The Function-Based Design for Sustainability Method

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The Function-Based Design for Sustainability Method

Over the last two decades, consumers have become increasingly aware and desiring of sustainable products. However, little attention has been paid to developing conceptual design methods that explicitly take into account environmental impact. This paper contributes a method of automated function component generation, and guided down-selection and decision-making based upon environmental impact. The environmental impact of functions has been calculated for 17 of the products found in the Design Repository using ReCiPe scoring in SimaPRO. A hierarchical Bayesian approach is used to estimate the potential environmental impacts of specific functions when realized into components. Previously, product environmental impacts were calculated after a product was developed to the component design stage. The method developed in this paper could be used to provide a criticality ranking based on which functional solutions historically have the greatest risk of causing high environmental impact. The method is demonstrated using a simple clock system as an example. A comparative case study of two phone chargers for use in third-world countries demonstrates the decision-making capabilities of this method, and shows that it is possible to compare the environmental impact of alternative function structures during the conceptual stage of design. With the method presented in this paper, it is now possible to make early functional modeling design decisions specifically taking into account historical environmental impact of functionally similar products. [DOI: 10.1115/1.4035431]

Keywords: sustainability, environmental impact, functional modeling, design decision-making, product design

1 Introduction

Sustainability in manufactured products is an increasingly important consideration that design engineers must take into account when designing new consumer products. A small but significant segment of the consumer market (15–30 million people in the USA as of 2009) will pay a premium for consumer products that are more sustainable than functionally identical competitor products [1]. However, efforts to create sustainable products often do not occur until after most major design decisions have been made, and manufacturing processes selection has begun [2,3]. This results in unsatisfactory sustainability due to compromises foisted upon sustainable manufacturing efforts [4].

Efforts to connect early phase conceptual design functional modeling with later analysis tools—such as for risk and reliability analysis, and for mission stage planning—have brought significant analytic capabilities earlier in the design process to help shape important early phase design decisions [5–8]. Analyzing significant design and manufacturing considerations in the very early stages of a design process can mitigate the risks of costly redesign. Thus, a method to analyze environmental impact during the earliest stages of design has the potential to improve product or system sustainability and may be used to make design tradeoff decisions.

1.1 Specific Contributions. This paper contributes the function-based design for sustainability (FDS) method, which enables automated functional solution generation and guided down-selection and decision-making based on environmental impact. The environmental impact of functions has been calculated for 17 of the products found in the Design Repository [9] (a product library where products are decomposed to the component and functional level) using SimaPRO [10] (a lifecycle assessment software product) and the ReCiPe [11] lifecycle assessment scoring method and dataset. This product data was created during a separate study of the relationship between sustainability and innovation [4], and we use it in this manuscript to demonstrate the FDS method. ReCiPe scores for every component are calculated based on the material, the manufacturing process, and the mass of the part. The ReCiPe method itself accounts for impacts during material extraction through end of life [11]. FDS uses a hierarchical Bayesian modeling approach to identify low environmental impact functional solutions for products during the early phases of design by using historical function–component information via mean and standard deviation statistics. Previously, product environmental impacts were calculated after a product was developed to the component design stage. The FDS method makes it possible to make early function-based modeling design decisions specifically taking into account environmental impact of the product or system.

More specifically, FDS is used to rank the importance of function alternatives or function-to-component design choices with respect to their potential to affect the finished product's environmental impact. The goal is similar to that of a risk priority number (RPN) in a failure modes and effects analysis (FMEA) [12]. The RPN is an aggregate score created for each potential failure

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identified in an FMEA, and it creates a basis for ranking the importance of potential failures. RPN ranking allows designers to prioritize their focus on mitigating the most important potential failures. Similarly, the FDS method provides a way to prioritize early design decisions based on their potential environmental impacts.

2 Background

The FDS method presented in this paper enhances the ability of the product design engineers to develop sustainable products. And while the broad concept of sustainability includes environmental, economic, and social factors, in this work, we focus specifically on improving sustainability through reducing environmental impact. Several key areas of existing research and industrial practice are relevant to understanding and implementing FDS. This section reviews specific details of several topics important to the method including: innovation and sustainability in design, life-cycle assessment, functional modeling and the design repository, functional and environmental impact, and hierarchical Bayesian modeling.

2.1 Innovation and Sustainability in Design. In recent decades, growing attention has been paid to the development of sustainable processes and products both for short and long-term issues [1,13–16]. In addition to consumer-driven needs and desires spurring companies to adopt sustainable design practices, companies wishing to participate in international markets must adhere to a number of different regulations (e.g., Refs. [17,18]). Such regulations have necessitated that many products be redesigned in order that they may continue to be sold in the European marketplace [19].

Several design tools have been developed to help companies comply with new regulations in Europe and elsewhere [20]. Most of the currently available tools are TRIZ-derived [21–24] and base their sustainability statistics on seven eco-innovation elements embodied in three categories including: (1) material reduction, (2) energy reduction, and (3) product durability [25–33].

While the TRIZ-based methods are useful for creativity and ideation within the context of sustainability, they are not appropriate for designers who wish to use a functional modeling approach to early conceptual system design [34]. Work has been done to link TRIZ's problem-solving approach with the philosophy of functional modeling [35] and to merge TRIZ's active principles with functional modeling [36], among other efforts [37–39]; however, a linkage between TRIZ and functional modeling has not been developed to allow sustainability information to move between TRIZ and functional modeling. Rather than developing such a linkage, we have chosen to develop a method (presented in this paper) to assess sustainability directly in functional modeling.

2.2 Life Cycle Assessment (LCA). Life cycle assessment (LCA) [40–42] has proven to be a valuable tool for a variety of purposes and industries [43–46]. While it is recognized that LCA can be applied to the design process [47], it is challenging to do so in the conceptual stages of design when sunk costs are low. Various applications of LCA into existing design methods have found varying measures of success in practice. Quality function deployment (QFD) [48–52] and TRIZ have [53] also seen LCA integration, but injecting life cycle requirements at this stage (prior to functional analysis) can artificially limit the solution space. Another drawback of many QFD-based methods is that product designers are not provided actionable solutions to design challenges. Instead, product designers must look to other sources for eco-innovative design solutions. The FDS method is formulated to address these issues by offering the designer actionable choices via comparisons between options at the functional stage of design.

