Proceedings of IDETC/CIE 2005
ASME 2005 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference
September 24-28, 2005, Long Beach, California, USA

IDETC/DTM-85293

FUNDESIGN – A FUNCTION-BASED METHOD FOR ADDRESSING UNCERTAINTY DURING THE DESIGN OF ENGINEERING SYSTEMS: REPRESENTATIONS AND KNOWLEDGE STORAGE

Ryan S. Hutcheson
University of Missouri-Rolla

Joseph A. Donndelinger
General Motors Research and Development

Daniel A. McAdams
University of Missouri-Rolla

Robert B. Stone
University of Missouri-Rolla

ABSTRACT

This paper outlines a function-based method for addressing design parameter uncertainty during the conceptual design phase of an engineering system. The method is given the name FUNdesign and represents a set of tools for obtaining and storing sensitivity information of functions from previous designs as well as tools for applying this information to designing new systems. To store the sensitivity information, functional models created using the Functional Basis are first created for previous designs. Performance models for each function in the model are then identified and a sensitivity analysis performed on each model with respect to each design parameter. This sensitivity information and its associated performance models are then stored according to functionality in an engineering design repository. The information stored in the repository is then used to aide the allocation of design and modeling resources during the design of a system with similar functionality. The specific focus areas of this paper are the sensitivity parameters and methods required to store the sensitivity information.

1) INTRODUCTION

During the design of engineering systems, uncertainty in the values of the design parameters of a system can greatly affect the system's performance. In order to quantify and reduce the effect of this uncertainty during the design process, resources must be allocated to accurately identify and model the impact of uncertainty in a system. Identifying these effects as early as the conceptual design process allows better resource allocation throughout the entire design process. However, often during the conceptual design of a system, little is known about the potential physical forms of the solution. Without this information, it is difficult to predict which particular sub-systems or components are the most affected by uncertainty in design parameter values.

The objective of this research is to develop a well-defined method for addressing the problem of identifying the areas of a system that are more susceptible to uncertainty as early as the conceptual design process. The proposed solution is a function-based method that uses sensitivity information from previous design efforts to identify potential sources of sensitivity to variation in new designs. This **F**unction-based method for addressing the **UN**certainty of system parameter values during conceptual **design** will be referred to as FUNdesign in the context of this paper. FUNdesign consists of the following major steps:

- Identify sources of significant sensitivity to variation in previous designs
- Relate this sensitivity information to the functionality of the investigated systems
- Store this information in a design repository
- Create a functional model of the system to be designed
- Use the knowledge stored in the repository to allocate modeling resources during the design of a new system based on common functionality

This paper focuses on the methods required to extract sensitivity knowledge from previous functions so that it can be stored and reused. The research is presented in four sections. The first section outlines the enabling technologies and contains a review of existing research in this area. Section two examines the identification and application of potential sensitivity measures for the FUNdesign process. The third section is an overview of the application of the FUNdesign knowledge extraction process to a human-powered flashlight example. The final section concludes the paper and presents future work.

1.1) Motivation

The problem of addressing the sensitivity of a design to uncertainty has been extensively researched. Most engineering design textbook devote entire chapters to robust engineering principles and the analysis of uncertainty (for example [1] and [2]). The methods commonly used in design engineering texts, such as Taguchi's method, rely on the analysis of sensitivity to uncertain parameter values using experiments or assumed performance models and parameter values. What is missing from this research is a method for applying these ideas during early conceptual design when little is known about a system's configuration or design parameter values. The purpose of the research presented in this paper is to identify a potential method for applying robust engineering principles early in conceptual design. The proposed solution uses a combination of average sensitivity and the unitless coefficient of variation of sensitivity to store sensitivity knowledge from previous design efforts and apply this knowledge to new designs of similar functionality. The measures were chosen after an evaluation of several approaches to quantifying sensitivity to parameter variation including nominal value measures, signal to noise ratios and new measures created during the course of the research. Section 2 contains an evaluation of the measures as well as the development of the measures suggested for FUNdesign.

