



Open Research Online

Citation

Booth, Joran W.; Reid, Tahira; Eckert, Claudia and Ramani, Karthik (2015). Comparing functional analysis methods for product dissection tasks. *Journal of Mechanical Design*, 137(8), article no. 081101.

URL

<https://oro.open.ac.uk/42688/>

License

(CC-BY-NC-ND 4.0)Creative Commons: Attribution-Noncommercial-No Derivative Works 4.0

Policy

This document has been downloaded from Open Research Online, The Open University's repository of research publications. This version is being made available in accordance with Open Research Online policies available from [Open Research Online \(ORO\) Policies](#)

Versions

If this document is identified as the Author Accepted Manuscript it is the version after peer review but before type setting, copy editing or publisher branding

Comparing Functional Analysis Methods for Product Dissection Tasks

Joran W. Booth*

School of Mechanical Engineering
Purdue University

Tahira N. Reid

School of Mechanical Engineering
Purdue University

Claudia Eckert

The Open University
Milton Keynes, United Kingdom

Karthik Ramani

School of Mechanical Engineering (and Electrical and Computer Engineering by Courtesy)
Purdue University

The purpose of this study is to begin to explore which function identification methods work best for specific design tasks. We use a 3-level within-subject study (n=78) to compare three strategies for identifying functions: energy-flow, top-down, and enumeration. These are tested in a product dissection task with student engineers who have minimal prior experience. Participants were asked to dissect a hair dryer, power drill, and toy dart gun and generate function trees to describe how these work. The function trees were evaluated with several metrics including the total number of functions generated, the number of syntactical errors, and the number of unique (relevant and non-redundant) functions. We found no statistical, practical, or qualitative difference between the trees produced for each method. We also found some generalized findings through surveys that the most difficult aspects of using functional decomposition include identifying functions, choosing function verbs, and drawing the diagram. Together, this may also mean that for novice engineers, simpler methods, such as enumeration, should be taught prior to more complicated methods so students can grasp core concepts such as identifying functions and structuring function diagrams.

1 Introduction

Functional decomposition is a process that is typically used to assist engineers with identifying essential functions

in various design tasks, including product dissection. It is an important tool used in industry to improve legacy products, understand competitor products, or help new employees learn about a company design. More generally, it is a type of problem solving strategy used by engineers to convert complex problems into abstractions [1], where they are easier to solve [2, 3]. The ability to do this effectively represents a high-level skill and deep learning [4]. However, functional decomposition is often ignored by engineers because it is perceived as being too easy, too hard, or not important [5]. This may simply be because engineers use design methods opportunistically [6], are taught conflicting definitions of “function” [7], or find competing claims to the “right” approach [8]. One approach to improving adoption is educating engineers as to when and why functional decomposition is most effective.

While prior literature explores why functional decomposition is important, there is virtually no discussion of when proposed methods are best for various tasks. These include pre-ideation, product dissection, reverse engineering, and process modeling. In order to explore this aspect of functional decomposition, we consider the process of identifying the function and structuring the diagram separately. Eckert et al. explored the function identification methods used by engineers with industry experience [9]. The methods found in this study correspond with common methods taught in design text books. However, many of these design texts ignore the distinction between functional decomposition for synthesis tasks (i.e. design and redesign) and analysis tasks (i.e.

*Address all correspondence to this author at boothj@purdue.edu

product dissection or reverse engineering). Prior studies have found that these two types of tasks are quite different [10], and represent different problem types [11].

In this study, we only explore function identification strategies for product dissection tasks, and leave other types of tasks for future studies. We also control for variations in diagram types by using function trees only. Other parameters of this study are found in table 1. This paper will describe the experimental design to test these methods. We report quantitative, mixed-methods, and qualitative results, and offer interpretations of these results.

Definitions

We define functions as “the solution-neutral [or embodiment-neutral] detailed description of what are the intentions for the products” [12]. When we use the term “method”, we mean the strategy an engineer uses to identify a function. Energy-flow is defined as tracing material, information, and energy flows through a device, and mapping functions to changes in these flows. Top-down is defined as the process of determining the overall function, followed by decomposing this into sub-functions, and continuing until functions are defined on the part level. Enumeration is defined as writing out whatever functions come to mind, with no specific strategy for identifying them. We consider these methods as independent of the diagram used to record the functions [9].

“Functional analysis” is used to mean the process of identifying functions for an already existing artifact or concept [1] (i.e. reverse engineering or dissecting products). “Functional synthesis” is defined as identifying functions in design where no artifact or embodiment exists (i.e. pre-ideation). We consider synthesis and analysis to be two different types of problem solving [13], and their related tasks to be unique types of problems [11]. Additionally, we agree that there is no single, correct function structure for synthesis or analysis [14, 15]. Hence in this paper, “functional decomposition” describes both synthesis and analysis simultaneously.

2 Background

Experimental findings by Eckert et al. found that engineers tend to use an energy-flow, top-down, or enumeration strategy for identifying functions in an unknown product, with some minor variations. Additionally, the participants in their study tended to analyze only as much as they needed, often mixing methods to suit their purposes [9]. Consequently, we searched design text books (Table 2) and literature to find what function identification methods are taught. We assume that there is a common core to decomposition that accepts multiple definitions of function and implementation, but ignore methodological differences between them [7]. We organized the methods in literature into three groups based on the recommended ways to identify functions: energy-flow, top-down, and enumeration (see Table 2). One text included methods which did not fit in our classification scheme [16], and are not compared in this study. However, we explore this other method with the methods in this paper in our other work [17].

2.1 Methods found in Literature and Usage

The most common method found in the literature search was the “energy-flow” approach, sometimes called “black-box” [1, 15, 18–22, 24]. This method is unique from the top-down and enumeration approaches because it primarily focuses on “horizontal” relationships between functions and explicitly considers material, energy, and information flows through a system [31]. Horizontal relationships ignore sub-functions and other levels of abstraction. Energy-flow can be used to produce hierarchical information by creating a flow-block diagram breaking each function into sub-diagrams; however, most authors only discuss an overall function and a single, detailed set of functions. Some versions of the “black-box” approach do not emphasize the types of flows, and instead focus on steps in a process.

The second most common method was enumeration [18, 26–30]. In these citations, the authors gave no specific direction regarding how to identify functions other than to simply list them out. Enumeration is sometimes paired with a list, function tree or function-means tree.

The least common method was the “top-down” approach [14, 18, 25]. This method works by selecting the top-most function, and breaking each function down into relevant sub-functions. This approach is sometimes paired with structure diagrams as a function-means tree. These hybrid diagrams seem to be used for design tasks only [18, 32], but could potentially be used to describe a product. This method explicitly explores the “vertical” relationships between functions, and thus aims at recording hierarchical information [31].

One textbook describes a method called the “Subtract and Operate Method” [16], though we identify this as the “bottom-up method”. This method is considered opposite to the top-down method, but considered to be identical [16, 33], and asks engineers to consider the individual functions of parts. We did not compare this method in this study, but another of our studies found that the cognition between the bottom-up and other methods appears to be different [34]. The results of this study are also compared in that paper.