2.3 Functional Modeling and the Design Repository. Functional modeling, the function-flow taxonomy, and the functional basis [13,14] have been developed in part to help product designers to determine the functional design of a product in the early stages of conceptual design [54–58]. As the design progresses, libraries of abstract historical product data, such as the Design Repository, allow for functional models to be developed into component designs through semi-automated processes. A restricted vocabulary of component types, which can be developed and matched to these functions using reverse engineering data, facilitates this process [50–61]. Function-based design continues to be extended [63–64] to allow interesting and useful analyses [65–76] to be performed by designers early in the conceptual stages of design [77–88]. Using traditional engineering approaches, such analyses are not possible until much later in the design process [89–93]. For example, efforts have been made to bring risk and reliability analysis into the earliest phases of design to prevent costly redesigns or retrofits from significant risk or reliability issues discovered late in the design process [5–8,94]. While design repositories can suffer from limited size, approaches such as information extraction and human computation have been used to improve the size of product data sets [95–97] and thus improve their predictive power.

2.4 Functional and Environmental Impact. Devanathan et al. have shown that it is feasible to associate environmental impact with a given function by using a function impact matrix (FIM) [98,99] to isolate functions that dominate product environmental impact. Individual component impacts can be determined and then mapped back to the functions that the components solve. FIM works by combining LCA with portions of QFD. FIM is developed by combining environmental impact data for each component in a product with a function component matrix, and then distributing impact data to the functions that define the product. FIM was developed to redesign existing products rather than design new products [98,99].

Gilchrist et al. [4] developed a method to compare the functional impact of existing products by directly linking functions to environmental impacts through FIM using ReCiPe 2008 [11], a dataset and LCA computational method, and information from SimaPRO [10], a LCA software package. Their work determines the most common component used to solve a particular function and investigates the method of manufacture of the average components [4,100]. From the work of Gilchrist et al., it was found that innovative products often fare worse in sustainability metrics than common products that solve the same functional design. While Gilchrist et al. method is useful for existing products that can be decomposed to a functional level, it allocates historical environmental impact evenly across all functions that a type of component has performed. This simple assumption detracts from the predictive power of the method when developing new products.

2.5 Hierarchical Bayesian Modeling. Hierarchical Bayesian modeling is a statistical modeling approach that combines Bayesian inference with hierarchical statistical modeling [101]. This approach has been applied to solve problems in a wide range of domains including geochemical parameter estimation [102], growth rate forecasting [103], speech recognition [104], relational learning [105], and reliability forecasting [106].

Gelman et al. [101] describe the hierarchical Bayesian modeling approach. They present an example in which a joint probability model is created for an overall rat population using (1) a noninformative hyperprior distribution representing current beliefs about rat tumor incidence and (2) new results from a series of experiments.

O'Halloran [107] use this hierarchical Bayesian approach—along with historical reliability data, the functional basis, and the component taxonomy—to develop a methodology for reliability prediction. Their methodology enables a designer to consider the probable reliability of candidate systems at the functional modeling stage of design. Each observation in O'Halloran's work is a failure rate for a real component. These observations are organized hierarchically according to their function classifications and component classifications. Failure rate probability distributions are calculated for each top-level function according to the component subpopulations within, which enables predictions about the future failure rates of any given function. Others have previously used hierarchical Bayesian approaches for a variety of purposes in engineering design in applications that include consumer preference modeling and marketing decision support (e.g., see Refs. [108–111]).

3 Methodology

The function-based design for sustainability (FDS) method consists of three distinct steps as shown in Fig. 1. The first stage requires collection and preparation of historical environmental impact data. The second stage establishes predictive probability distributions of environmental impact for each function–component combination in the historical dataset. The third stage uses these probability distributions to provide guidance to design engineers.

3.1 Step 1: Data Preparation. The data preparation phase involves the collection of historical product data from the designer's domain. This reflects the approach used in function-based failure prediction methodologies based on the historical failure data [5–8,89,112–116]. In the example and case study presented in Sec. 4, a convenience sample of 17 consumer products is used (with ReCiPe scores calculated for each component) to demonstrate the approach. These products are cataloged in the Design Repository [9] and were used in a previous sustainability study [4]. To create this test set, cradle-to-grave environmental impact scores are queried from SimaPRO based on the materials and manufacturing processes that make up each component. The end-of-life scenario is assumed to be landfilling, and packaging and shipping are assumed to be equal across all products. The three ReCiPe endpoint indicators are aggregated into a single unitless performance metric using the hierarchist weighting and normalization method. Use phase impacts are estimated for each type of component based on expected lifetimes and duty cycles of the product and component.

Given a set of products similar to the product being designed, each component in each product is assigned a functional basis function, a component taxonomy type, and an environmental impact score. Impact scores are aggregated by shared function–component pairings within each product and normalized to product mass.

The data preparation procedure begins by processing each product separately. For each product, each component's impact score in $\boldsymbol{I}$ is divided by its parent product's total mass (m_p) as shown in Eq. (1). The mass normalization produces a vector of impact density observations ($\boldsymbol{y}$) that enables comparison of general component taxonomy types across multiple products. For example, if all other factors are held equal, the environmental impact of two electric motors that comprise 20% of a product's mass will be identical in this analysis, regardless of whether that product's mass is 10 kg or 100 kg. For any analysis that uses this data, the outcome is interpreted as a relative historical likelihood that a given type of component will contribute significantly to a product's overall environmental impact. Figure 2 provides an example of the data preparation stage. The ReCipE score of the first gear in the Polaroid Pogo (3.05×10^{-5}) is divided by 218 g to produce a normalized ReCiPe score of 1.40×10^{-7}. The normalized scores for both gears in the Polaroid Pogo are then summed together to create a single entry for (gear, change mechanical). This entry is grouped with the corresponding score from the Garage Door Opener to produce a vector of observations for (gear, change mechanical)

$$\boldsymbol{y} = \boldsymbol{I}/m_p \tag{1}$$

In the remaining discussion, y_{ijk} will refer to one normalized impact observation (i) within one function–component pair (j)

