customer needs list. In this experiment, however, they are asked to read a "How-to Manual" detailing the functional model derivation methodology and to produce a model at the secondary (or basic) level of classification. This manual contains excerpts from Stone and Wood (1999) and two additional examples on how to create a functional model using the functional model derivation method.

3.3 Experiment #3

In order to test the utility of the functional model derivation method for original design, experiment 3 asks for a functional model of an original design problem. The subject is given two pieces of information. The first is the following design problem: "Design a power supply for radios in which human mechanical energy is stored and delivered as electrical energy." Since no form is specified, we give the initial process choices of human energy to mechanical energy to electrical energy. This is necessary to compare the subjects' functional model. The second piece of information was a detailed customer needs list, which can be seen in Table 4.

Table 4: Human Powered Power Supply Customer Needs List (5 = most important)

Customer Need	Importance
Easy to input energy	5
Quiet	4
Long lasting energy supply	5
Easy to connect/detach to radio	4
Supply 12V DC	5
Transportable and small package	5
Impact resistant	2
Doesn't slide on slick surfaces	3
Lightweight	4
Cost	4
Stylish	3

4 RESULTS

In this section, we analyze the results from the previously discussed functional modeling experiments. For participants in this experiment, test subjects from both academia and industry were recruited. For the results presented in this paper, only participants that completed all three experiments are included, resulting in a final sample size of 21. Before the experiment was given, each test subject was asked to complete a questionnaire. This questionnaire is used to determine the skill level of each test subject and summarized in Table 5. From this questionnaire we determined that the average functional modeling skill level for the participants in this experiment is very low. For 70 percent of the participants, this experiment is their first introduction to functional modeling. Most of the test subjects have designed a product at some point in their career, but their overall knowledge of a systematic design process is very low. Even with the low functional modeling skill level of the test subjects, the results are very encouraging.

Table 5: Demographics of Test Subjects

	Number of Test Subjects
Gender	
Male	18
Female	3
Education Level	
MS	20
Ph.D.	1
Number of Functional Models Created	
0-5	16
5-10	3
10-50	1
>50	1
Average Number of Products Designed	3 Products

4.1 Repeatability Gains and Uniqueness in Terms of Vocabulary

Analysis of the data shows that there is a substantial reduction in the size of the sub-function space used to describe a product's functionality when the functional model derivation method is used. These results are shown in Table 6.

Table 6: Changes observed between experiments 1 and 2 for the Nerf® Ball Blaster

	Experiment 1: Non-basis Functions	Experiment 2: Basis Functions	% Change
No. of unique sub-functions	152	73	(-) 52
Average no. of sub-functions	16	19	(+) 19

In the first experiment, the test subjects use 152 distinct sub-functions to describe the Nerf® Ball Blaster. When the functional model derivation method is followed in experiment 2, only 73 distinct sub-functions are used to describe the Nerf® Ball Blaster. This is a reduction in the size of the sub-function space by 52 percent. This reduction in sub-function space size can be attributed to the limitation the functional basis places on individual expression of product function. While the knee-jerk reaction of many designers is to avoid limitations on expression, in this case the limited vocabulary of the functional basis improves the clarity of the functional model for communication purposes.

Another interesting point shown in Table 6 is that as the size of the sub-functions space decreases from experiment 1 to 2, the average number of sub-functions present in a functional model increases from 16 to 19 – a 19% increase (the standard deviations are 6.96 and 5.50, respectively, for the two experiments). This is a result of specifying that all subjects model the product at a specific level of detail, forcing most subjects to use multiple sub-functions to express former high-level functions.

The sub-function space and the sub-function frequency for experiment 2, ordered from most to least frequent, can be found in Table 7. This table also identifies the sub-functions of the control functional model (shaded in gray). The control functional model is our quasi-unique functional model for the Nerf® Ball Blaster that we obtained following the derivation method outlined in Section 3. Of the top 20% (15 sub-functions) most frequently occurring sub-functions, 93% (14) are found in our control functional model, lending support to our claim that the functional model derivation method leads to a quasi-unique functional model. Additionally, 11 sub-functions of the control's 28 distinct sub-functions were identified by at least 50% of the participants.