The majority of the past work describes functional decomposition as a step prior to concept generation. However, the same methods are sporadically applied to other design activities, such as reverse engineering [1, 14, 15, 18, 21, 25–27], task analysis and FMEA [20, 30], functional allocation [15], axiomatic design [29], and cost analysis [22]. The terminology used between all these sources is also inconsistent. For example, the terms “functional decomposition” and “functional analysis” are sometimes used to refer to a design task only [19, 20, 24, 28–30], a reverse engineering or product dissection only [25–27], or both [1, 14, 15, 18, 21]. In another example, some authors use “reverse engineering” and “product dissection” interchangeably [18, 21], whereas others do not [26].

Only a few authors cite more than one method, and only two of the books we reviewed identified all three [16, 18]. These two are also among the few to describe more than one type of function diagram. We also note that the diagram type recommended for an identification method is not always con-

Table 1. Parameters used by this study, in bold; the levels chosen for the study, in gray; and alternate levels for future research

Eng. Expertise	Training	Scale	Complexity	Strategy	Diagram Type	Design Task
Novice	None	Component	Low	Enumeration	Function Tree	Product Dissection
Graduate	Introductory	Product	Medium	Energy-Flow	Function-Means	Reverse Engineering
Professional	Some	System	High	Top-Down	FFBD	Ideation (Redesign)
Expert	Practiced			Bottom-Up	Flow-Chart	Ideation (New Design)
	Expert				List	FMEA
					FAST	Cost Allocation
					Electronic	Eng. Modeling

sistent. In all, this seems to speak to the several traditions surrounding functional decomposition [8].

2.2 Related Work

Significant past work has focused on improving the energy-flow method. Examples of this research focus on improving taxonomy structures [35, 36], the functional basis [37], and instructional methods [38]. Several studies have compared functional decomposition with axiomatic design [32], explored functionality in bio-inspired design [39], or applied functional decomposition techniques to analogical design [40]. However, to the best of our knowledge, there are no empirical studies comparing energy-flow, top-down, and enumeration. We also failed to find studies that test which methods are best suited for which tasks [10].

3 Methodology

This study aimed to evaluate which methods are most effective for product dissection. Product dissection is used in industry and academia to understand new or competitor products or help new employees learn about a company design. For the purposes of this study, "most effective" is defined as providing the best understanding to the student of how the device works. This led to our first research question. Additionally, the literature suggests practice enhances performance when doing functional decomposition [38]. However, industry adoption remains low [5], suggesting that something is inhibiting engineers from using it. We developed our second research question to understand what is most difficult for engineers about the process.

1. Which functional decomposition methods is most effective for students?
2. Which aspects of functional decomposition in general prove to be most difficult for students?

Several metrics are used to approximate this understanding. The number of functions is used as a proxy for the level of detail a student used to examine a device. The number of unique functions is used to approximate how comprehensive the understanding was. Other metrics are used to explore function tree shape and errors, which give an approximation

of understanding of the method itself, and relate to the effectiveness of the method.

3.1 Design of Experiment

In order to answer the first research question, we used a quantitative design of experiment (DOE) where each participant would create a function tree based on the given artifact. To maximize the use of the students, we used a 3-level, within-subject DOE (i.e. 3x3 Latin square), where each student used a different method on each artifact over a 4 week period. This DOE is common in product comparison studies [41], and has the advantage of multiplying the number of samples. It also reduces the effect of uncontrolled variables, such as self-selection bias [42]. One negative effect of this experimental design is that some effects are conflated; in this case, the product and time effects are conflated, meaning that time dependent effects (i.e. learning effects) will not be distinguishable from effects due to which product was used.

The first research question was then converted a priori into four alternate hypotheses. Due to the prior literature, we expected the top-down method to have more vertices on each level, and generally larger function trees, as measured by geodesic distances and total number of vertices. However, we expected the energy-flow strategy to have more unique functions and fewer errors. We also expected the enumeration method to be the most prone to ignore or have fewer unique functions. Finally, we expected to see better results from participants who were a higher class level or had prior experience with functional decomposition. These expectations are reflected in the metrics described in section 3.5.

- H0 - There is no difference between the energy-flow, top-down, and enumeration methods
- H1 - There is a difference between the energy-flow and top-down methods
- H2 - There is a difference between the energy-flow and enumeration methods
- H3 - There is a difference between the top-down and enumeration methods
- H4 - The more experienced students will perform better than the less experienced students

"Unique function" refers to the number of syntactically

Table 2. Engineering design textbooks and their treatment of functional decomposition

Authors	Method	Reverse Eng.	Design	Wording Used in Text
Dym & Little [18]	Energy-flow	x	x	Black boxes / transparent boxes
Ulrich & Eppinger [15]		x	x	Functional decomposition
Cross [19]			x	Functional analysis
Stoll [20]			x	Functional analysis / decomposition
Ullman [21]			x	Functional modeling / decomposition
Pahl & Beitz [1]		x	x	Establishing function structures/Analysis of existing systems
Ullman [21]		x		Product decomposition
Dieter [22]			x	Functional decomposition
Dieter and Schmidt [23]			x	Functional decomposition
Hyman [24]			x	Functional analysis
Otto and Wood [16]		x	x	Functional modeling
Dym & Little [18]	Top-down		x	Function-means tree
Cunniff et al. [14]		x	x	Functional decomposition / reverse eng.
Phillips [25]		x		Functional decomposition
Otto and Wood [16]		x	x	Function trees
Dym & Little [18]	Enumeration	x	x	Enumeration of functions
Dym & Little [18]		x		Reverse engineering / dissection
Horenstein [26]		x		Reverse engineering
Sheppard [27]		x		Mechanical dissection
French [28]			x	Functional analysis
Magrab [29]			x	Functional analysis / decomposition
Priest & Sánchez [30]			x	Functional allocation
Otto and Wood [16]	Other		x	the FAST method
Otto and Wood [16]	Other		x	the Subtract and Operate

non-redundant functions in the tree, and is a measure of comprehensiveness. This metric is explained in more detail in section 3.5.2, and the other metrics in section 3.5.

3.2 Procedure

Participants were asked to dissect three products (see Figure 1), over the course of four weeks, and use three methods for determining the functionality of those products (see Table 3). The point of dissecting products was to explain “how it works” (point 1, in Tomiyama et al. [5]). All participants dissected a hair dryer on week one, a power drill on week 2, and a toy dart gun on week 4. Data was collected over a four week period in October 2012. All sessions were held on Thursdays and group A met at 9:30AM, group B at 11:30AM and group C at 1:30PM each week.