1.2) Enabling Technologies

There are three key enabling technologies of the FUNdesign process. The first is standardized functional modeling. Creating functional models using a standard process and taxonomy allows design knowledge to be shared between designs based on common functionality. Function-based modeling is not a new concept but has undergone significant research in the past few years to introduce standardization in modeling and representation. The next key technology is function-based system performance modeling. Function-based performance modeling breaks down the mathematical modeling process of a system into a series of smaller modeling tasks for each function in the system. This modeling process was developed early in the research and provides a framework for the modeling required by FUNdesign. The final enabling technology is the proposed function-based sensitivity analysis.

1.2.1 Functional Modeling

Functional modeling is a form-independent method of representing systems [3-12]. A functional model consists of the energy, material and signal flows into and out of a system and the functions that are performed on these flows to transform them from an input to a desired output state.

The FUNdesign method requires a standard list of functions and flow terms in order to capture and reuse sensitivity knowledge. To this end, it is recommended that the Functional Basis be used. The Functional Basis is a list of function and flow terms, verbs and nouns respectively, that has been developed in a joint effort between NIST, The University of Missouri-Rolla, and The University of Texas-Austin [13,14]. The Functional Basis was originally developed to represent electro-mechanical systems but has been successfully used to model other systems such as information and control systems (13). The functions and flows are broken into three categories: primary, secondary and tertiary. Primary functions and flows are generally used in black-box models. Secondary terms are more specialized and are used in the functional models themselves. Tertiary terms offer an additional level of specification if more detail is required when creating models. The Functional Basis consists of three primary flows, twenty secondary flows, eight primary functions and twenty-one secondary functions.

Creating a functional model involves five steps. The first step (1) is to identify flows that address customer needs. These needs can be identified through customer surveys and past design efforts [1,2,15]. Once the needs are identified, they are mapped to the inputs and outputs of the system. These inputs and outputs are stated in the Functional Basis. The next step (2) is to create a black-box model of the system. This model contains all the inputs and outputs of the system along with an overall function that describes the system. Function chains are then created to represent the operations performed on a flow to transform it from an input to an output (step 3). These chains are then aggregated to produce an overall functional model (step 4). The next step (5) is to verify that all customer needs are met within the functional model. Functions are added to the model to address any needs that have not been satisfied. The result is a model that describes the function of a system separate from its form in a standardized language [1,14].

1.2.2 Function-based System Performance Modeling

In order to perform a function-based sensitivity analysis, performance models must be associated with each function in the system. These models are created using the function-based system performance modeling process. This process involves the following steps [16]:

- Define overall performance goals for the system
- Create a functional model for the system
- Define input and output states for each function
- Create a model for each function that relates its output to its input
- Aggregate these models to create a system performance model

This process allows performance models to be created for each function in a system in addition to a model for the system as a whole. The performance models for each function can then be used to find the sensitivity of each function to design parameter uncertainty. This allows the engineering knowledge gained during sensitivity analysis to be mapped back to individual functions.

1.2.3 Sensitivity Analyses and Uncertainty

The final enabling technology is the function-based sensitivity analysis. In order to classify the sensitivity of a function to parametric uncertainty, a sensitivity history must be established. To generate this history, the sensitivity of functions must be identified from previous design efforts. To form a complete data set, the sensitivity of a function must be analyzed across multiple domains and well as multiple solutions within specific domains. Additionally, sensitivity parameters must be identified to codify and store the sensitive information so that it can be applied to new design efforts. The parameters must also be broadly applicable to various domains as well and model types. An attempt to identify such parameters is presented next.

2 SENSITIVITY MEASURES

The FUNdesign process requires the storage of sensitivity information associated with functionality. To accomplish this, well-defined sensitivity measures with broad application are required. The measures must be applicable to systems with nominal values for design parameters as well as systems with nominal ranges for design parameters. For ranged sensitivity problems, a measure is required to express the shape of the sensitivity curve over an output range. The first step in identifying or developing applicable measures is to define the sources of variation. Three sources of variation are considered: modeling uncertainty, input variables and design variables. Figure 1 shows how these sensitivities fit within the function-based design framework. Modeling uncertainty is a result of the assumptions made during the modeling of a system. These modeling assumptions result in uncertainty between the predicted performance of model and actual performance. Variation in the input variables results from controlled changes in input values as well as noisy functions upstream in the functional flow and noisy inputs to the overall system. Variation in design variables is a result of variation in the physical parameters that govern a system's performance. The nominal values for these design variables as well as their tolerances are identified during design. Designers require the performance of a system to be sensitive to the design variables in order to adjust the performance of a system to meet requirements (the signal component in a signal to noise problem). Unfortunately, this sensitivity also causes undesirable changes in performance due to deviations from the nominal value that appear during manufacturing or throughout the systems life (the noise component). Uncontrollable input variation causes undesirable performance fluctuations in the output while controllable design variation allows an engineer to tune the performance output. The focus of this paper is generally on the effect of uncertainty in design parameters on the performance of a system since these parameters fall under the control of the designer. However, the identified sensitivity measures can also be applied to input parameters. By combining the measures to produce an overall measure of sensitivity for multiple solutions of a function, it should be possible to address the problem of model uncertainty by identifying functions with large variations in sensitivity across multiple implementations. The combination of the sensitivities for a function is left as future work.