Table 7: Sub-Function Space For Nerf® Ball Blaster

Experiment 2			
Sub-function	Frequency	Sub-function	Frequency
import human	0.952	stop solid	0.143
import solid	0.952	actuate me	0.095
guide solid	0.810	couple solid	0.095
import he	0.810	distribute pe	0.095
export solid	0.762	indicate solid	0.095
import gas	0.667	secure me	0.095
store solid	0.619	store he	0.095
distribute em	0.571	supply me	0.095
import em	0.571	supply solid	0.095
store gas	0.571	transmit em	0.095
convert he to me	0.524	actuate pe	0.048
distribute me	0.429	acutate pe	0.048
guide gas	0.381	allow dof to solid	0.048
secure solid	0.381	change he	0.048
convert he to pe	0.333	change me	0.048
import me	0.333	change pe	0.048
store me	0.333	convert em	0.048
transmit me	0.333	convert me to ae	0.048
transport gas	0.333	convert me to te	0.048
change gas	0.286	convert pe to ae	0.048
export gas	0.286	convert pe to he	0.048
stabilize solid	0.286	export signal	0.048
transmit he	0.286	guide em	0.048
convert me to pe	0.238	guide me	0.048
actuate solid	0.190	guide pe	0.048
convert pe to me	0.190	guide signal	0.048
export human	0.190	import signal	0.048
export me	0.190	measure solid	0.048
transmit pe	0.190	position solid	0.048
transport solid	0.190	position signal	0.048
display signal	0.143	regulate solid	0.048
export em	0.143	secure gas	0.048
export he	0.143	stop gas	0.048
export pe	0.143	stop me	0.048
indicate status	0.143	store pe	0.048
sense signal	0.143	supply gas	0.000
stabilize me	0.143		

Legend:
ae = acoustic energy em = electromagnetic he = human energy
me = mechanical energy pe = pneumatic energy te = thermal energy

In Figs. 3 and 4, one of the more remarkable cases of improvement in the clarity and level of detail of the functional model resulting from the functional model derivation method is shown. The two figures below show the progression of one test subject's functional model before and after following the method.

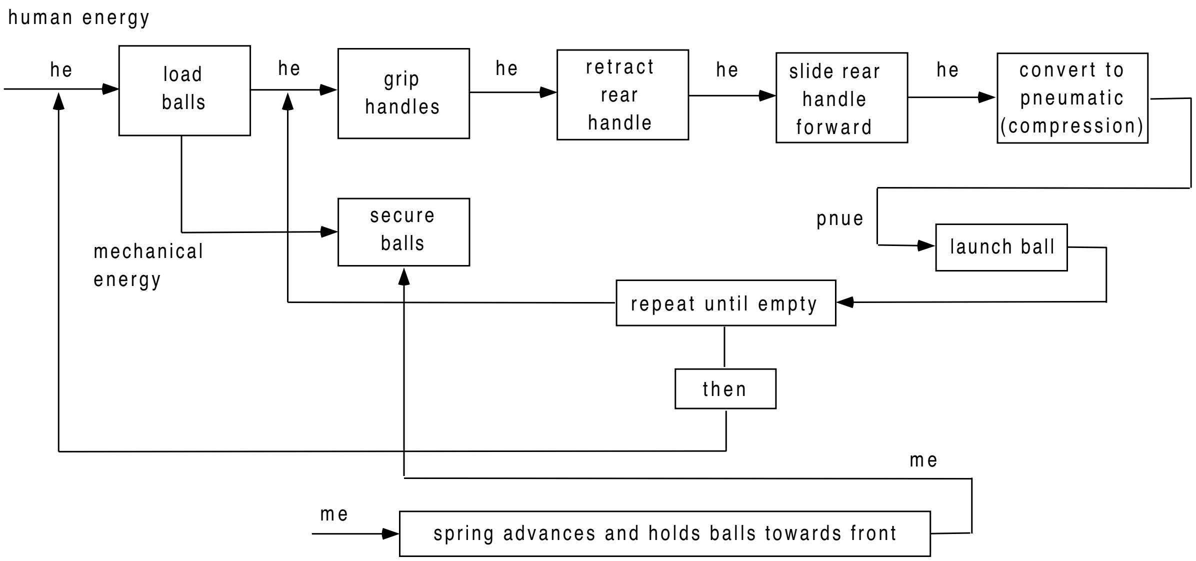

Figure 3: Subject A's functional model of the Nerf® Ball Blaster without following the functional model derivation method