Each session followed these steps:

Table 3. Experimental layout over the 4 week period. EF = Energy-Flow, TD = Top-Down, EN = Enumeration

	Wk 1	Wk 2	Wk 3	Wk 4
	Dryer	Drill		Dart Gun
Group A	TD	EF	N/A	EN
Group B	EN	TD	N/A	EF
Group C	EF	EN	N/A	TD

1. Introduction, explanation of the task, and handing out pre-survey (first session only) and instruction materials (every session)
2. Description of what a function is and instructions on



Fig. 1. A hair dryer, power drill, and toy dart gun

how to create a function tree

3. Instructions on how to use the function identification method assigned for the session, followed by an example of the method using a simplified lobe pump drawing
 4. Time for students to individually disassemble product and create function tree
 5. Turn in function trees, return to course instruction (product description), reassemble products, and complete a post-survey
- Steps 1-3 took approximately 15 minutes each session.
 - Step 4 took approximately 45-60 minutes
 - Step 5 took approximately 20 minutes

When the students were instructed on how to create a function tree, they were also instructed they should make a rough draft of their functions prior to organizing them into a tree. For energy-flow, they were told to map out the energy, information, and material flows in a diagram on a rough draft, and to recursively break each function into sub-functions. They were told to place these functions into a tree diagram. For enumeration, students were instructed to list out the functions, and then organize these into a tree, while also filling in gaps. For the top-down method, they were told to identify the overall function and then break each parent function into children functions.

In order to ensure consistency between instructions in each session, we provided detailed instructions on how to accomplish these steps. These described what a function is, how to create a function tree, an example function tree, instructions on how to use each method, and instructions on how to convert their rough draft into a function tree. Students were also provided with the pruned function verb list [35] to aid them when choosing verbs for their functions.

3.3 Population

Participants were selected based on their participation in a product dissection class at Purdue (ME 297), and thus is a convenience sample. The class focuses solely on product dissection in 2 hour lab sessions. Participants were told that the activity would help them prepare for the final project in the class, where they have to describe how a product of their choosing works.

Each group consisted of varying numbers of participants due to how scheduling for the class was conducted. Group A had 8 participants; group B had 12 participants; and Group C had 6 participants. Over all sections, 10 students identified as sophomores, 8 as juniors, and 7 as seniors with one not reporting and no freshmen, although the class is open to them. All participants were studying mechanical engineering.

Table 4. Metrics used in prior research on functional decomposition

Name	Metric Type
Conformance metric [43]	Raw count (M1)
Exact/approximate scoring [35]	Raw count (M1)
Unit of information [44]	Raw count (M1)
# spoken functions [12]	Raw count (M1)
# levels of abstraction [12]	Qualitative
# levels of hierarchy [12]	Tree depth (M2)
# func. on a hierarchy level [12]	Branch width (M3)
Completeness of func. analysis [12]	Raw count (M1)
Rubric (Energy-Flow only) [38]	Error count (M4)
# parts exposed [45]	Raw count (M1)
# same features [45]	Raw count (M1)

3.4 Independent Variable - Identification Method

The independent variables used were chosen due to their common usage by engineering professionals [9].

- Energy-Flow - Identify the flow of mass and energy through a system. Each transformation of energy, mass, or information is a function. This should be done separately on various levels before constructing a tree, breaking each function into a group of functions.
- Top-Down - Start with the highest level of abstraction (the whole machine) and determine overall function. Break down into sub-systems and determine functions of each of these systems. Iteratively become more detailed for each level. Write these functions into a tree.
- Enumeration - Write down relevant functions as they seem appropriate in whatever order they come to mind. Organize these into a tree. Participants were told the name of this method was “important things first” [9].

3.5 Dependent Variables

Appropriate metrics for this study were drawn from prior studies (Table 4). The majority of these were drawn from Eckert et al. We added a unique functions metric to this set to measure the comprehensiveness of each tree and replaced one metric (M2) by using average and maximum geodesic distances instead. We did not include other graph metrics due to lack of relevance for hierarchies. We did not use the metrics used by Nagel et al. [38], nor the standard function taxonomy [37], since these are specific to the energy-flow process only.

The dependent variables are related to prior metrics (from Table 4) and include:

- Vertices (M1) - the total number of phrases on a diagram, all of which are treated as functions.

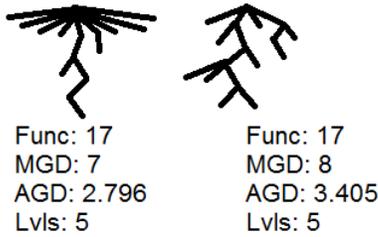


Fig. 2. The pair of geodesic distance metrics (AGD and MGD) are lower for the flat tree than for the bushy tree, even when the number of tree levels is the same

- Number of unique functions (Uniq. Func.) - the number of non-redundant phrases in a diagram. This measures how comprehensive a tree is. Details are discussed below
- Tree efficiency (Efficiency) - the ratio of unique functions to vertices. This shows how much of the tree is non-redundant.
- Maximum Geodesic Distance (Max GD, M2) - the largest of all the shortest paths in the diagram
- Average Geodesic Distance (Avg GD, M2) - the average of the shortest paths between all nodes in the diagram
- Number of syntax errors (Errors, M4) - the number of phrases not written as a verb-phrase or left blank. More detail below.
- Error ratio - the ratio of errors to vertices.
- Number of vertices on a hierarchy level (Func. Lvl X, M3) - the number of phrases on each hierarchy level.
- Error ratio on each hierarchy level (Err. Lvl X) - the ratio of errors on each level to vertices on each level.
- Perceived usefulness of activity (Survey) - student responses of how useful each method was on a scale of 1 (low) to 10 (high).

3.5.1 Geodesic Distance Metrics

The combination of the average and maximum geodesic distances (GD's) measure the "flatness" and "bushiness" of the trees. A pair of low GDs indicates flatness, and a pair of high GDs indicates bushiness. These metrics allow us to distinguish between flat and bushy trees whereas simply counting the number of levels in a tree does not (Figure 2). This metric is also meaningful for non-hierarchical diagrams, such as network maps, whereas the number of levels is meaningless (Figure 3). This metric was important for our dataset since 1-3 diagrams had nodes with more than one parent, making them no longer "trees". Finally, using two metrics instead of one allows us to distinguish between two trees where one of the two metrics matches (Figure 4).

3.5.2 The Syntax Errors Metric

The number of syntax errors metric was chosen because it is easy to apply and generally consistent, although the results of this metric are approximations. Initially, we used a more comprehensive set of error metrics which looked at

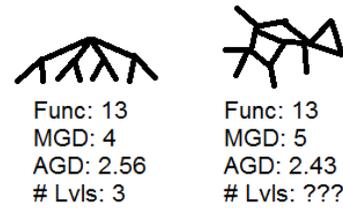


Fig. 3. The geodesic distances are robust to diagrams that are not hierarchies

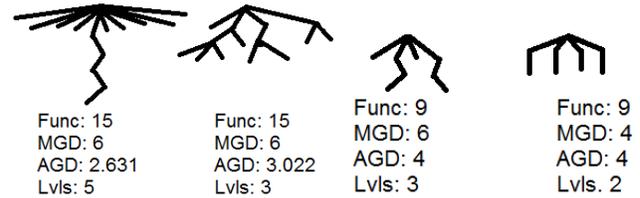


Fig. 4. The pair of geodesic distances (AGD and MGD) is still lower for the flatter trees even when one of the two is the same

particular types of errors, but this was too subjective and expensive to be useful. We also avoided qualitatively judging each phrase as a function, part, behavior, or other type of information because of the ambiguity of some of these types of information. We found that syntax errors typically corresponded with other types of errors, such as describing design requirements. Errors include phrases that begin with an adjective (C3.3.2, Table 6), a noun (C1.3.1, Table 6), or other non-verb parts of speech. We also counted phrases beginning with generic verbs such as "to provide" or "to be" as errors. Only 1.0% of phrases coded this way were actually functions. We favored this metric over a more comprehensive metric because it could be applied more consistently, objectively, and still yield reasonably good results.