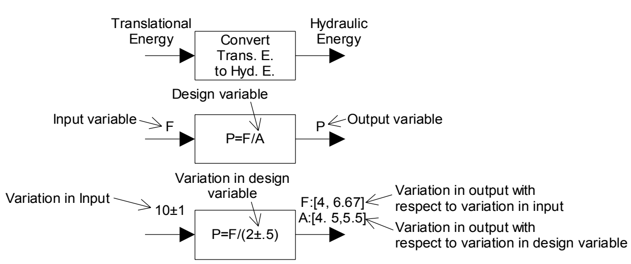

Figure 1 – Sensitivity and Functions

2.1 Nominal Value Measure

Typically, the procedure used to find the sensitivity of a performance output is to find the first partial derivative of the output with respect to the variable of interest at some nominal value, multiply this by the expected change in the variable of interest and then normalize the result to the value of the performance metric at the nominal value. The result is a unitless measure that expresses how sensitive a function is to a particular variable at a nominal value. The formula for a standard sensitivity analysis appears in Equation 1. An example of this equation in use appears in Figure 2.

$$\left.\frac{\partial F}{\partial x_i}\right|_{x_i,nom} \cdot \frac{\delta x}{F(x_i, nom)} \quad (1)$$

Function:	Sensitivity (x):	Sensitivity (a):
$F(x) = ax^3$	$\left.\frac{\partial F}{\partial x}\right\|_{x,nom} = 3ax^2 = 60$	$\left.\frac{\partial F}{\partial a}\right\|_{x,nom} = x^3 = 8$
Nominal Values: $a = 5$ $\delta x = .01$ $x = 2$ $\delta a = .03$	$\left.\frac{\partial F}{\partial x}\right\|_{x,nom} \cdot \frac{\delta x}{F(x,nom)} = .015$	$\left.\frac{\partial F}{\partial a}\right\|_{x,nom} \cdot \frac{\delta a}{F(x,nom)} = .006$

Figure 2– Nominal Value Sensitivity Analysis

2.2 Ranged Measures

The nominal value approach works well for systems that have a single nominal output value, but is insufficient for systems whose output must vary over a nominal range. An example of such a system is an automobile suspension system. The performance outputs of a suspension (camber, caster, bump steer, etc.) must be "well-behaved" over a range of input values (the travel of the suspension up and down). Using the sensitivity measure shown in Figure 2, several nominal values must be selected and many sensitivity analyses must be done to capture the sensitivity information required during a concept selection process. In order to represent this information in a more concise manner, and provide a well-defined procedure for analyzing the sensitivity of systems with nominal output ranges, an average sensitivity measure is required.

To develop this sensitivity measure, several methods were investigated. The underling theory to all of these approaches was to find an average value for the sensitivity across the nominal output range and normalize this to produce a unitless single-value measure to represent the sensitivity of a function with respect to each input and design variable. The sensitive average will be labeled as S for the remainder of this paper. Multiple methods were research for normalizing the average sensitivity. Eventually, normalizing to the standard deviation of the sensitivity was selected as the best candidate method for capturing the desired sensitivity information. The resulting measure represents the coefficient of variation of the sensitivity across the range of interest.