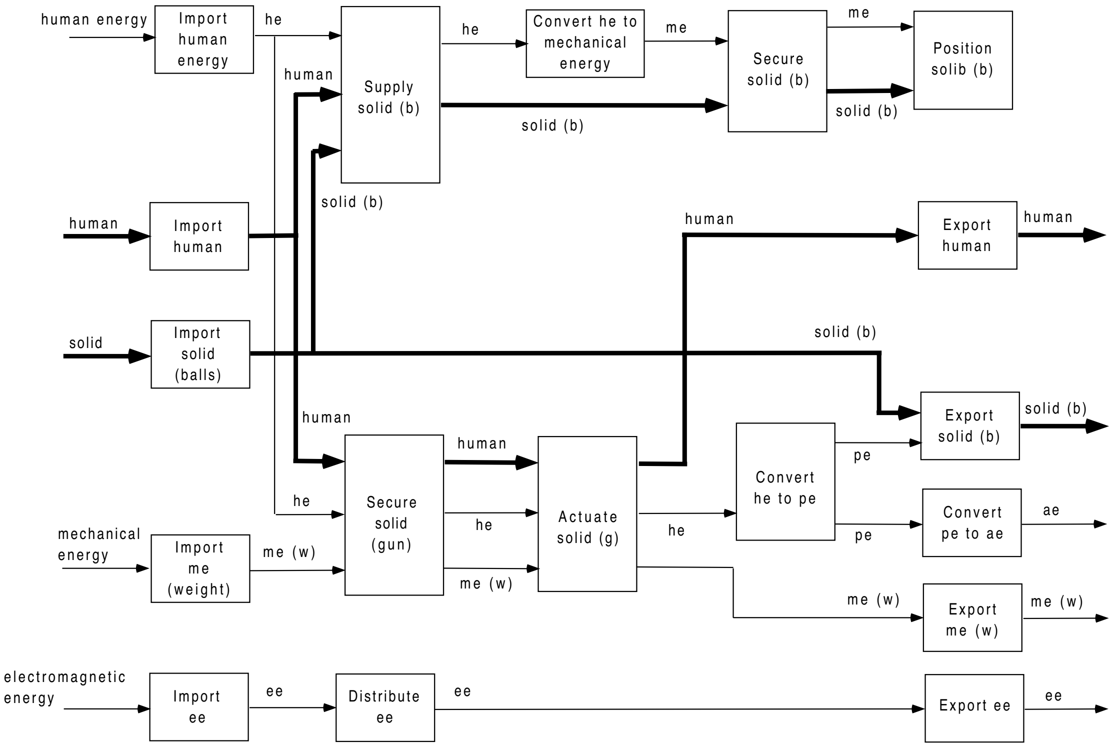

Figure 4: Subject A's functional model of the Nerf® Ball Blaster following the functional model derivation method

4.2 Original Design Results

Original design can often be one of the most difficult areas to apply functional modeling. In experiment 3, the results show that our participant pool used 82 distinct sub-functions to describe the human power supply. The sub-function space can be seen in Table 8 in descending order of frequency. As in experiment 2, looking at the top 20% (17 sub-functions) most frequently occurring sub-functions we find that 65% (11 sub-functions) are found in our control functional model. From the sub-function space we see that at least 50% of the test subjects identify 8 sub-functions from the 22 distinct sub-functions of the control (control sub-functions shaded in gray).

Table 8: Sub-Function Space For Power Supply

Experiment 3			
Sub-function	Frequency	Sub-function	Frequency
import human	0.857	stop ee	0.095
secure solid	0.810	transmit em	0.095
store ee	0.714	actuate signal	0.048
import he	0.667	change ee	0.048
convert me to ee	0.619	change shape	0.048
import solid	0.619	change solid	0.048
couple solid	0.524	convert aee to dee	0.048
convert he to me	0.476	convert ce to dee	0.048
distribute me	0.476	convert ce to ee	0.048
supply ee	0.429	convert ee to ae	0.048
guide solid	0.381	convert ee to ce	0.048
store me	0.381	convert em	0.048
transmit ee	0.381	convert me to ae	0.048
export ee	0.333	convert me to me	0.048
import me	0.333	convert pe	0.048
regulate ee	0.333	convert pe to ee	0.048
distribute em	0.286	convert re to aee	0.048
position solid	0.286	convert signal	0.048
stabilize me	0.286	export em	0.048
transmit me	0.286	export me	0.048
actuate solid	0.238	guide ee	0.048
export solid	0.238	guide em	0.048
import em	0.238	guide he	0.048
indicate Status	0.238	guide me	0.048
transfer he	0.238	import ee	0.048
allow dof	0.190	regulate signal	0.048
change me	0.143	regulate solid	0.048
convert he to ee	0.143	sense ee	0.048
measure ee	0.143	sense load	0.048
sense signal	0.143	stabilize solid	0.048
separate solid	0.143	stop ae	0.048
actuate ee	0.095	stop me	0.048
actuate me	0.095	store ae	0.048
change ae	0.095	store ce	0.048
change he	0.095	store dee as ce	0.048
display position	0.095	store he	0.048
distirbute ae	0.095	store solid	0.048
export human	0.095	transmit pe	0.048
extract solid	0.095	transmit signal	0.048
import signal	0.095	transport solid	0.048
regulate me	0.095	supply me	0.000

Legend:
ae = acoustic energy
me = mechanical energy
ce = chemical energy
aee = alternating electrical energy
em = electromagnetic
pe = pneumatic energy
ee = electrical energy
dee = direct electrical energy
he = human energy
te = thermal energy
re = rotational energy

4.3 Finding the Important Functions

In addition to documenting the frequency with which our experimental subjects use the sub-functions of the control functional model, we also investigate the ability of designers to identify the most important sub-functions in terms of customer needs. For any product, there is a set of sub-functions that directly meet the high level customer needs. Other sub-functions that are necessary to completely describe the product's functionality, but do not directly address any customer needs, are called *carrier* functions. Carrier functions are still important, but the overall function of the product is still discernable without their inclusion. Thus, an additional hypothesis is that the functional derivation method leads to functional models among different designers that capture the most important sub-functions in terms of customer needs.