In conducting this analysis, we first used Wordnet in Python to calculate tokens and parts of speech. Since Wordnet defaults to nouns rather than verbs, we then manually corrected the output based on our experience with the products and context of the class. In our manual analysis, we biased toward assuming each phrase began with a verb.

3.5.3 The Unique Functions Metric

The number of unique functions refers to the number of functions that are semantically different in an individual's function tree. Functions created by the participants are manually grouped based on semantic similarity and observations in the class. This is different than the number of unique phrases generated by a participant, which would simply omit identical phrases. By using semantic similarity, we can distinguish functions whose meanings may overlap with similar functions but indicate a different part, step in the operation, or purpose. This metric is used because it allows us to get an idea of how well the participant understood the device. One of the difficulties of this metric is that it is very expensive to generate and relies heavily on the experience of the coder to decipher natural language meanings, similar to the

subjectivity of an ethnographic study. Therefore, this metric is a mixed-methods approach. In our analysis, we biased ourselves toward considering all functions separate from the others, and only grouped them if there was clear evidence that they described the same function and corresponded to the same structure.

We did not attempt to create a master tree and compare the trees to this template. The reason we did not do this is there is no a single, unique solution that is most appropriate [14, 15], and doing so would make the experiment prone to errors of omission by the researchers who prepare the tree. Instead, we used the number of unique functions as a relative measure to compare each participant with the others.

3.6 Controlled Variables and Covariates

Since we considered each functional decomposition method to be independent of the diagram used to record the functions, we kept the diagram type the same for every function identification method. In this work, the function tree was the chosen diagram type. We did this to control for effects due to diagram type and because engineers tend to mix and match methods [9]. We also had a researcher provide the instruction, rather than the class instructors, in order to control for variations in instruction. Further, the amount of time and emphasis placed on each set of instructions was equal for each method. Examples of these responses and other data can be found in Table 5.

- Class level - freshman, sophomore, junior, or senior
- How often participant dissects things on their own - never/rarely, sometimes, often
- Prior experience with dissecting this product - yes / no
- Learned functional decomposition before - yes / no.

3.7 Analysis Procedure

We followed a specific process to gather the data prior to the statistical and qualitative analyses. This began by transcribing the function diagrams and surveys into Excel. Then we used the following steps:

1. Convert each function tree into an outline numeral system (E.g. root node = B7, branch nodes = B7.1, B7.2, etc., children of branches and leaf nodes = B7.2.1, B7.2.2, etc.). If a branch is not connected to the tree, put an "x" in place of the parent indicator (e.g. B7.X.1).
2. Determine the part of speech (POS) of the first word of every phrase. When a POS is ambiguous (e.g. "switch"), assume verb unless the context clearly shows otherwise. (See Table 6)
3. Determine the unique functions
 - (a) Group all phrases by similar meaning and define a "generalized" function for each group
 - (b) Review list of generalized functions for repetitions, and combine repeated generalized functions (prune list)
 - (c) Sort all functions by generalized functions and review each phrase to make sure all phrases in the

Table 5. An excerpt of data gathered for 3 participants. TD = Top-Down, EN = Enumeration, EF = Energy-Flow

Participant Code	A7	B2	C3
Method	TD	EN	EF
Class Level	Sen.	Jun.	Soph.
Dissect things on own?	Rarely	Rarely	Often
Taken apart device before?	No	No	No
Used func. decomp. before?	No	No	No
Post Survey	5	5	9
Unique Functions	7	7	12
Vertices	13	14	16
Edges	12	13	15
Max GD	8	7	4
Avg GD	3	3.18	2.69
Syntax Errors	0	0	9
% Syntax Error	0.00	0	0.563
Functions Level 1	1	0	1
Functions Level 2	3	2	4
Functions Level 3	5	5	11
Errors Level 1	0	0	0
Errors Level 2	0	0	0
Errors Level 3	0	0	9

group share the same meaning. Split groups into two meanings as necessary. (Table 7)

- (d) Sort all functions by outline order (by participant) and review each phrase to make sure its generalized function makes sense in context. Define new generalized functions if necessary. (Table 8)
- (e) Repeat steps c-d at least 3 times.

The semantic grouping was conducted by the authors. We then calculated the non-graph metrics per participant, per session (i.e. vertices, number of unique functions, errors, error rate per level, etc.). In order to calculate the graph metrics (avg. and max GD), we used NodeXL, a plug in for Excel. Since the graph metrics require a complete diagram, we inserted blank nodes or unconnected branches using a placeholder node. See Table 5 for examples of what this data looks like when compiled.

4 Quantitative Results

Several examples of the function trees produced by students are found in the appendix. Since a within-subject experimental design was used, a univariate ANOVA was performed in SAS with the participant code and the device/week

Table 6. Examples of functions and the Part of Speech (POS) associated with the first word of the node

Func. ID	Submitted Phrase	POS
B9.1	Meow	BLANK
C3.3.2	Protective screens and housing	ADJ
B8	Drill	VERB
A6.1.1.1	Switch directions	VERB
C1.3.1	Switch moves back and forth	NOUN

Table 7. Vertices sorted by generalized functions

Func. ID	Submitted Phrase	Gen. Func.
B12.1.3	Push air out by propeller	Move air
B13.1	Intake air	Move air
B14.1	Provide air	Move air
A1	Provide a flow of heated air	Move hot air
A2	Supply hot warm air	Move hot air
A7.2	Eject hot air	Move hot air

Table 8. A portion of the function tree for participant B2. Node B2.2.1.1 was changed from "control flow rate" due to context

Func. ID	Submitted Phrase	Generalized Function
B2.1	Provide comfort	Spread forces over hand
B2.2	Move air	Move air
B2.2.1	Input air	Move air
B2.2.1.1	Turn on fan	Drive fan
B2.2.1.1.1	Spin blades	Drive fan
B2.2.2	Output air	Move air
B2.2.3	Adjust air flow	Control flow rate

factor as blocking factors. The model for the statistical analysis considered main effects only due to the DOE.

In validating the ANOVA analysis, we tested the normality of the data and homogeneity of variance in SPSS [46]. Since the dependent variables are probably not independent of each other, we analyzed each separately to satisfy the independence assumption for ANOVA. A few variables are borderline-normal, but we treat them as normal anyway. The near-normal variables have a higher chance of detecting a statistical difference where there is none [46], with a slightly increased risk of a type-I error for the vertices metric. Assuming an alpha of 0.05, all the dependent variables except the number of vertices met the variance criteria.

Table 9. Significance of main effects (methods) on various dependent variables. Non-significant level responses omitted. Significant values in dark gray and near significant values in light gray.