The first step in the calculating the coefficient of variation (CV) of sensitivity is to find the sensitivity of the performance function throughout the nominal range of the input variable. The performance model is represented as a function of two variables, i and x. The variable i represents the input to the function while the set x contains the design variables for a system. To find the sensitivity of the function, the first partial derivative of the function with respect to the variable of interest must be calculated. This can be done analytically (Equations 2 and 3) or numerically using partial differencing. To analytically find the average value of the partial derivative, an integral approach is suggested. The average value of a function can be found using Equation 4.

$$s_i = \frac{\partial f(i, x_n)}{\partial i} \quad (2) \qquad s_{x_n} = \frac{\partial f(i, x_n)}{\partial x_n} \quad (3)$$

$$\bar{f}(x) = \frac{\int_a^b f(x)\,dx}{b-a} \quad (4)$$

For the case of the input variable, the average sensitivity reduces to the form shown in Equation 5. For design variables, this average cannot be reduced and is found using Equation 6.

$$S_i = \frac{f(i_f, x_n) - f(i_0, x_n)}{i_f - i_0} \quad (5) \qquad S_{x_n} = \frac{\int_{i_0}^{i_f} \frac{\partial f(i, x_n)}{\partial x_n} di}{i_f - i_0} \quad (6)$$

The value of CV is determined by dividing the standard deviation of the sensitivity by its mean value (Equation 7). The CV can be found for both discrete and continuous sensitivities.

$$CV = \frac{\sigma_S}{S} \cdot 100\% \quad (7)$$

For CV values close to zero, the mean value of the function is much greater than the standard deviation. This situation occurs for functions that exhibit a proportional relationship between the output and variable of interest. Increasing values of CV represent larger variation in the sensitivity. An example of the application of CV to a ranged sensitivity problem is presented next.

2.3 Example

To demonstrate how the S and CV parameters are calculated and used, three functions are considered: $F(i,x)=xi^3$, $F(i,x)=xi$ and $F(i,x)=xi+x*\sin(2*pi*i)$. The variable x is considered a design variable while i is considered an input variable. The domain of each function is [0,5]. The value of x for each function was chosen such that the range for each function is [0,125]. Figure 3 shows graphs of each function. Note that even though the functions share start and end points, how each function gets from start to end is drastically different.

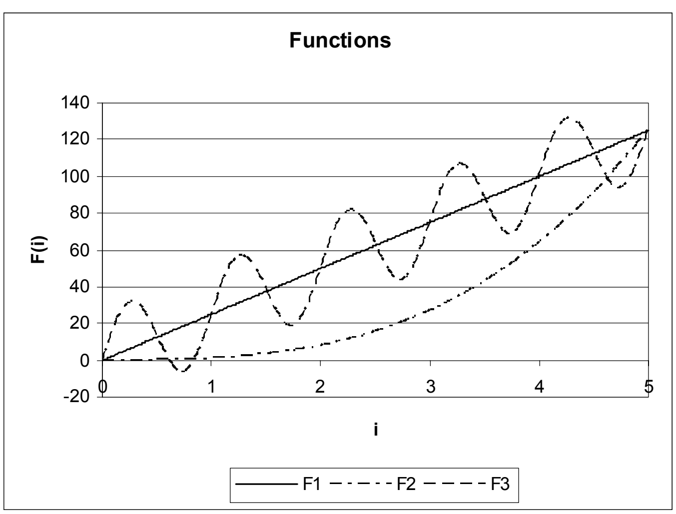

Figure 3-Function Values

Figure 4, shows the sensitivity of the functions with respect to the input parameter i. For the first function, the sensitivity is a constant 25. The second function's sensitivity is one leg of a parabola. The sensitivity of the third function is a sin wave with an amplitude of 25*4*pi that is shifted up by 25 units. Using the formula for S, the average values for the sensitivities were found to be 25 for all functions. This results from all functions beginning at (0,0) and ending at (5,125). The coefficients of variation for the three functions are 0%, 89.63% and 439.66% respectively. As the value of the CV for the sensitivity increases, the variation from the mean increases. The value of the CV for first function's sensitivity represents the most consistent effect of input on output. The third function's sensitivity varies the greatest.

An engineer can determine this same result by simply looking at a side-by-side comparison of the graphs. However, this presents a completely different problem when a computer is trying to compare multiple solutions to a function. By calculating the CV of sensitivity for each function, it is a simple task for a computer to calculate and store the sensitivity and associated variation of a performance model with respect to a variable.