4.3.1 Analysis Methodology

To compare the experimental subjects' functional models generated in experiments 2 and 3 with the respective control functional models, we borrow from the theory used to develop quantitative functional models (McAdams et al., 1999; Stone et al., 2000). This approach allows functional models to be converted into their quantitative counterpart and easily manipulated mathematically. Each functional model is converted into a product vector by correlating the weighted customer needs to flows and then following the flows through the sub-functions, as outlined in Fig. 5. The sub-functions are assigned the values of the customer need weighting to form the product vector. For carrier functions, a value of one is assigned in order to document the function's presence in the product.

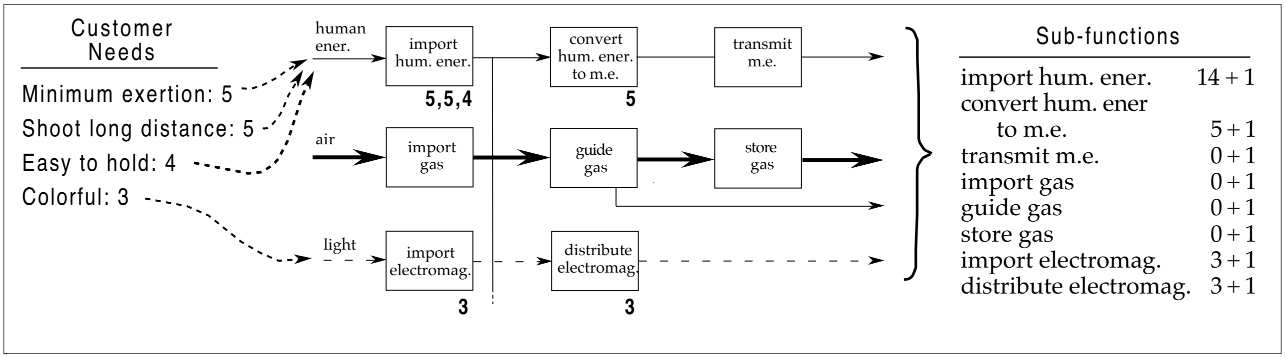

Figure 5. Schematic view of correlating customer needs to sub-functions to produce a customer need weighted product vector.

For example, in Fig. 5, the customer needs *minimum exertion*, *shoot long distance* and *easy to hold* for the Nerf® Ball Blaster map to the flow human energy and are associated with the sub-functions import human energy and convert human energy to mechanical energy accordingly. The weighted sub-function value is then computed, with a '1' added to all sub-functions to account for carrier functions. Note for the ball blaster, import human energy is an important sub-function to model as it addresses several highly rated customer needs.

The product vectors are arranged into a *mxn* product-function matrix, Φ (McAdams et al., 1998; Stone et al., 1999b & c). Each element ϕ_{ij} is the cumulative customer need rating for the *ith* function of the *jth* product. We normalize this matrix to take into account differences in the number of customer needs and functions for each subject's functional model, to remove biases for any one product.

Once implemented, the normalized version of $\mathbf{\Phi}$, N, has elements

$$\nu_{ij} = \phi_{ij}\left(\frac{\overline{\eta}}{\eta_j}\right)\cdot\left(\frac{\mu_j}{\overline{\mu}}\right), \tag{1}$$

where the average customer need rating is

$$\overline{\eta} = \frac{1}{n}\sum_{i=1}^{m}\sum_{j=1}^{n}\phi_{ij}, \tag{2}$$

the total customer need rating for the *jth* product is

$$\eta_j = \sum_{i=1}^{m}\phi_{ij}, \tag{3}$$

the number of functions in the *jth* product is

$$\mu_j = \sum_{i=1}^{m}H\left(\phi_{ij}\right), \tag{4}$$

and the average number of functions is

$$\overline{\mu} = \frac{1}{n}\sum_{i=1}^{m}\sum_{j=1}^{n}H\left(\phi_{ij}\right), \tag{5}$$

where H is a Heaviside function, n is the number of products and m is the total number of different sub-functions for all products. Normalizing the Φ matrix provides a level playing field on which to compare products. The averaging and scaling technique defined above is an intuitive way to account for variations in customer needs and functional models. We may now use this representation to determine the critical functions across the domain or any sub-domain of products. For our purposes of comparing functional models of the same product by different designers, we pre-multiply $\mathbf{N}'$ by its transpose to generate the similarity matrix as follows:

$$\mathbf{\Lambda} = \mathbf{N}'^{T}\,\mathbf{N}', \tag{6}$$

where the elements represent the similarity or commonality of important functions that functional models share. Note that **N**' is the normalized product matrix where its columns are again normalized to unity for convenience (in terms of comparing two functional models). A value of one indicates two functional models are completely similar and a value of zero indicates they are completely dissimilar.