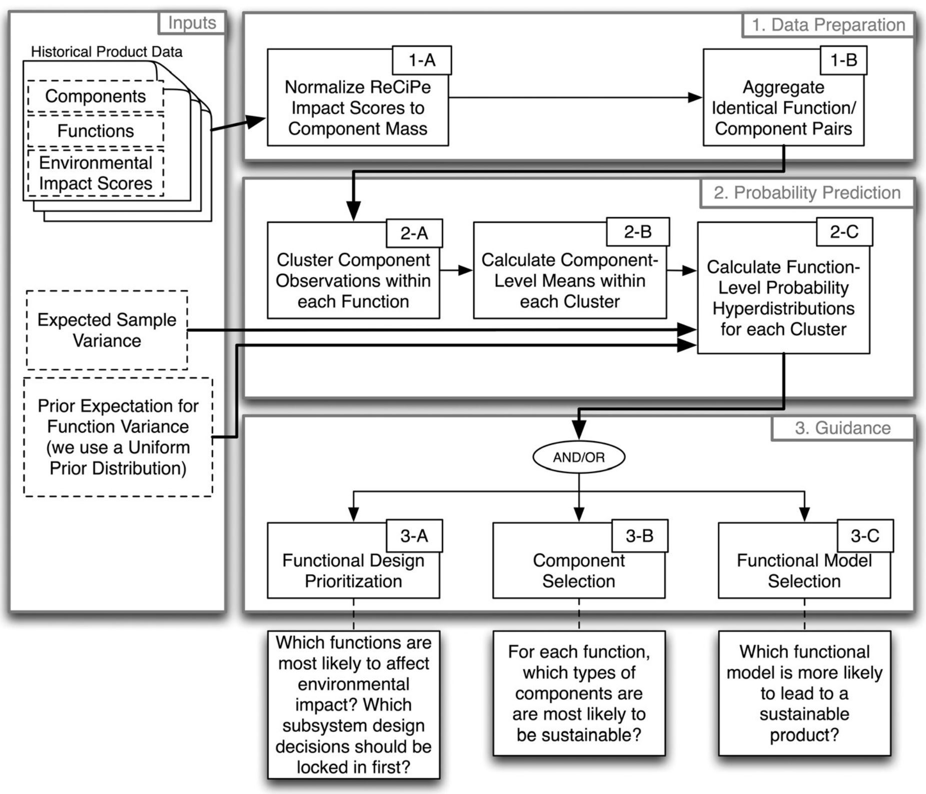

Fig. 1 FDS methodology overview

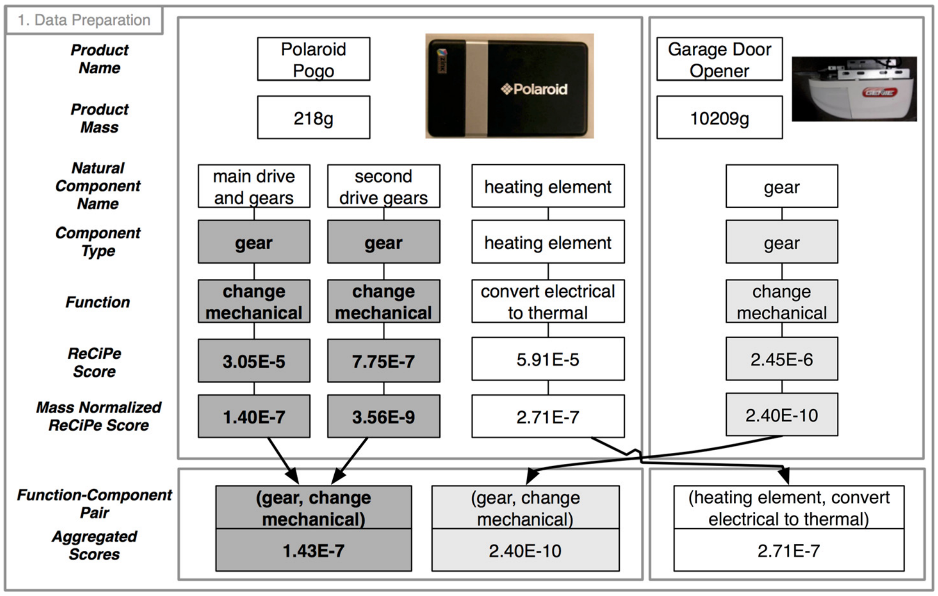

Fig. 2 Data preparation

within one product (k). The vector $\boldsymbol{y}_{*j}$ represents an outcome of the data preparation stage, containing a normalized set of environmental impact observations i for a specific function–component pairing j. In Fig. 2, $y_{1,(\text{gear,change mechanical}),\text{Poloroid Pogo}} = 1.40 \times 10^{-7}$ and $y_{2,(\text{gear,change mechanical}),\text{Poloroid Pogo}} = 3.56 \times 10^{-9}$; while $y_{*,(\text{gear,change mechanical})} = [1.43 \times 10^{-7}, 2.40 \times 10^{-10}]$.

The mass normalization builds in the implicit assumption that in a given problem domain, the nuances of that domain have a strong effect on the range of masses in potential alternatives. It is not useful to compare the environmental impact of a car engine to the environmental impact of a lawnmower engine; the mass of the car engine will almost always be larger (and therefore lead to a higher environmental impact) because the car engine has more mass to move. When generalizing the impact of engines in general, it is more useful to examine each component's contribution as a percentage of its mass in the system because it abstracts away some of this domain specificity.

After normalization, components with the same functional basis function and component taxonomy type (within each product) are aggregated into a single function–component pair. Mass-normalized impact scores with the same function–component designation are summed as shown in Eq. (2), where N is the number of observations for function–component pair j, and y_{ijk} is the impact density of one function–component pair within a given product. In Fig. 2, the normalized scores of the two "gear" components in the Polaroid Pogo are summed to produce a single aggregated score for (gear, change mechanical), in this case 1.43×10^{-7}

$$y_{.jk} = \sum_{i=1}^{N} y_{ijk} \tag{2}$$

Normalizing and aggregating components into single function–component pairs addresses component taxonomy categories that distribute their impact across many discrete component observations within a single product. For example, the environmental impact of a 20 g circuit board is assumed to be roughly comparable to the environmental impact of two 10 g circuit boards. Summing impact observations with identical function and component types creates a raw aggregated impact observation for each unique function–component pair in a product.