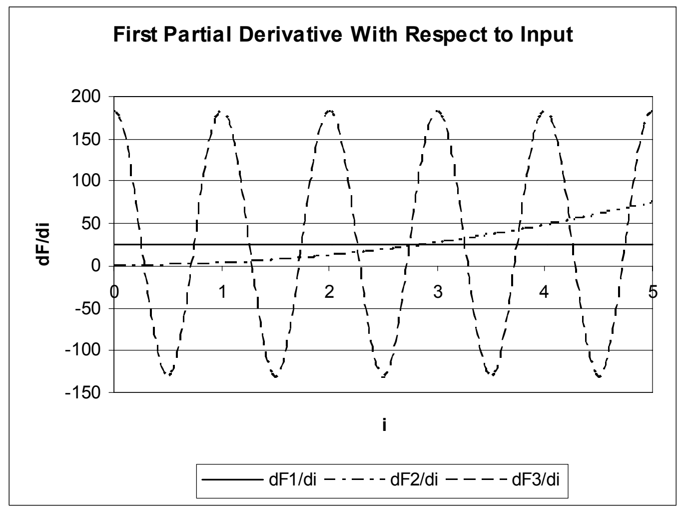

Figure 4-Sensitivity With Respect to Input

Figure 5 shows the graphs for the sensitivity analyses of the functions with respect to the design variable x. As seen in the graph, the first and third functions are less sensitive to changes in x than the second function. The average values for the sensitivity of the functions with respect to x are: 2.5, 31.3 and 2.5 respectively. The values of CV for the functions are 57.91%, 113.60% and 60.37% respectively. The values of S and CV for the design variable provide two important pieces of information about the sensitivity of the function. The low value of S for the first and third functions relative to the second shows that the second function is much more sensitive to changes in the value of x. The higher value of the CV for the second function shows that this function exhibits larger variation in sensitivity across the range of the input. Changing the value of x for the second function has a greater effect on the output than the other functions but this effect varies greatly over the range of the input. The results of this example appear in Table 1.

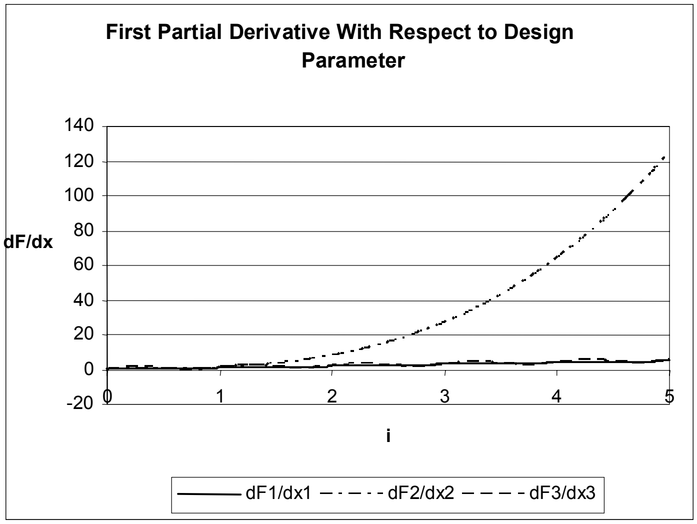

Figure 5-Design Parameter Sensitivity

	∂F$_1$/∂i	∂F$_1$/∂x	∂F$_2$/∂i	∂F$_2$/∂x	∂F$_3$/∂i	∂F$_3$/∂x
S	25.0	2.5	25.0	31.3	25.0	2.5
Cv	0.0%	57.9%	89.6%	113.6%	439.7%	60.4%

Table 1-Sensitivity Analysis Results

2.4 Sensitivity Measures and FUNdesign

By applying these sensitivity measures to functions from previous designs, it is possible to extract and store design knowledge for use in future designs of systems with similar functionality. To accomplish this task, performance models must be associated with specific functions. The sensitivity of these models to the various design parameters in the model must then be found and stored in a design repository along with the performance model. This represents the FUNdesign knowledge storage process. When designing a new system, a conceptual functional model must be created to identify functions required in the design. The repository should then be searched to identify performance models and associated sensitivities for each function in the conceptual design. This information allows a designer to evaluate specific solutions to functions based on their sensitivity to design parameters. Additionally, this information provides a means of allocating resources during future design efforts by identifying specific functions and/or parameters than are sensitive to variation. These steps represent the application of FUNdesign to a new system.