The formation of a product vector (to produce $\mathbf{\Phi}$ and eventually $\mathbf{\Lambda}$) is dependent on the assignment of customer need weights to sub-functions. That assignment is inherently subjective, so we compute the sensitivity of the $\mathbf{\Lambda}$ matrix to changes in the initial customer need weight assignments. The sensitivity of $\mathbf{\Lambda}$ to a change in initial customer need rating of one point is identified as ε in the results that follow and, in general, show a change only in the second decimal place of $\mathbf{\Lambda}$ elements (McAdams et al., 1999).

4.3.2 Experimental Results

The product vector for the control functional model of the Nerf® ball blaster is shown in Table 9. The 21 functional models from the participants are aggregated together to form the $\mathbf{\Phi}$ matrix, as described in the previous section. It is normalized and the similarity matrix is calculated using equation 6. The results comparing participants with the control functional model are shown in Table 10. To aid in interpreting the results, if every participant had created a functional model identical to the control, then all projections of the participants' product vector onto the control product vector would produce a value of '1'. The results demonstrate that the functional modeling derivation method allows designers to find virtually all of the customer need based important sub-functions. The sensitivity calculation, also shown in Table 10, further demonstrates that the similarity values are significant to the second decimal place.

For the original design experiment, i.e. Experiment 3, similar calculations are made. The control product vector is shown in Table 11 and the similarity results for the participants functional models when compared against the control are shown in Table 12. The similarity values are not as high for the original design experiment as they are for the existing product experiment. However, they do indicate that the functional model derivation method does lead designers to identify a significant number of important functions for an original design (when no form is specified). This is extremely encouraging and viewed as a significant confirmation of the repeatability of functional model derivation method.

Table 9. Product vector for the control functional model of the Nerf® Ball Blaster.

Sub-function	CN value
convert he to me	6
convert pe to me	1
convert me to pe	6

display signal	1
distribute em	4
distribute me	4
export em	4
export gas	1
export human	1
export solid	6
guide gas	1
guide solid	1
import em	4
import gas	1
import he	15
import human	8
import solid	6
indicate status	1
regulate solid	1
secure solid	6
stabilize me	1
stop gas	1
store gas	1
store me	1
store solid	6
supply gas	1
supply me	1
transmit me	1
transmit pe	6

Table 10. Similarity results of the participant functional models when compared against the control.

ID	λ	ε
Control	1	-0.0100
14	0.922	-0.0101
11	0.919	-0.0104
9	0.967	-0.0098
2	0.875	-0.0098
8	0.861	-0.0103
16	0.860	-0.0097
12	0.855	-0.0099
21	0.837	-0.0111
4	0.826	-0.0106
13	0.818	-0.0103
15	0.816	-0.0107
5	0.814	-0.0117
6	0.810	-0.0106
20	0.800	-0.0115
1	0.799	-0.0103
10	0.797	-0.0111
19	0.793	-0.0106
3	0.754	-0.0095
17	0.750	-0.0113
18	0.749	-0.0109
7	0.681	-0.0114

Table 11. Product vector for the control functional model of the human powered generator.

Sub-function	CN value
actuate me	1
change me	1
change ee	6
convert he to me	6
convert me to ee	6
couple solid	8
distribute ae	5
distribute me	3
export human	1
export solid	1
import he	6
import human	10
import solid	5
indicate status	1
secure solid	4
separate solid	5
stabilize me	5
store me	6
supply me	1
transmit ee	6
transmit me	1

Table 12. Similarity results of the participant functional models when compared against the control for the human powered generator.

ID	λ	ε
Control	1	-0.00444
9	0.729	-0.00270
15	0.724	-0.00408
20	0.697	-0.00358
11	0.683	-0.00242
14	0.662	-0.00409
16	0.651	-0.00396
19	0.649	-0.00453
21	0.634	-0.00256
13	0.614	-0.00243
2	0.597	-0.00254
6	0.556	-0.00183
12	0.555	-0.00216
3	0.506	-0.00209
7	0.504	-0.00279
10	0.500	-0.00224
18	0.499	-0.00557
8	0.496	-0.00284
4	0.489	-0.00269
1	0.462	-0.00222
5	0.450	-0.00118
17	0.425	-0.00387

4.4 Topological Repeatability of Functional Modeling

In this section, the topology of the functional models is evaluated. By topology, we are referring to the specific flow connections between sub-functions of the functional model. In the previous section only the sub-function space was evaluated, but in order to test the uniqueness of the functional models they must be evaluated topologically. First, the functional models created in experiments 2 and 3 are entered into an adjacency matrix. The adjacency will matrix allow us to compare the functional models without a dependence on the spatial orientation (Kurfman *et al*, 2000).

The control functional model, for each experiment, is entered into its own the adjacency matrix. Next, all of the functional models are entered into the adjacency matrix and then combined into a frequency adjacency matrix. Shown in Fig. 6 is a fragment of the frequency adjacency matrix for the Nerf® Ball Blaster.