Next, each y_{ijk} score is binned such that every unique function–component pair has a vector of environmental impact densities gathered from all products in the dataset. Equation (3) describes this process wherein each product's summed impact score y_{jk_K} is one element in the vector $\boldsymbol{y}_{*j}$. For example, Fig. 2 shows the creation of a two-element vector of normalized scores—one from the Polaroid Pogo and one from the Garage Door Opener—for the (gear, change mechanical) pair. This vector will contribute to predicting the impact of the "change mechanical" function

$$\boldsymbol{y}_{*j} = \left(y_{.jk_1},\ y_{.jk_2}, y_{.jk_3},\ \ldots,\ y_{.jk_K}\right) \tag{3}$$

As a result of aggregating the mass-normalized impact scores in this manner, design guidance that uses this data is based on the share of a product's overall environmental impact contributed by any given function–component pair. A key difference between using historical data to predict environmental impact instead of reliability [107,117] is that environmental impact is sensitive to component mass, while the failure modes and mechanisms that drive reliability are more consistent with respect to mass. As such, while historical reliability methods can ignore component mass, environmental impact scores must account for component mass.

The outcome of the data preparation stage is a set of historical observations that describe the environmental impact for each function–component pairing in each product. Using function–component pairings at this stage rather than grouping each impact observation directly under functions supports the hierarchical approach used in the probability prediction stage.

3.2 Step 2: Probability Prediction. The second step of the method applies a hierarchical Bayesian approach [101] to generate probability distributions of environmental impact for each function. This approach builds on the approach developed by O'Halloran [107] that uses a hierarchical Bayesian approach to generate function-level hyperdistributions for reliability prediction. Equations (4)–(9) in this paper are reproduced from O'Halloran's work [107].

The inputs to the probability prediction stage are the impact scores from the data preparation stage and an expected sample variance of environmental impact for each type of component. The outputs are sets of Bayesian hyperparameters (mean and standard deviation) for function-level normal probability distributions describing the probability density of environmental impact for each function.

A hierarchical Bayesian approach is selected for this method because of the natural hierarchy that exists between functions and components. A single function can often be satisfied by a variety of components. As a consequence, each group of children in this natural hierarchy (groups of components) provides information to make predictions about its parent (function).

Different components performing the same function can exhibit nonrandom covariance over a wide range of properties such as mass, material, and manufacturing process. This leads to natural divisions in groups of components that perform the same function. For example, the environmental impact of components in the function–component pairing (import electrical energy, battery) is much different than that of components in (import electrical energy, electric cord). All distributions in this methodology are assumed to be unimodal and normal, although this is not always an accurate assumption when these component subgroups exist. To combat the issue of nonrandom variation amongst different components that perform the same function, components under each function are clustered into natural groups. A function–component pair's membership in a cluster is determined using the mean value of its normalized scores.

Clustering is performed using Ward's linkage [118] where the number of clusters is defined to be equal to the quantity of different orders of magnitude in the set of component means. Determining the number of clusters in this way makes the following assumption: if the environmental impact observations of two components differ by an order of magnitude, then, a single normal distribution created from both is assumed to be a poor approximation of the population. The clustering step leads to hyperdistributions where the assumption of unimodality is more appropriate. A separate function-level hyperdistribution is created for each component cluster, and these cluster distributions can be used to guide component selection while minimizing environmental impact.

After clustering has been completed, hyperparameters are calculated for each function. A function can have several separate sets of hyperparameters if the function's components were grouped into multiple clusters. First, the sample mean $\bar{y}_{\cdot j}$ and sample variance σ_j^2 for each component cluster are calculated as shown in Eqs. (4) and (5). N and n_j are the number of observations for each component, and y_{ij} is a single observation for component j. The variance for all components σ^2 is assumed to be equal to a fixed value (In the Case Study section of this article, σ^2 is arbitrarily set to 1.5×10^{-6} for all components)

$$\bar{y}_{\cdot j} = \frac{1}{n_j} \sum_{i=1}^{N} y_{ij} \tag{4}$$

$$\sigma_j^2 = \frac{\sigma^2}{n_j} \tag{5}$$

Next, the precision-weighted average $\hat{\mu}$ and total precision V_μ^{-1} of each cluster are calculated according to Eqs. (6) and (7). The weighting factor w_j is equal to the number of observations for component j. τ^2 is the actual function-level standard deviation, which is later sampled across a span of evenly spaced values to numerically calculate the probability of τ given evidence y to determine $p(\tau|y)$.

$$\hat{\mu} = \frac{\sum_{j=1}^{J} \frac{1}{\sigma_j^2 + \tau^2} (w_j) \bar{y}_{\cdot j}}{\sum_{j=1}^{J} \frac{1}{\sigma_j^2 + \tau^2} (w_j)} \tag{6}$$

$$V_\mu^{-1} = J \sum_{j=1}^{J} \frac{w_j}{\sigma_j^2 + \tau_j^2} \tag{7}$$

While $\hat{\mu}$ serves as the function-level mean, further calculation is needed to determine function-level standard deviation τ. Equation (8) applies Bayes' theorem with a noninformative uniform prior ($p(\tau) = 1$) to find the posterior distribution $p(\tau|y)$. The standard deviation hyperparameter is taken at its expected value: where its probability density is the highest (Eq. (9)). These equations are reproduced from O'Halloran's work [107], which in turn sources them from Ref. [101]

$$p(\tau|y) \propto p(\tau) V_\mu^{1/2} \left(\prod_{j=1}^{J} \left(\sigma_j^2 + \tau^2\right)^{-1/2} \exp\left(-\frac{\left(\bar{y}_{\cdot j} - \hat{u}\right)^2}{2\left(\sigma_j^2 + \tau^2\right)} \right) \right)^J \tag{8}$$

$$E[\tau] = \frac{\sum_{i=1}^{I} p(\tau|y)_i \tau_i}{\sum_{i=1}^{I} p(\tau|y)_i} \tag{9}$$

3.3 Step 3: Guidance. The function-level hyperdistributions developed in Step 2 can provide valuable design guidance, specifically with respect to making function-to-component design choices. The approach can also compare alternative functions or functional models based on the same information. In general, function-level hyperdistributions with low mean and standard deviation are preferred. Low mean indicates low environmental impact, and low standard deviation indicates low variability in this prediction.