3 HUMAN-POWERED FLASHLIGHT EXAMPLE

To illustrate the application of FUNdesign sensitivity knowledge storage, an example was conducted for the energy storage system of a human-powered flashlight. Several commercially available units are currently being offered. Three such flashlights were used to generate sensitivity information for use in the design of a new flashlight. Each flashlight satisfies the same overall function, to store human energy in the form of electrical energy and then convert this stored energy to light. However, the lower-level functions used to solve the overall function differ between the flashlight concepts.

Identifying the individual functions in each concept that have the greatest effect on the performance of the flashlight as a whole can provide insight into which functions should have more design time and resources allocated. In addition, information regarding the sensitivity of performance with respect to design parameters can be used to identify parameters whose variation must be better controlled. Through FUNdesign, the problematic functions and design parameters were identified and the results of the analysis used to store knowledge that can be used for designing a robust flashlight concept or other system with similar functionality.

3.1 Design Goals

The goals of the human-powered flashlight design are to store as much human energy as possible is a given period of time and to store this energy proportional to time. The reasoning for the first goal is obvious; more energy stored in the flashlight allows more energy to be released as light. To accomplish this goal, the efficiency of each function in the design must be optimized to develop an efficient overall design. The FUNdesign process was used to determine which functions and associated design parameters had the greatest effect on the overall energy storage efficiency of the flashlight.

The second goal in the design of the flashlight is a result of the use of human energy to power the light. When someone is charging the flashlight, they are not going to charge it for an exact predetermined amount of time. It the energy storage rate is linear, a 15 second charge will store half the energy of a 30 second charge. The sensitivity parameters introduced earlier provide a convenient way of quantifying the satisfaction of these goals. S, the average sensitivity, is a measure of how much energy is stored versus time on average. The coefficient of variation of the sensitivity is used to quantify the behavior of the sensitivity across an input range. Combined, the S and CV measures were used to represent how changes in design parameters affect the performance of the system both in average magnitude and behavior.

3.2 Functional Models

The first step in the FUNdesign knowledge storage process of the flashlight was to create a functional model for the system. As reviewed earlier, this process begins with the selection of a black box function. Since the purpose of the human-powered flashlight is to use human energy to create light, the overall function was chosen to be Convert Human Energy to Optical Energy. This function is represented in Figure 6.

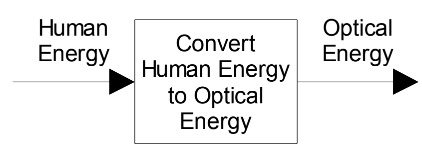

Figure 6 – Human-powered Flashlight Black Box

The next step in the functional modeling process was to create conceptual function chains. For the flashlight, only one chain was considered (one input and one output were modeled in the black box). This chain represents the transformation and storage of the human energy entering the system. This energy must first be imported into the system. This is accomplished with the Import Human Energy function. Next, this energy should be converted into electrical energy. This conversion is labeled Convert Human Energy to Electrical Energy. The electrical energy is then stored via the Store Electrical Energy function. To release this energy, a Supply Electrical Energy function is then needed. An Actuate Electrical Energy function is then used to turn the flashlight on and off. Finally, the Convert Electrical Energy to Optical Energy function is used to convert the electricity into light. This chain of functions is listed in Figure 7.

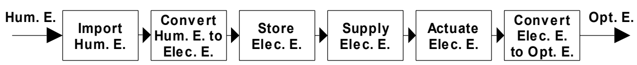

Figure 7 – Human-powered Flashlight Conceptual Model

Once a conceptual functional model has been created, lower-level process specific models can be developed for each concept. For the flashlight example, three different concepts were considered. The first concept analyzed used a crank and a gearset linked to a rotary generator to produce electrical energy. The energy was stored in a capacitor. To represent this concept functionally, the transformation of input energy to stored energy must be analyzed. After energy is input into the system by the human operator, it is converted into rotational energy by the crank. The gearset then changes the rotational energy by increasing the rotational velocity while decreasing the transmitted torque. The rotational energy is then turned into electrical energy via a rotary DC generator. This sequence of functions is represented with the Functional Basis in the following function chain:

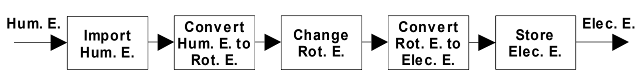

Figure 8 –Crank Flashlight Model

The next concept considered was a flashlight that converted a shaking motion into electrical energy. The force of shaking the flashlight was converted into electrical energy by a linear generator. This energy was also stored in a capacitor. A functional model for the shake flashlight concept appears in Figure 9.