		Functions						
		…	Import em	Import gas	Import he	Store gas	Store solid	…
Inputs			10: 62 8: 5	7: 62	5: 90			
Functions	…							
	Guide gas					7: 33		
	Guide solid					1: 5	1: 38 5: 14	
	…							

Flow Legend

1	Solid	5	Human Energy	9	Pneumatic Energy	13	Chemical Energy
2	Human	6	Thermal Energy	10	Electromagnetic		
3	Mechanical Energy	7	Gas	11	Target		
4	Acoustic Energy	8	Signal	12	Electrical Energy		

Figure 6: Excerpt From the Nerf® Ball Adjacency Matrix

The frequency adjacency matrix is read by starting at the specified row and reading over to the specified column. The flow, represented by a code in the cell *ij*, originates from the sub-function listed for that row *i* and enters the specific sub-function listed for the column *j*. Each cell in the matrix displays the flows and the percentage of subjects who have the same flow connections. For example, in Fig. 6, flow 10, which refers to electro-magnetic energy, enters the system through the sub-function *import em* and 13 of the 21 participants (62%) identified this connection. This process is then repeated until all of the functional models are entered. If all of the functional models were identical, then the percentages shown in each cell would be '100'.

In order to display this information in a more understandable context, a modification to the frequency adjacency matrix is made. Tables 13 and 14, on the following pages, show this modification of the frequency adjacency matrix for experiments 2 and 3 respectively. In this matrix, only the sub-functions used in the control functional model are displayed. The cells that are highlighted follow the flows used in the control functional model, and the specific flows contained in the control are bolded. The table also displays flow connections that are used incorrectly. As the data shows, there are discrepancies between the control functional model and the test subjects' functional models. The results from experiment 2, however, are the most encouraging. From experiment 2, functions such as *import em, import he, import human,* and *import solid* all show a high percentage of identification. *Export solid* also shows a high percentage of identification, but seems to be the only output that was consistently identified. Unfortunately, functions such as *supply gas, secure solid,* and *transmit me* were not identified.

The results from experiment 3 are less encouraging than the results from experiment 2. There is a high percentage of identification of the *import human, import solid,* and *stabilize me* sub-functions. Unfortunately, no other flow connections were identified by more than 28.57 percent of the test subjects. In fact 16 connections that were contained in the control were not identified by any of the test subjects.

Table 13: Adjacency matrix for experiment 2

Experiment #2		Sub-Functions																												
		convert he to me	convert me to pe	convert pe to me	display signal	distribute em	distribute me	export em	export gas	export solid	guide gas	guide solid	import em	import gas	import he	import human	import solid	indicate status	regulate solid	secure solid	stabilize me	stop gas	store gas	store me	store solid	supply gas	supply me	transmit me	transmit pe	Output Flows
Input Flows		5: 5 8: 5			**8: 19** 11: 5	8: 10 10:10		**8: 0**				3: 5 7: 5	**10:62** 8: 5	**7: 62**	**5: 90**	**2: 95** 5: 14 8: 14	**1:100** 2: 10 5: 19 3: 5	**8: 0**		3: 5	**3: 14**							3: 10		
Sub-Functions	convert he to me		3: 5				3: 5					3: 10								5: 5				**3: 19**				**3: 10** 5: 5		2: 10 4: 5 6: 5
	convert me to pe								**7: 0**																				**9: 19**	2: 5 3: 5 7: 5
	convert pe to me								7: 5	3: 10 1: 5		**3: 0** **1: 0**																3: 5		2: 5
	display signal																	8: 10 11: 5												**8: 0**
	distribute em							**10:14**																						6: 10 8: 24 10:33
	distribute me	2: 5																			3: 5									**6: 10** 1: 10 2: 14 3: 5 4: 10 8: 5
	export em																													**8: 5** **10:10**
	export gas											7: 5 3: 5																		**7: 10** 4: 5 5: 5
	export solid						1: 5 3: 5		5: 5 7: 10			1: 5 3: 5																		**1: 67** **3: 33** 7: 10 4: 10 8: 14 9: 5
	guide gas																					**7: 0**	**7: 33**						7: 5	
	guide solid									**1: 38** **3: 24** 2: 10 5: 10 7: 14 9: 5										1: 10			1: 5		**1: 38** 5: 14			1: 5		1: 24 2: 5 3: 14 4: 10 7: 14
	import em					**10:52** 8: 5																								
	import gas		2: 5 3: 5 5: 5								**7: 33**												7: 19				5: 5			
	import he	**5: 12**															5: 10			5: 5	5: 5							5: 5		
	import human	2: 5 5: 5					2: 10					2: 5			2: 10 5: 10 8: 5		2: 19			2: 10	**2: 10** 3: 5 5: 5									2: 5
	import solid									1: 5		**1: 43** 5: 14								1: 5					1: 29 2: 14 5: 10		2: 5 3: 5			2: 5 3: 5 8: 5
	indicate status																													**8: 10** 11: 5
	regulate solid																												**1: 0**	
	secure solid			1: 5			**3: 0**												**1: 5**						1: 5 2: 5 3: 5 5: 5			1: 10	1: 5	
	stabilize me	5: 5																												**2: 14** **3: 19** 5: 5 8: 5
	stop gas								7: 5					2: 5 3: 5 5: 5								7: 5				**7: 0**				
	store gas		7: 5						7: 5																	**7: 0**				8: 5
	store me						9: 10																				**3: 5**	3: 5		
	store solid									1: 5		1: 19 2: 10 3: 5 5: 5						**8: 5**		**1: 10**									1: 5	2: 5 3: 5 5: 5
	supply gas		**7: 0**																											
	supply me																											**3: 5**	3: 5	8: 5
	transmit me		**3: 5** 5: 5				3: 10			1: 5 3: 5		1: 10 5: 5 7: 5		3: 5						**3: 0**										3: 5 4: 5 5: 5 8: 5
	transmit pe			**1: 5** **9: 5**								1: 10 3: 5 7: 5 9: 5																		