If the goal is to optimize with respect to sustainability, then each function distribution's score S can be calculated by the inverse of the sum of its standard deviation τ and its mean $\hat{\mu}$ according to Eq. (10). Each of these terms is scaled by a weighting factor to capture designer priorities about which property to prioritize. Ranking importance by low scores prioritizes distributions with low means and low standard deviations—i.e., function distributions with consistently low environmental impact.

$$S = \frac{1}{w_{\hat{\mu}} \hat{\mu} + w_\tau \tau} \tag{10}$$

If sustainability is a constraint rather than an optimization variable, then a z-score can be used to rank function distributions based on the likelihood that they will meet a predefined environmental impact target according to Eq. (11), where μ is the mean, σ is the standard deviation, and x is the target value

$$z = \frac{\hat{\mu} - x}{\tau} \tag{11}$$

The raw numbers produced by Eqs. (10) and (11) are not meaningful without context. The S and z scores are only assessed relative to one another to produce a rank ordering of priority.

4 Example

In this section, an focusing on the conceptual design of a mechanical clock is presented to demonstrate the FDS method's mechanics. A Design Repository was populated with 17 common consumer products such as an orbital sander, a CD player, a vacuum cleaner, a camera, and other products. Environmental impact data were calculated as per Step 1 of the FDS methodology.

An initial conceptual design of a mechanical clock might lead to the function chain in Fig. 3. This chain may exist as part of a

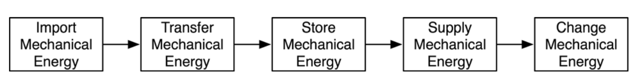

Fig. 3 Functional model of a manually operated mechanical clock

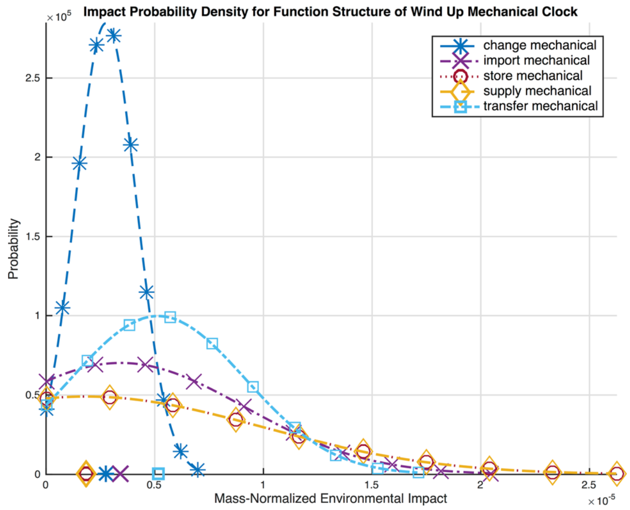

Fig. 4 Probability density of each function in a mechanical clock functional model

larger model that also includes secondary functionality like using mechanical energy to indicate a signal (e.g., using a clock face) or protecting sensitive components from undesirable forces (e.g., impact) or materials (e.g., water).

The chain in Fig. 3 indicates that mechanical energy will be imported and stored for later use (in this case, moving the clock hands). Applying the algorithm from the FDS methodology in Step 2 shown in Eqs. (10) and (11) leads to the function distributions described by Fig. 4 and Table 1. These distributions were generated with a uniform prior density for the mean and an assumed sample variance of 1.5×10^{-6} for mass normalized ReCiPe scores.

Guidance is provided by FDS per Step 3 of the methodology in prioritizing for which subfunctions to perform component selection and detail design. The scores and priority ranks in Table 1 are given by Eq. (10) using uniform weights of $w_{\hat{\mu}} = 1$ and $w_\tau = 1$. For each function with multiple clusters, it is assumed that the best (least impactful) one is selected. This is the case for the "transfer mechanical energy" function. The outcome suggests that for the available historical impact data in the consumer product domain, the functions of "store mechanical energy" and "supply mechanical energy" have the greatest historical risk of causing high environmental impact.

One notable drawback of fitting a predictive probability distribution to historical data is that a sufficient number of samples is needed in order to assume that a normal distribution is a good approximation of the data. In this case study, this assumption only holds true for the 53 observations in "transfer mechanical energy." The other four functions have five or fewer observations, so these results should be viewed only as demonstrative of the method, and not as evidence about the relative environmental impacts of these functions.

Rectifying this drawback requires expanding the design repository with additional products that contain observations of functions of interest. Assuming that all functional models are created at the secondary level (their most expressive level [79]), there are 420 unique functions (21 verbs and 20 objects). Using the common heuristic that 30 samples enables the normality assumption according to the central limit theorem [119] (in the absence of a priori data to test for normality), 13,600 samples would be required for such a database to provide predictive power for any conceivable functional model. Given an average product size of approximately 37 functions in the Design Repository, as few as 368 products could enable FDS on a full set on any functional model. Because some function data must be split into multiple groups when component data violates assumptions of normality and unimodality, some functions are separated into multiple clusters. The total number of required products in the database scales linearly with the number of component clusters per function, as shown in Eq. (12). For example, if every function's component data contained two distinct modes, the database would require 736 products. While there are certainly some assumptions built into this calculation, it informs the feasibility of a database to support FDS. Further, it highlights the importance of reliable digital product data and data mining techniques to gather a variety of well-formed computable product data.

$$\text{Size} = (\text{verbs})(\text{objects})(\text{component\_clusters\_per\_function}) \quad (12)$$

Guidance is further provided with respect to component selection. For functions that have been solved by a wide variety of components, it is likely that some of the components tend to make up a much larger proportion of the product's total impact than others. The clustering stage of the algorithm groups together with function–component pairs have similar orders of magnitude in their mass-normalized environmental impact scores. Table 2 shows five clusters for the "transfer mechanical energy" function. The component groupings shown in Table 2 provide a starting point for selecting components to satisfy the "transfer mechanical energy" function. Cluster 3 is the best-case cluster, possessing the smallest means and standard deviations of its components' impact observations. Alternatively, if only one type of component is suited to the task, then, the designer has information about which function level means and standard deviations to select when comparing "transfer mechanical energy" to other functions. Notably, the small quantities for the parameters in Table 2 mean that their impacts manifest as cumulative effects over many units (i.e., millions of products produced). Their real value in this context is in enabling relative comparisons between design alternatives rather than providing absolute measures of sustainability gain—a much more challenging issue.