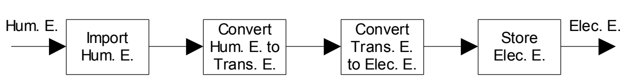

Figure 9 –Shake Flashlight Model

The final concept considered was a variant of the crank flashlight. This flashlight stored the rotational energy from the crank with a constant force spring. Once the spring was fully wound, the energy stored within it was transmitted through a gearset to a rotary DC generator. As with the preceding concepts, this energy was stored in a capacitor. The functional model for this concept appears in Figure 10.

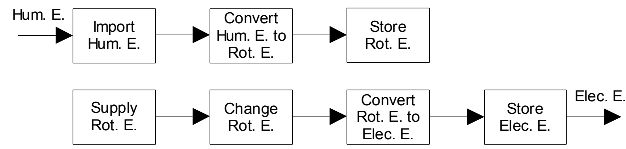

Figure 10 -Crank Spring Flashlight

3.3 Performance Models

The next step in the FUNdesign process for the flashlight was to create performance models for the concepts. To create these models, performance equations for each function were created and then aggregated to produce an overall performance model. Since the energy stored in the flashlight is a function of time, differential equations were used to model each function. Simulink and Matlab were used to graphically represent and solve these differential equations for each flashlight. The crank model appears in Figure 11 along with a model for the Convert Human Energy to Rotational Energy function in Figure 12.

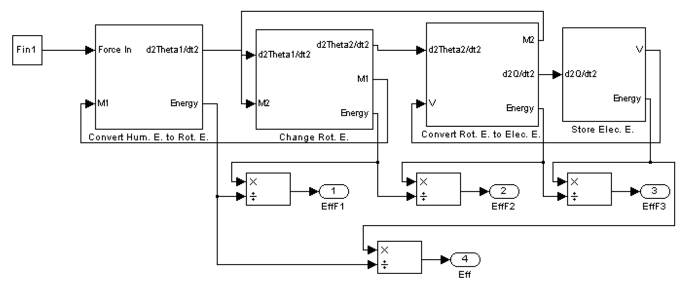

Figure 11 -Crank Flashlight Simulink Model

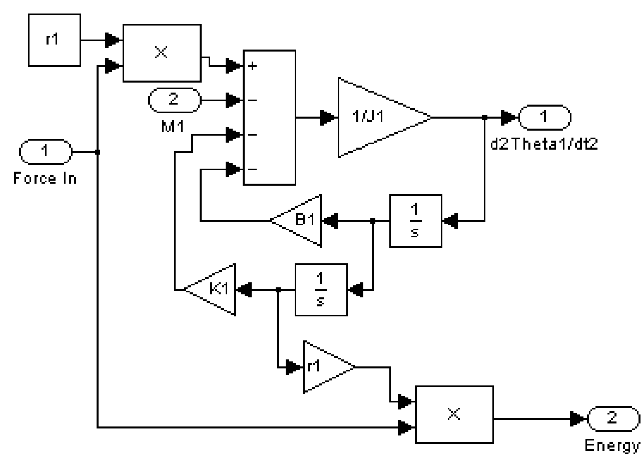

Figure 12 –Convert Human Energy to Rotational Energy Simulink Model

In Figure 11, the four blocks at the top represent the models for each function in the system. The box labeled *Fin1* represents the force input to the system. The connections between the blocks show the flow of energy as a flow (angular acceleration) and effort (moment). Efficiencies are calculated for each function using the three blocks in the middle of the diagram and for the overall system in the bottom block. These blocks use the energy inputs from each function block to calculate efficiency.