Table 14: The adjacency matrix for experiment 3

		Sub- Functions																						
Experiment # 3		actuate me	change ee	change me	convert he to me	convert me to ee	couple solid	distribute ae	distribute me	export ee	export human	export solid	import he	import human	import solid	indicate status	secure solid	separate solid	stabilize me	store me	supply me	transmit ee	transmit me	Output Flows
Input Flows		3: 5 8: 5			5: 10		1: 10 5: 10		**3: 10** 5: 5				**5: 29** **8: 10** 2: 5	**2: 119** 5: 10 8: 5	**1: 57** 2: 19 3: 24 5: 33 8: 10	10: 5	1: 10 2: 10 3: 10 5: 5		**3: 43**					
Sub- Functions	actuate me					3: 5										**8: 0**				3: 5	**3: 0**			**6: 0**
	change ee																					**12: 5**		
	change me					3: 10	**3: 0**												**3: 0**	3: 10			**3: 0**	**6: 0**
	convert he to me			**3: 5**		3: 33 8: 5	2: 5	**3: 0**			2: 5									3: 5			**3: 5** **8: 0**	2: 19 3: 5 4: 24 5: 5 6: 19
	convert me to ee		12: 5					**12: 0**								8: 5 12: 5						**12: 14**		3: 10 4: 29 6: 10
	couple solid																**1: 10** **3: 0** 2: 19 5: 5	**1: 0** **3: 0**				1: 5 12: 5		1: 5 2: 5 4: 10 5: 10 6: 5 8: 5 12: 5
	distribute ae																							**6: 5** 4: 5
	distribute me				2: 10														3: 5				**3: 5** 2: 5 5: 5	3: 29 1: 14 4: 14 6: 29 8: 5
	export ee																							**12: 24** 8: 5
	export human																							**2: 14** 5: 5
	export solid										2: 5 5: 5													**1: 5** 2: 10 3: 5
	import he				**5: 7** **8: 0** **3: 0**		5: 10		5: 5								5: 5		5: 5				1: 5 5: 10	2: 5
	import human				2: 14		2: 14		2: 14		**2: 0**		2: 5		2: 14		2: 14 5: 10		2: 19 3: 5 5: 5				2: 14	2: 5
	import solid					1: 5 3: 5	**1: 7** 2: 5 3: 10 5: 10		1: 5 3: 5								1: 14 2: 14 3: 5 5: 14			1: 5			1: 5	1: 5 3: 5
	indicate status																							**8: 12** 1: 5 2: 5 3: 5 10: 5 12: 5
	secure solid						1: 5		1: 5 3: 10							1: 5 2: 5 5: 5	2: 5	1: 5 2: 19				2: 5	**1: 0** **3: 0**	1: 19 2: 19 3: 24 4: 5 5: 5 6: 10
	separate solid										2: 5	**1: 5** 2: 5				**8: 0**								**3: 5** 1: 5 2: 14
	stabilize me																						**3: 10**	2: 5 6: 5
	store me	**3: 0** **8: 0**				3: 10	**3: 0**									8: 5			**3: 0**					4: 5
	supply me																						**3: 0**	
	transmit ee		**12: 0**				**3: 0**			**12: 10**							12: 5							1: 10 2: 5 3: 5 4: 5 8: 5 12: 5
	transmit me			3: 5		**3: 0**			**3: 10**			**1: 0**						**3: 0**		**3: 0** 4: 5 5: 5				**3: 7** 1: 5 2: 19 5: 14

5 CONCLUSIONS

5.1 Statistically Speaking

Two additional measures recorded from the experiments are used to make inferences about the repeatability of the functional model derivation method: similarity with and % of sub-functions identified in the control functional model. First, the data is checked for normality. Since the sample size of this experiment is small, the Shapiro-Wilk's Test is used to test for normality in the data. As a second check, a normal probability plot is created for all of the data. Both tests indicate the data is normal.