Contextual information and human reasoning skills play an important role in applying the results of the analysis. Using these results a designer can isolate "store mechanical energy" and "supply mechanical energy" as key functions that are likely to influence environmental impact. The designer may then focus on designing an environmentally friendly torsional "spring" component to serve the role of storing energy, prioritizing design decisions that affect this component ahead of other functions and components.

The next highest priority function—"transfer mechanical energy"—has five clusters. In this case, selecting a cluster is straightforward. Cluster 3 possesses not only the most favorable S score, but also contains components that would transmit intentionally created low magnitude mechanical energy in a clock. Clusters

Table 1 Mechanical clock design function prioritization

Function	Total observations	Number of clusters	Score	Mean	StDev	Priority
Change mechanical	5	1	2.40×10^{05}	2.76×10^{-06}	1.40×10^{-06}	4
Import mechanical	2	1	1.10×10^{05}	3.43×10^{-06}	5.68×10^{-06}	3
Store mechanical	4	1	1.00×10^{05}	1.84×10^{-06}	8.13×10^{-06}	1
Supply mechanical	4	1	1.00×10^{05}	1.84×10^{-06}	8.13×10^{-06}	1
Transfer mechanical	53	5	1.09×10^{05}	5.15×10^{-06}	4.00×10^{-06}	2

Table 2 Transfer mechanical energy component clusters

	Function–component pairs	Function mean	Function StDev
Cluster 1	Transfer mechanical_housing	1.05×10^{-04}	5.53×10^{-04}
Cluster 2	Transfer mechanical_bracket	4.99×10^{-05}	3.46×10^{-05}
	Transfer mechanical_container		
	Transfer mechanical_support		
Cluster 3	Transfer mechanical_actuator	5.15×10^{-06}	4.00×10^{-06}
	Transfer mechanical_belt		
	Transfer mechanical_clamp		
	Transfer mechanical_coupler		
	Transfer mechanical_electric plate		
	Transfer mechanical_electric switch		
	Transfer mechanical_friction enhancer		
	Transfer mechanical_gear		
	Transfer mechanical_hinge		
	Transfer mechanical_key		
	Transfer mechanical_knob		
	Transfer mechanical_lever		
	Transfer mechanical_link		
	Transfer mechanical_regulator		
	Transfer mechanical_seal		
	Transfer mechanical_securer		
	Transfer mechanical_sensor		
	Transfer mechanical_shaft		
	Transfer mechanical_sled		
	Transfer mechanical_spring		
	Transfer mechanical_sprocket		
	Transfer mechanical_tube		
	Transfer mechanical_unclassified		
	Transfer mechanical_valve		
	Transfer mechanical_wheel		
Cluster 4	Transfer mechanical_electric motor	2.10×10^{-03}	1.22×10^{-02}
Cluster 5	Transfer mechanical_stabilizer	3.38×10^{-03}	3.38×10^{-03}

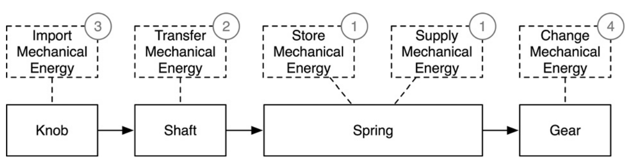

Fig. 5 Clock energy chain component selection

1, 2, and 5 are more appropriate for transferring unintentional or system-wide mechanical energy, such as using a "housing" or a "bracket" to absorb impacts or vibrations. Cluster 4's electric motor transfers mechanical energy as a side effect of converting electrical energy into mechanical energy—a behavior that is not desirable in our human-powered clock. After selecting Cluster 3, a designer may then select a shaft component as in Fig. 5, followed by a knob to import mechanical energy and a gear assembly to change mechanical energy. This shows that the FDS method can reclaim an expected clock design from sustainability data that does not contain data for a clock—that aggregated environmental impact data from other contexts produces reasonable results in a new design context.

5 Comparative Model Case Study

The developing world encompasses between 2.1 and 6.6 billion people by some estimates and contains an estimated purchasing power of 5 trillion USD [120,121]. 17% of the world's population does not have access to electricity [122] yet in Africa, 60% of the population had access to mobile phones in 2010 (up from 11% in 1999). In Kenya in 2011, 93% of households had a mobile phone. In 1999, less than 3% of Kenyan households had access to a mobile phone [123–125]. Several different options are available for people to charge mobile phones when they do not have access to electricity from the grid, including solar charging [121], wind charging [126], paying a merchant to charge the device [127], secondary battery charging [128], thermal electric charging [129], and mechanical charging [127]. As being connected via a mobile phone, it becomes more important to people in the developing world [130,131], and mobile phone adoption is expected to increase [132]. Thus, a robust market exists for phone chargers that do not require electrical grid power. One such option that we analyze here is a mechanically powered phone charger design. This case study demonstrates FDS as an enabler of environmental impact-based comparison between two alternative functional concepts of a phone charger for the developing world.