Response	DF	F Value	P Value
Vertices	2	0.7	0.5037
Uniq. func.	2	0.21	0.8145
Efficiency	2	0.17	0.8468
Max GD	2	3.21	0.0506
Avg GD	2	2.21	0.1221
Errors	2	0.47	0.6308
Error Ratio	2	0.85	0.4364
Func. Lvl 3	2	3.65	0.0348
Func. Lvl 6	2	2.58	0.0883
Post Survey	2	0.55	0.5817

Table 10. Average values by method for selected variables. EF = Energy-Flow, TD = Top-Down, EN = Enumeration

	Vert.	Uniq. Fn.	Eff.	Mx. GD	Err. Rt.
EF	11.57	9.32	77.68%	4.780	17.37%
TD	12.95	9.20	75.93%	4.959	12.37%
EN	13.24	9.52	78.24%	6.115	12.73%

4.1 ANOVA Results and Discussion

Although the study is exploratory, a significance of 0.05 is used to determine significance. The p-values for the independent variable (method) its effects on the several dependent variables are seen in Table 9. Effect size is not reported since the sample size (n=78) is less than 100 and statistical significance is not sufficiently affected by n.

There are no significant effects by the method used on most of the measured responses (see Table 9). There is a significant difference in the number of functions on level 3 (p = 0.0348), and near-significance in the number of functions on level 6 (p = 0.0883) and the max GD (p = 0.0506). With more samples, these may test as significant. However, the differences in the functions on each level is probably not meaningful since consecutive levels were not significant as well. Also, there does not appear to be any practical difference between the average values for each method (see Table 10.)

A few covariates were significant (p < 0.05) or near-significant (0.05 < p < 0.10). Those who had taken the device apart before perceived the activity as less useful (p = 0.0448), but also made more syntax errors (p = 0.0034). However, these results are probably subjective since they are not coupled with other effects such as error rate, unique functions, or other metrics. The error ratio by class level (p = 0.0706)

Table 11. Error ratio by class level ($p = 0.0706$)

Sophomore	18.39%
Junior	14.69%
Senior	5.357%

was near-significant (but not total errors), and corresponded with a practical difference in performance (Table 11). This variable may become significant with more data or a population with a wider range of experience. Additionally, more than half the participants (14) reported not having learned functional decomposition before. Many of these were juniors and seniors, who had been taught functional decomposition in a required sophomore design class. This supports findings that engineering students often forget methods demonstrated early in their education [47].

We did detect a possible learning effect over the testing period; however, this effect cannot be distinguished from the effects due to the device. The tree efficiency increased each week ($p < 0.0001$) from 65.7% to 79.8% to 86.3% in the last week. However, the error rate and other significant measures did not show a consistent trend. This may correspond to prior findings that practice improves performance [38].

4.2 Hypotheses Summaries

Hypotheses H1-H3 are rejected because the responses do not show enough significant effect from the method used. In addition, if there were undetected statistical biases in the ANOVA analysis, these would point to finding a difference. The p-values for these tests are high enough to fail to reject the null hypothesis. The error rate committed by different class levels decreased with more experience (Table 11), but the result is above the 0.05 level ($p = 0.0706$). The practical difference between these is significant. Thus, we would expect a statistical difference with a larger sample size. H4 is tentatively accepted.

- H0 - There is no difference between the energy-flow, top-down, and enumeration methods (failed to reject)
- H1 - There is a difference between the energy-flow and top-down methods (rejected)
- H2 - There is a difference between the energy-flow and enumeration methods (rejected)
- H3 - There is a difference between the top-down and enumeration methods (rejected)
- H4 - The more experienced students will perform better than the less experienced students (tentatively accepted)

5 Qualitative Results and Discussion

The second research question was explored by asking participants what was the hardest part of the dissection activity. The participant responses were qualitatively categorized by content and compiled into a few categories describing the nature of the comment, as seen in Figure 5. The largest number of these focused on the dissection itself, where holding on to parts, dealing with stripped screws, etc. was the most

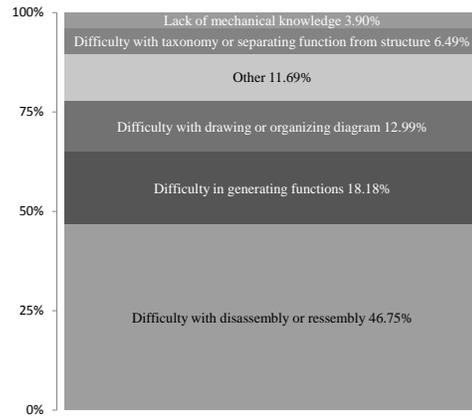


Fig. 5. Aggregated comments by percentage over all sessions

difficult parts. Ignoring these, we explore the other issues brought up.

5.1 Difficulty with Generating Functions

The largest number of comments regarded difficulty with the physical disassembly and reassembly process. After this, the next most numerous comments related to difficulty with generating functions. Among this group, students often described the difficulty of breaking a parent function into children functions. One student reported difficulty with “Coming up with subfunctions and sub-sub functions.” Furthermore, many of the submitted phrases are not functions.

5.2 Difficulty with Diagramming

Many other participants also commented that the hardest part about the session was “the function tree”. Some said, “I understand the components by taking it apart, not by writing about it.” Another said, “I really don’t like this. It’s much easier for me to just write it down in traditional writing or explaining it to somebody. I’m always just worried about if I’m doing it right.”

These individuals seemed to be inhibited by the requirement to use a function tree, instead of allowing other diagram types. Also, we had encouraged students to create rough drafts, but we found very few of these. It seemed most students preferred to do the tree in one shot, or reorganize in their head. This seemed quite difficult in the case of energy-flow, since energy-flow is better with horizontal (flow) diagrams than vertical ones (trees) [31], and may have added an extra mental step. This may have been alleviated if students had been given multiple diagram types to work with, or if rough drafts had been enforced.

5.3 Difficulty With the Syntax

We observed that many students struggled maintaining the verb-phrase syntax. Often, participants conflated parts and functions, despite a strong emphasis on distinguishing between parts and functions during the instructions. Some struggled with “Separating statements about what components are in the device from function statements”. It seems that the functions associated with certain parts are so obvi-

ous that engineers find it difficult or superfluous to create a function-phrase to describe it (e.g. “wheel” vs. “transmit rotational forces to ground”).

Related to this, some student struggled with “coming up with good verbs to describe functions”. It seems that they did not use the list of common function verbs provided [35]. This seems to indirectly correspond with findings that reduced function taxonomies lead to easier use and interpretability [35]. In a different study, whose data are not presented in this paper, we asked one student why he did not use the list. He said he had forgotten it was even there. This study did not explore why these lists were not used, but this would be an interesting question for future work.

5.4 Difficulty with the Methods

While few participants commented on the function identification methods, one brought up that “(I) did not understand the distinction between the last approach (enumeration) and this one (top-down).” Another described difficulty with “recognizing what the energy flow is (i.e. tracing the energy flow) in the NERF gun.” These comments suggest that the identification methods may not have been sufficiently clear for the participants, though it is hard to say how common this was. Many participants did not seem to understand the energy-flow method well, although there is evidence that many attempted to identify flows through the device.