In order to determine if there is an improvement in the subjects' ability to identify sub-functions from experiment 1 to experiment 2, a t-test for dependent means is performed. Performing a t-test determines if the differences between the two means of experiment 1 and 2 are by chance, or because of a real difference between the means. When the t-test between experiment 1 and 2 is performed, there is a significant difference ($p = 0.0001$). Additionally, a t-test comparing the average number of sub-functions per functional model between experiment 1 and 2 shows that the increase in complexity (i.e., the increased number of sub-functions used) is significant ($p = 0.0039$). Therefore we conclude that when the functional model derivation method is followed for the Nerf® Ball Blaster, the test subjects are able to identify more of the control functional model's sub-functions and are able to express the product's functionality at a greater level of detail.

Considering Table 15 below for experiment 2, a 95% confidence interval for μ, the true average similarity for the population similar to those tested is (.7649, .8236), and a prediction interval for the similarity of any one randomly chosen from the population is (.6565, .9320). A 95% confidence interval for μ, the true average % sub-functions identified for the population similar to those tested is (35.33, 45.46), and a prediction interval for the % sub-functions of any one randomly chosen from the population is (16.63, 64.15). For example, at the 95% confidence level, as few as 16.63% or as many as 64.15% of the sub-functions of the Nerf® ball blaster could be identified by a subject, similar to those who participated in this test, using the functional model derivation method. The results for experiment 3 are similar to those obtained from experiment 2, as shown in Table 15.

Table 15: Experiment #2 and #3 Statistical Inferences

	Mean	**Confidence Interval**	**Prediction Interval**
Experiment #2			
Similarity	0.7942	(.7649, .8236)	(.6565, .9320)
% Sub-Functions Identified	40.39	(35.33, 45.46)	(16.63, 64.15)
Experiment #3			
Similarity	.5708	(.5206, .6211)	(.3350, .8067)
% Sub-Functions Identified	35.50	(29.10, 41.90)	(5.488, 65.51)

In order to determine if these conclusions would be consistent with other products, more experiments testing the functional model derivation method on other products need to be conducted. The results from these tests then need to be compared to each other to determine if the functional model derivation method gives more repeatable results for other products. These results are, however, encouraging at this point.

5.2 General Thoughts

This experimental study leads us to make conclusions in five areas.

- Clarity in communication is increased by the functional basis vocabulary. The functional model derivation method definitely improves the clarity with which designers can communication product function. This fact is borne out by a simple comparison of the sub-function space between experiment 1 and 2. It is also shown to be a statistically significant by the t-test.

- Specifying a level of detail improves repeatability, as shown between experiment 1 and 2. The experiments also show that specifying a level of detail leads to functional models with more sub-functions, indicating that the functional modeling derivation method generates more complete functional models. This statement, too, is shown to be statistically significant.

- Deriving a functional model is more repeatable for redesign than original design cases. Although the repeatability results of the original design case (experiment 3) are lower than the case of the existing product, they do show a measure of repeatability. One possible reason for this lower level of repeatability is the difficulties of creating a functional model for an original design. One must remember that many of test subjects participating in this experiment are new to functional modeling and may not have completely learned the skills required to complete such a difficult task. Also, the control functional models (in both experiment 2 and 3) are generated by designers with extensive functional modeling experience.

- In terms of generating unique or quasi-unique functional models, the functional model derivation method appears to lead designers toward a unique model. In both experiments 2 and 3, the majority of the top 20% most frequently occurring sub-functions (of the total observed sub-function space) are found in the control functional model. As expected, more of the control's sub-functions are identified in the redesign case (experiment 2) than the original design case (experiment 3). From another standpoint, if we consider the control functional model to be the "correct" functional model with *n* sub-functions, then we can measure the method's ability to produce unique functional models by calculating the percentage of the control's sub-functions found in the top *n* most frequently observed sub-functions. With this approach, of the participants' top 28 most frequently occurring sub-functions in experiment 2, 68% are found in the control. Similarly for experiment 3, of the participants' top 22 most frequently occurring sub-functions, 64% are found in the control.

- Flow connectivity is not repeatable at this point. While the adjacency matrix shows some flow connections are repeated (up to 100% frequency), few have a frequency over 20%. It is possible that the adjacency matrix is not the best metric for flow connectivity repeatability, as one simple permutation of a function chain will show as a deviation from the control. However, it is more likely that the task of creating function chains in the functional model derivation method requires more specification. This is an area for future work.

Overall, the functional modeling derivation method significantly improves repeatability. Our research leads us to conclude that achieving a *unique* functional model from different designers is possible in terms of the sub-function space, but may not be realistic topologically. These conclusions are based on a relatively small sample size. As we indicated in Section 5.1, larger populations are needed to make more broad-based statements about repeatability and uniqueness characteristics of this method. Additionally, additional products (for both redesign and original design) need to be examined in future experiments.

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