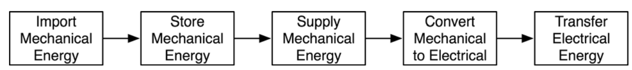

Fig. 6 Mechanical phone charger functional model 1—store as mechanical energy

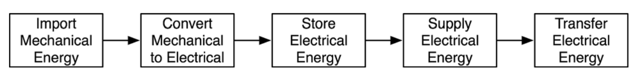

Fig. 7 Mechanical phone charger functional model 2—store electrical energy

The two alternative functional concepts of the mobile phone charger both use mechanical energy to provide power, but the way that each concept stores the energy is different. The first (Fig. 6) stores and supplies energy in mechanical form (e.g., springs, flywheels, or gravitational potential energy). The second (Fig. 7) stores and supplies energy in electrical form (e.g., capacitor). We assume that the remaining functions are identical between systems, enabling a valid comparison of the differences

Table 3 Mechanical phone charger 1 results

Component cluster	Function	Priority	Score (maximize)	Mean	StDev	Clusters
Best case	Convert electrical to mechanical	2	1.08×10^{05}	3.72×10^{-06}	5.57×10^{-06}	2
	Import mechanical	3	1.10×10^{05}	3.43×10^{-06}	5.68×10^{-06}	1
	Store mechanical	1	1.00×10^{05}	1.84×10^{-06}	8.13×10^{-06}	1
	Supply mechanical	1	1.00×10^{05}	1.84×10^{-06}	8.13×10^{-06}	1
	Transfer electrical	4	1.58×10^{05}	3.84×10^{-06}	2.48×10^{-06}	5
User selected	Convert electrical to mechanical	2	8.49×10^{01}	1.48×10^{-03}	1.03×10^{-02}	2
	Import mechanical	4	1.10×10^{05}	3.43×10^{-06}	5.68×10^{-06}	1
	Store mechanical	3	1.00×10^{05}	1.84×10^{-06}	8.13×10^{-06}	1
	Supply mechanical	3	1.00×10^{05}	1.84×10^{-06}	8.13×10^{-06}	1
	Transfer electrical	1	1.55×10^{01}	9.29×10^{-03}	5.53×10^{-02}	5
Worst case	Convert electrical to mechanical	2	8.49×10^{01}	1.48×10^{-03}	1.03×10^{-02}	2
	Import mechanical	4	1.10×10^{05}	3.43×10^{-06}	5.68×10^{-06}	1
	Store mechanical	3	1.00×10^{05}	1.84×10^{-06}	8.13×10^{-06}	1
	Supply mechanical	3	1.00×10^{05}	1.84×10^{-06}	8.13×10^{-06}	1
	Transfer electrical	1	1.36×10^{-01}	4.91×10^{-01}	6.84×10^{00}	5

Table 4 Mechanical phone charger 2 results

Component cluster	Function	Priority	Score (maximize)	Mean	StDev	Clusters
Best case	Convert electrical to mechanical	2	1.08×10^{05}	3.72×10^{-06}	5.57×10^{-06}	2
	Import mechanical	3	1.10×10^{05}	3.43×10^{-06}	5.68×10^{-06}	1
	Store electrical	1	2.90×10^{03}	1.44×10^{-04}	2.00×10^{-04}	1
	Supply electrical	1	2.90×10^{03}	1.44×10^{-04}	2.00×10^{-04}	1
	Transfer electrical	4	1.58×10^{05}	3.84×10^{-06}	2.48×10^{-06}	5
User selected	Convert electrical to mechanical	3	1.08×10^{05}	3.72×10^{-06}	5.57×10^{-06}	2
	Import mechanical	4	1.10×10^{05}	3.43×10^{-06}	5.68×10^{-06}	1
	Store electrical	2	2.90×10^{03}	1.44×10^{-04}	2.00×10^{-04}	1
	Supply electrical	2	2.90×10^{03}	1.44×10^{-04}	2.00×10^{-04}	1
	Transfer electrical	1	1.55×10^{01}	9.29×10^{-03}	5.53×10^{-02}	5
Worst case	Convert electrical to mechanical	2	8.49×10^{01}	1.48×10^{-03}	1.03×10^{-02}	2
	Import mechanical	4	1.10×10^{05}	3.43×10^{-06}	5.68×10^{-06}	1
	Store electrical	3	2.90×10^{03}	1.44×10^{-04}	2.00×10^{-04}	1
	Supply electrical	3	2.90×10^{03}	1.44×10^{-04}	2.00×10^{-04}	1
	Transfer electrical	1	1.36×10^{-01}	4.91×10^{-01}	6.84×10^{00}	5

These results can be used to facilitate all three types of design guidance shown in Fig. 1—component-level (3-B), function-level (3-A), and functional model level (3-C). These strategies are summarized in Table 5

Table 5 Design guidance using FDS

Guidance type	Strategy
Component-level	By inspection, choose components to satisfy function from historical environmental impact scores
Function-level	Create a triangle distribution for each function based on the best case, worst case, and most probable component clusters for given design context. Compare replacement functions by testing for significant differences between triangle distributions
Functional model-level	Compare two models with Mann Whitney U test on models' environmental impact scores

between concepts. For a designer prioritizing sustainability, these two functional models form the basis for comparing two conceptual alternatives within the context of the overall system. The key results of an FDS analysis are shown in Tables 3 and 4.

The following measures are taken to ensure sufficient data can be extracted from the limited data set. The set of 17 products in the data set contains only one observation each for the functions "export electrical energy" and "convert mechanical energy to electrical energy." To mitigate this issue, export electrical energy is considered as "transfer electrical energy." Additionally, the function convert mechanical energy to electrical energy is instead represented as "convert electrical energy to mechanical energy" based on the general principle that an electric motor driven in reverse is an electric generator.

5.1 Component Level Guidance. As part of the FDS method, historical data for components within each function are clustered. In selecting between different clusters, the designer receives component-level feedback (3-B) about the impact of a specific choice. For example, FDS clusters circuit boards and electric wires into different groups, where the circuit board group has a much higher historical impact. This suggests that electric wire or other components in its cluster should be used where possible. This type of guidance was shown in greater detail in the mechanical clock example.

5.2 Function Level Guidance. Given the similarity of the models, many of the best and worst case component selections produce identical importance rankings. With respect to function-level guidance (3-A), however, comparing scores for storing mechanical energy (1.00×10^{05}) against those for storing electrical energy (2.90×10^{03}) suggests that it will be easier to create a low environmental impact system by storing energy mechanically.

Additionally, a variety of secondary tests can further inform design decisions when selecting between replacement functions.

When generating function hyperdistribution parameters, each functional concept can be analyzed separately according to its best-case, worst-case, and most likely (human assessed) component clusters. Human input is critical because it injects contextual information about the model under investigation. For example, one of the clusters for transferring electrical energy includes an electric wire, an electric socket, and brushes (as in a brushed motor). A second cluster contains electromagnets and housings. In the context of phone chargers, the designer is able to specify that electric wires and sockets are more likely solutions than electromagnets and housings.