5.5 Scope of the Diagram and Stopping Point

Many participants struggled with knowing the scope of the assignment. Some mentioned “trying to decide what is worth mentioning.” One struggled with “Knowing when a function was decomposed fully - [it] seems to just keep going.” There seemed to be a general sense that too great of detail was not necessary. Dym and Little state that diagrams do not need to be too detailed, and doing so may not improve functional understanding [18]. This may also correspond with too many functions inhibiting the interpretability of the tree [35]. Interestingly, most of the participants that made these sorts of comments produced large and complete function trees, with very few syntax errors, and were among the best submitted.

5.6 Mechanical and Electrical Components

Close to 4% of participants reported difficulty with understanding mechanical and electrical components. Some of this may simply be due to the lack of exposure sophomores and juniors have, having not handled much hardware before. Those who described difficulty with electrical parts were juniors and seniors, but this can also be explained by being ME majors. Taken together, this seems to suggest that engineers with less experience with hardware and components would have a more difficult time analyzing a device. This may correspond with findings that younger engineers struggle more with identifying parts [9].

5.7 Other Issues Reported

We also observed that some students did not see the point of functional decomposition, sometimes complaining about it. This corresponds with prior papers on this topic [5].

In this particular experiment, this could also have to do with the particular motivations the students had in participating. Several students had taken the class to have fun, and the additional workload may have seemed a burden to some of them.

The study did not find qualitative differences between the functions trees generated by each method. Each method seemed equally likely to produce a core set of functions. The diagram types found in each method were also similar to the others. Overall, there is not enough qualitative evidence to conclude that there is a difference between the trees generated by the various methods. This supports the quantitative results from this study.

6 Implications

These results imply that top-down, enumeration and energy-flow methods perform the same for novice designers. Since some of these methods take significantly more effort to learn, this further implies that simpler methods are preferable at an early stage of learning design. There may be several reasons for why no difference was found between the methods: prohibitive cognitive loads, lack of mechanical knowledge, lack of practice using the methods, mental set fixation, or any combination of these. Additionally, for some students, certain methods may not be easy to use because they conflict with their learning style. Also, if product complexity is a factor, it may be that certain functional decomposition methods work better for complex products than for simpler ones (as used in this study), or designs which are not mature and are still developing. On the other hand, these methods may also perform the same for either of these situations.

6.1 Cognitive Loads

The students described several tasks which were especially difficult, which may signify high cognitive loads. These include generating functions, diagramming, distinguishing parts from functions, and understanding the methods. Cognitive load theory may explain some of these observed problems. There are three categories of cognitive load [48]. Intrinsic cognitive load (ICL) is high when the complexity of information to be learned or the task is high. We observed many students attempted to generate functions in one go, without creating a rough draft first. This probably contributed to cognitive load. Extraneous cognitive load (ECL) results when the learning material is difficult to follow. Germane cognitive load (GCL) represents the level of expert skill. It is most likely that each of these played a part in the observed effects [49]. The students complained of both not knowing some parts and having difficulty with creating the tree, forming verbs, etc., corresponding with a ICL effect [4]. Low motivation also contributes to a high ICL, and it is possible that this affected the student performance [5]. Some students also complained that they did not understand the methods, and our instructional period may not have been sufficient, as mentioned before. This would contribute to the ECL. It is also possible that when students did not understand a method for identifying functions, they made their own [50]. Finally, the lack of expertise, lack of familiarity

with the problem, and abstract nature of the task would all contribute to the GCL [11].

6.2 Instruction Methods

Since our instruction followed the interventions used at many universities, and those described in textbooks, this study may suggest the need to revise these models. Specifically, changes should include more directed practice [48], guided examples [38, 48], and clear illustration of the benefits of functional decomposition [5, 48]. This also confirms work by those who have worked to improve functional decomposition curricula [38].

6.3 Purpose of Task and Complexity of Product

The purpose of the task and product complexity may have influenced our results. Since the purpose of the task was to understand “how it works”, it is quite possible that the trees were only superficial, and therefore hid any real differences between the methods. However, this may indicate that for this type of task, a complicated function diagram is not necessary [1]. Also, the products may not have been complex enough to highlight any real differences between the methods. Complicated methods may not hold any advantage for products of this level of complexity.

If these explanations are true, further studies would be needed to distinguish what activities need a certain level of detail, method, or type of diagram. We do not expect that functional decomposition methods would behave the same in a design task as it would in a product dissection task. Diagram types probably also perform differently. In the study by Nagel et al., for example, function diagrams were judged on the basis of completeness and conservation of flows [38]. This level of rigor may not be necessary before ideation [1, 18]. However, a comprehensive flow block diagram may be very appropriate during detailed design after a concept has been chosen or when reverse engineering a competitor’s product.

6.4 Other Implications

In this study, it was seen that participants tend to fixate on the name of the part, rather than actually determining its function or meaning within the entire system. For some parts, the name itself may imply the function (e.g. “motor”), and may lead some engineers to simply write the part name instead of translating it into a function. This may be further compounded by known parts that have unknown or assumed functions. Therefore, the students may have seen a part and simply ignored its other functions because they already felt they had a grasp on what it does. Interestingly, this seems to correspond to a tendency in young children to name and categorize unknown objects by their functions or purpose [51, 52]. While untested, it is reasonable to hypothesize that the fixation on part names is a vestige of this early developmental cognition.

Another possible reason for the observed results is different methods may perform better for people with certain learning styles. Since functional decomposition is a form of abstraction [1, 18], and abstraction is the deepest level of

learning [4], it follows that learning styles may have an effect on individual performance with a particular method. Other possible explanations include mental-set fixation [3], which could potentially reduce performance over a long session. However, we did not have any clear confirmation this was occurring in our study.

7 Conclusions

The results of this study suggest that there is no difference between energy-flow, top-down, and enumeration methods of functional decomposition for product dissection for beginner designers. This result is evaluated using statistical tests, qualitative analysis, and examining practical differences in results. The result that there is no difference may be due to a few reasons. The methods may cause high cognitive loads in the participants. This cognitive loads could be due to complexity of the task, the information embodied in the artifacts, the instruction on how to use the methods, or lack of experience with the method or components. It is also possible that students who did not understand a method made their own up [50]. The level of complexity of the products are similar, and differences in complexity probably did not bias the study. It is possible devices of much greater complexity would yield different results between the methods. It is also possible that for simply understanding how something works, each method will perform the same. We also noted that the way functional decomposition is taught may inhibit students [38]. However these results are interpreted, they suggest that the methods do not always operate the same in every design task.

These results may also have some education implications. When teaching functional decomposition, algorithmic approaches, such as energy-flow or top-down, may be too much for most students. It may be better to simply focus on the concepts of functionality and diagramming, and introduce algorithmic methods later. We also observed that in general, students struggled to identify function phrases, despite being given a taxonomy, and had difficulty constructing the diagram. Beginner engineers generally struggled to distinguish between functions, behaviors, structures, or design requirements. We also noted that many students tended to fixate on part names, especially when the name is commonly known and implies its function (e.g. “motor”).

There are some limitations to this study. As mentioned above, it is possible that the complexity of the products was too low, or that student motivation was not high enough to show any real differences. Also, only one type of diagram was used, which may have imposed too much extra work when using the energy-flow or enumeration methods. Additionally, the statistical analysis cannot separate the effects due to time / learning and the effects due to the artifacts. Finally, the purpose of the task used in this study was to create a generic description of a product. Other studies, argue for the merit of functional modeling in a specific design context, such as defining a mechanical design space [36], decision making [53], or satisfying customer needs [54].

Future work should focus on 1) determining how dif-

ferent diagrams work in conjunction with each method, 2) improving instruction for functional decomposition, 3) determining how these methods perform in other design tasks, and 4) exploring the effects of other contributing factors such as learning styles, personality, etc. Table 1 shows the parameters laid out for this study and the levels we chose. We recommend that future researchers use these or similar parameters to define their studies so future work in decomposition can be compared, and we can identify gaps in knowledge, pedagogy, and theory.

Future work may also explore how outside theories, such as constructivism or construal theory, contribute to our understanding of functionality, and how different levels of expertise affect identifying functions. In a broader vision, functional decomposition should also continue to be compared to alternate abstraction methods, such as analogical design, axiomatic design, bio-inspired design, and design for affordances.

Acknowledgments

We would like to thank Katherine Frangos and the instructors of ME 297 for their cooperation and help. We would also like to thank Senthil Chandrasegaran, and others for their help in executing the experiment and feedback on the drafts.

References

- [1] Pahl, G., and Beitz, W., 1996. *Engineering Design: A Systematic Approach*. Springer, New York.
- [2] Ho, C.-H., 2001. "Some phenomena of problem decomposition strategy for design thinking: Differences between novices and experts". *Design Studies*, **22**(1), pp. 27 – 45.
- [3] Jansson, D. G., and Smith, S. M., 1991. "Design fixation". *Des. Stud.*, **12**(1), pp. 3 – 11.
- [4] Bransford, J. D., Brown, A. L., and Cocking, R. R., eds., 2000. *How People Learn: Brain, Mind, Experience, and School*. National Academy Press, Washington D.C.
- [5] Tomiyama, T., van Beek, T. J., Alvarez Cabrera, A. A., Komoto, H., and D'Amelio, V., 2013. "Making function modeling practically usable". *AIEDAM*, **27**, 8, pp. 301–309.
- [6] French, M. J., 2002. *Engineering Design Synthesis*. Springer, New York, ch. 2: Insight, design principles and systematic invention, pp. 19–34.
- [7] Vermaas, P. E., 2013. "The coexistence of engineering meanings of function: Four responses and their methodological implications". *AIEDAM*, **27**(8), pp. 191–202.
- [8] Vermaas, P. E., and Eckert, C., 2013. "My functional description is better!". *AIEDAM*, **27**, 8, pp. 187–190.
- [9] Eckert, C., Ruckpaul, A., Alink, T., and Albers, A., 2012. "Variations in functional decomposition for an existing product: Experimental results". *AIEDAM*, **26**, pp. 107–128.
- [10] Eckert, C., 2013. "That which is not form: The practical challenges in using functional concepts in design". *AIEDAM*, **27**, Aug., pp. 217–231.
- [11] Jonassen, D. H., 2000. "Toward a design theory of problem solving". *Educational Technology: Research and Development*, **48**(4), pp. 63–85.
- [12] Eckert, C., Alink, T., Ruckpaul, A., and Albers, A., 2011. "Different notions of function: Results from an experiment on the analysis of an existing product". *J Eng Design*, **22**(11-12), pp. 811–837.
- [13] Schacter, D. L., Gilbert, D. T., and Wegner, D. M., 2009. *Psychology*, 2nd ed. Worth Publishers, New York, ch. 9: Language and Thought, p. 376.
- [14] Cunniff, P. F., Herrmann, J. W., Schmidt, L. C., Zhang, G., and Dally, J. W., 1998. *Product Engineering and Manufacturing*. College House Enterprises, LLC, New York, ch. Chapter 5: Functional Decomposition, pp. 81–93.
- [15] Ulrich, K. T., and Eppinger, S. D., 2000. *Product Design and Development*. McGraw-Hill, New York.
- [16] Otto, K., and Wood, K., 2001. *Product Design: Techniques in Reverse Engineering and New Product Development*. Prentice Hall, Upper Saddle River, NJ.
- [17] Booth, J. W., Bhasin, A. K., Reid, T. N., and Ramani, K., 2014. "Evaluating the bottom-up method for functional decomposition in product dissection tasks". In Proceedings of ASME IDETC/CIE, no. 35393.
- [18] Dym, C. L., and Little, P., 2000. *Engineering Design: A Project-Based Introduction*. John Wiley & Sons, USA.
- [19] Cross, N., 2000. *Engineering Design Methods*. John Wiley & Sons, New York.
- [20] Stoll, H. W., 1999. *Product Design Methods and Practices*. Marcel Dekker, Inc., New York.
- [21] Ullman, D. G., 2003. *The Mechanical Design Process*, 4 ed. McGraw-Hill, New York.
- [22] Dieter, G. E., 2000. *Engineering Design: A Materials and Processing Approach*. McGraw-Hill, New York.
- [23] Dieter, G. E., and Schmidt, L. C., 2009. *Engineering Design*. McGraw-Hill, New York.
- [24] Hyman, B., 2003. *Fundamentals of Engineering Design*. Prentice Hall.
- [25] Phillips, A., 2002. "Functional decomposition in a vehicle control system". In American Control Conference, 2002. Proceedings of the 2002, Vol. 5, pp. 3713 – 3718 vol.5.
- [26] Horenstein, M. N., 2002. *Design Concepts for Engineers*. Prentice Hall, Upper Saddle River, NJ.
- [27] Sheppard, S. D., 1992. "Mechanical dissection: An experience in how things work". *American Society for Engineering*.
- [28] French, M., 1999. *Conceptual Design for Engineers*. Springer, New York.
- [29] Magrab, E. B., 1997. *Integrated Product and Process Design and Development: The Product Realization process*. CRC Press, New York.
- [30] Priest, J. W., and Sanchez, J. M., 2001. *Product Development and Design for Manufacturing: A Collaborative Approach to Productivity and Reliability*, 2nd ed. Marcel Dekker, Inc., New York.