These points can then define a triangular probability density function (PDF) to support significance tests between the impact of alternative functions [133]. For example, given two triangular PDFs for the functions "store electrical" versus "store mechanical," we can test for whether there exists a significant difference in environmental impact of replacing one function with the other. One simple approach is to uniformly resample points from each PDF, and then perform a Kolmogorov–Smirnov test to determine whether the difference between replacement functions is significant [134,135]. Performing this test for store electrical versus store mechanical is trivial in the context of this case study because there is only one component cluster for each function, but doing so with 100 resamples for each returns a significant difference between functions ($p = 1.55 \times 10^{-45}$). Given a large database with more samples, this result would be nontrivial to achieve via inspection.

5.3 Model Level Guidance. When comparing two complex functional models with the same black box function, it may not be possible to replace functions in a one-to-one manner. For these situations, a Mann Whitney U test can assess whether the impacts between models are significantly different [136]. For this test, all alignable (isomorphic) identical functions should be omitted (e.g., "import mechanical" in both models). For the two models in this case study, a Mann Whitney U test does not provide confidence that the system-level models are significantly different ($p = 0.33$). This suggests that either (1) a finer grained function-level analysis would be more appropriate (as is the case here) or (2) there is no significant detectable difference in the models' predicted environmental impact.

6 Discussion

The FDS method is beneficial to product designers wishing to optimize environmental impacts of a new product still in the conceptual stages of design. Early conceptual designs can be analyzed for sustainability using functional model representations of the designs and the FDS method. Existing design repositories are used to provide clusters of component solutions to functions. While the preceding case studies use a subset of product data from the Design Repository, the method is applicable to any set of product information that is cataloged according to functions, components, and environmental impacts. Designers can then choose between these functions and components to help minimize environmental impacts and maximize sustainability of the product design. Historical data from existing products provide guidance on the likely outcome of a new product being designed.

While the FDS method assumes that a design repository will be populated with similar products to the new product under development, there may be benefits to populating a design repository with existing products that are unrelated to the new product. For instance, populating a design repository with children's toys while designing a new product for an automotive application could provide new component solutions that are sustainable and satisfy functional requirements. In this case, the potential of finding a novel solution increases, while the risk of making an inaccurate prediction also increases. Care should be exercised to use a dataset of products that are not so completely unrelated to the new product that most component solutions are completely untenable, such as with attempting to use children's toys while designing a satellite. While we make no attempt in this work to address the larger issue of assessing conceptual distance between problems and datasets in a sustainability context, a rich database and a metric for computing pairwise conceptual distance between products would enable analyses on different database subsets with different internal similarity cutoffs. The appropriate similarity cutoff between products in a dataset will likely always depend on the specific context and application of the sustainability analysis.

Some potential drawbacks to FDS exist, such as the assumption that the environmental impact of a component is dominated by its mass (independent of the quantity of components). An extension of FDS could investigate mitigating this potential limitation using techniques such as component-specific penalty functions that represent the increased environmental costs associated with producing and shipping multiple components. Further, material sustainability does not always vary linearly with mass, as in the case of lightweight composites. Another extension of FDS may add additional layers of hierarchy to the model for the most critical drivers of sustainability. Given sufficient data, such an extension may model information at the function–component–process level instead of the function–component level.

Another issue that practitioners should be aware of with FDS is that abstracting real world observations into the fuzzy front end of design introduces error into the FDS methodology. High variation in a single function–component pair may violate the normality assumption, and thus, potentially damage the validity of FDS predictions. The component clustering step is intended to mitigate this risk such that each cluster can be approximated as a normal distribution. High variation of this type (and that within a single function–component pair) would also have the general effect of increasing the uncertainty within that function, increasing its priority in the FDS results—a generally desirable behavior. A limited amount of this type of variation would still produce an actionable ranking of functions. However, systemic variation of this type within a given dataset would yield predictions of questionable validity. In this case, other types of clustering, models, or abstractions may produce better results.

7 Future Work

Several areas of potential future expansion of the FDS exist including extensions to the decision support provided by FDS, applying Bayesian priors to specific important functions, and applying Bayesian inference to functional or component environmental impact data.

Extensions to the decision support of FDS could include automated individual function assessment, full functional model comparisons, and automated functional model evolution process based upon sustainability criteria. While FDS currently connects functions to potential component solutions, product designers must select which component solutions are appropriate for the product. An automated method of component solution selection may save designers time and accelerate the new product design process.

Applying Bayesian priors based on the expected mass corresponding to various functions may be useful to skew FDS results toward the least environmentally impactful component solutions to functional requirements. For instance, if a designer knows that the function "change mechanical energy" will encapsulate many different control mechanisms (as in a clock), then, it would be informative to capture this expectation as a Bayesian prior. Similarly, providing Bayesian inference to update datasets with information from products as they are being designed may be useful to help steer development of other portions of a product or to aid in the development of the next new product. The method could be further improved by introducing a method to estimate the data variance of the observed components, which in this study was arbitrarily selected.

8 Conclusion

The FDS method presented in this paper helps to address the growing demand for sustainable consumer products by providing product designers with a tool to assess environmental impact of functional selections in functional models created during the conceptual phase of product design. Automated guidance on choosing the most sustainable component solutions for functions is provided by FDS through a process of clustering and hierarchical Bayesian modeling. Environmental impact data comes from ReCiPe scoring found in SimaPRO, and product decomposition information comes from the Design Repository. Existing LCA and environmental impact assessment methods calculate environmental impact after a product has been developed to the component level. FDS assesses environmental impact during the conceptual phase of design by providing insights into which functional solutions historically have the greatest risk of causing high environmental impact via mean and standard deviation statistics. The conceptual design of a clock was presented to illustrate the mechanics of FDS, while the case study of phone charger concept variants demonstrates the breadth of guidance provided by the method. Although the dataset used in both case studies is insufficient to validate FDS, it is sufficient to demonstrate significant promise of the technique. Given a set of historical data, FDS may enable a designer to make early functional modeling design decisions specifically based on environmental impact of the product.

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