- [31] Kirschman, C. F., and Fadel, G. M., 1998. “Classifying functions for mechanical design”. *ASME J Mech Design*, **120**, pp. 475–482.
- [32] Ringstad, P., 1997. “A comparison of two approaches for functional decomposition: The function/means tree and the axiomatic approach”. In *ICED*, no. 11.
- [33] Schmekel, H., and Sohlenius, G., 1989. “Functional models and design solutions”. *Annals of the CIRP*, **38**(1), pp. 129–133.
- [34] Booth, J. W., Bhasin, A. K., and Ramani, K., 2014. “Art meets engineering design: An approach for reducing sketch inhibition in engineers during the design process”. In *Proceedings of ASME IDETC/CIE*, no. 35278.
- [35] Caldwell, B. W., Thomas, J. E., Sen, C., Mocko, G. M., and Summers, J. D., 2012. “The effects of language and pruning on function structure interpretability”. *ASME J Mech Design*, **134**, pp. 1–11.
- [36] Stone, and Wood, 2000. “Development of a functional basis for design”. *ASME J Mech Design*, **122**, pp. 359–370.
- [37] Hirtz, J., Stone, R., McAdams, D., Szykman, S., and Wood, K., 2002. “A functional basis for engineering design: Reconciling and evolving previous efforts”. *Res. Eng. Design*, **13**, pp. 65–82. 10.1007/s00163-001-0008-3.
- [38] Nagel, R. L., Bohm, M., and Linsey, J., 2013. “An investigation into the effectiveness of an algorithmic approach to teaching functional modeling”. In *Proceedings of ASME IDETC*, no. 12658.
- [39] Nagel, J. K. S., Nagel, R. L., Stone, R. B., and McAdams, D. A., 2010. “Function-based, biologically inspired concept generation”. *AIEDAM*, **24**, pp. 521–535.
- [40] Qian, L., and Gero, J. S., 1996. “Function-behavior-structure paths and their role in analogy-based design”. *AIEDAM*, **10**, pp. 289–312.
- [41] Proctor, R. W., and Zandt, T. V., 2008. *Human Factors in Simple and Complex Systems*, 2nd. ed. CRC Press, New York.
- [42] Seltman, H. J., 2009. *Experimental design and analysis*. Tech. rep., Department of Statistics at Carnegie Mellon (Online Only), November 1.
- [43] Caldwell, B. W., Ramachandran, R., and Mocko, G. M., 2012. “Assessing the use of function models and interaction models through concept sketching”. In *Proceedings of ASME IDETC*, no. 71374.
- [44] Curtis, S. K., Harston, S. P., and Mattson, C. A., 2012. “Characterizing the effects of learning when reverse engineering multiple samples of the same product”. *ASME J Mech Design*, **135**.
- [45] Toh, C., Miller, S., , and Kremer, G. E. O., 2012. “The impact of product dissection activities on the novelty of design outcomes”. In *Proceedings of ASME IDETC*, no. 70421.
- [46] Keselman, H. J., Huberty, C. J., Lix, L. M., Olejnik, S., Cribbie, R. A., Donahue, B., Kowalchuk, R. K., Lowman, L. L., Petoskey, M. D., Keselman, J. C., and Levin, J. R., 1998. “Statistical practices of educational researchers: An analysis of their ANOVA, manova and ancova analyses”. *Review of Educational Research*, **68**(3), Fall, pp. 350–386.
- [47] Lee, Y. S., Gero, J., and Williams, C. B., 2012. “Exploring the effect of design education on the design cognition of two engineering majors”. In *Proceedings of ASME IDETC*, no. 71218.
- [48] Hollender, N., Hofmann, C., Deneke, M., and Schmitz, B., 2010. “Integrating cognitive load theory and concepts of human computer interaction”. *Computers in Human Behavior*, **26**(6), pp. 1278 – 1288.
- [49] Lawson, B., and Dorst, K., 2009. *Design Expertise*. Elsevier, New York, ch. Chapter 2: Understanding Design, pp. 23–50.
- [50] Hayes-Roth, B., and Hayes-Roth, F., 1979. “A cognitive model of planning”. *Cognitive Science*, **3**, pp. 275–310.
- [51] Sobel, D. M., and Buchanan, D. W., 2009. “Bridging the gap: Causality-at-a-distance in children’s categorization and inferences about internal properties”. *Cognitive Development*, **24**(3), Jul, pp. 274–283.
- [52] Asher, Y. M., and Kemler Nelson, D. G., 2008. “Was it designed to do that?: Children’s focus on intended function in their conceptualization of artifacts”. *Cognition*, **106**(1), Jan, pp. 474–483.
- [53] Lin, L.-Z., Huang, L.-C., and Yeh, H.-R., 2012. “Fuzzy group decision-making for service innovations in quality function deployment”. *Group Decision and Negotiation*, **21**(4), Jul, pp. 495–517.
- [54] McAdams, D. A., Stone, R. B., and Wood, K. L., 1999. “Functional interdependence and product similarity based on customer needs”. *Res. Eng. Design*, **11**, pp. 1–19.

Appendix: Raw Data from Three Participants

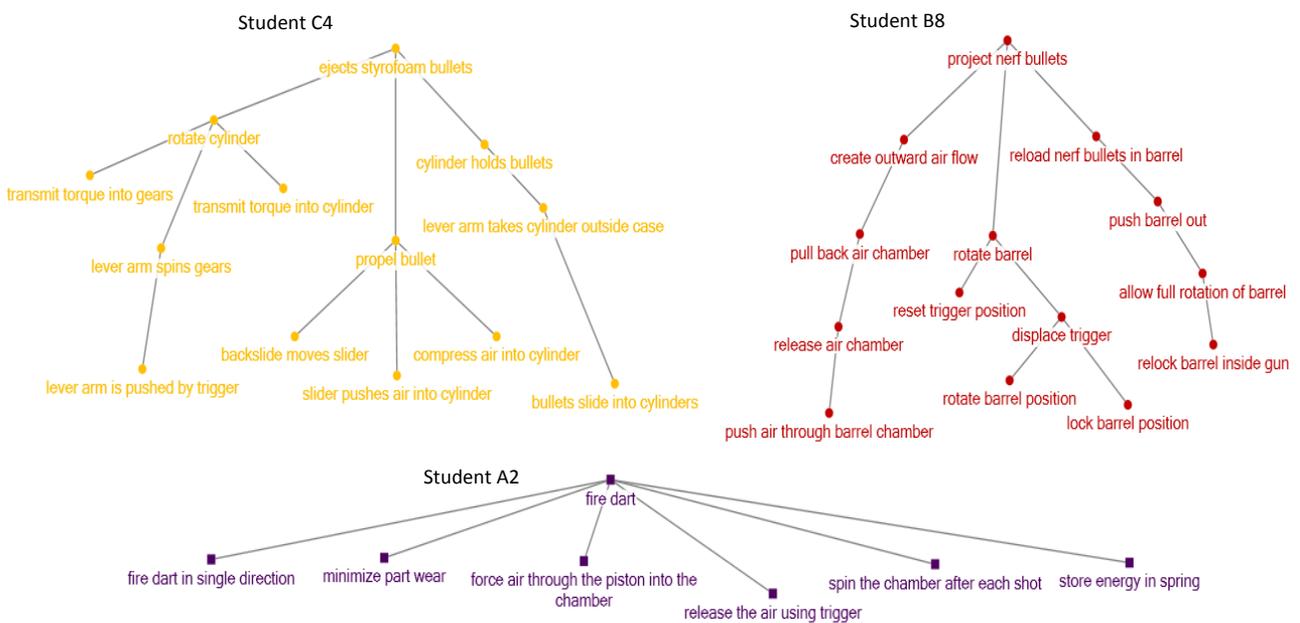


Fig. 6. These three function trees are digitized submissions of raw data collected from three participants. All three of these trees are for the NERF gun, but each tree is generated using a different function identification strategy.