Figure 12 is a model for an individual function. The model represents a second order differential equation that describes the motion of a crank with a constant input (*Force In*). The moment that is fed back to the model from functions downstream in the functional flow is represented as the input *M1*. The energy input to the model is calculated by the bottom block and output as *Energy 2*.

Parameter values for the models were obtained based on available parts or empirically chosen to produce the desired output. To insure that the concepts exhibited equal nominal performance, a goal of 150J of stored energy after 30 seconds of charging was selected. This amount of energy will power a 150 mA Xenon bulb for five minutes. For each concept, the design variables were chosen to result in 150J of stored energy from 180J of input energy after 30 seconds. An example of the efficiently versus time relationship appears in Figure 13. The values of the design parameters for each system appear in Tables 2, 3 and 4 for the Crank, Shank and Crank-Spring concepts respectively.

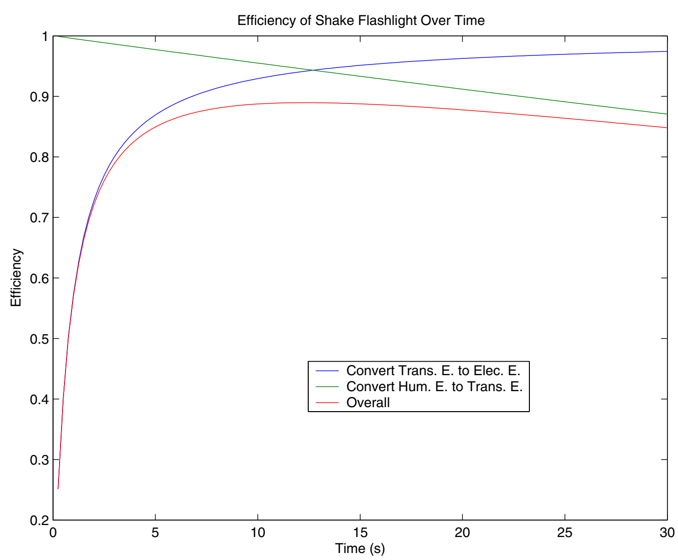

Figure 13 – Shake Flashlight Efficiency versus Time

Table 2 – Crank Flashlight Variables

Variables	Value	Unit	Description
F_{in1}	10	N	Input force
r_1	0.2	m	Radius of crank
J_1	0.001	kg/m2	Moment of inertia of crank
B_1	0.0001	N*m*s/rad	Friction of crank
X_2	0.0212	Unitless	Gear ratio
J_3	0.0005	kg/m2	Moment of inertia of generator
B_3	0.00001	N*m*s/rad	Friction of generator
K_3	0.2		Back EMF and Torque constant
L_3	0.1	H	Inductance of generator
R_3	5	Ohm	Resistance of generator
C_4	0.1	Farad	Capacitance

Table 3 – Shake Flashlight Variables

Variables	Value	Unit	Description
m_1	0.4	kg	Mass of flashlight
B_1	0.01	N*s/m	Friction between handle and magnet
K_2	0.29		Back EMF and force constant
L_2	0.0796	H	Inductance of generator
R_2	0.0011	Ohm	Resistance of generator
C_3	0.0796	Farad	Capacitance

Table 4 – Crank-Spring Flashlight Variables

Variables	Value	Unit	Description
F_{in1}	10	N	Input force
r_1	0.2	m	Radius of crank
J_1	0.01	kg/m2	Moment of inertia of crank
B_1	0.0333	N*m*s/rad	Friction of crank
M_2	1.9	N*m	Moment of constant force spring
J_2	0.01		Moment of supply reel
B_2	0.0333		Friction of supply reel
X_3	0.0265	Unitless	Gear ratio
J_4	0.0002	kg/m2	Moment of inertia of generator
B_4	0.00001	N*m*s/rad	Friction of generator
K_4	0.25		Back EMF and Torque constant
L_4	0.1	H	Inductance of generator
R_4	4	Ohm	Resistance of generator
C_5	0.1	Farad	Capacitance

3.4 Sensitivity Analysis

After the nominal performance was equalized for each concept a sensitivity analysis was performed for each function in the concepts. The objective of this analysis was to find which functions were more affected by uncertainty in the values of the design parameter. To determine the sensitivity of each function, a normalized time-averaged sensitivity was used. This value was computed by finding the first partial derivative of the efficiency with respect to the variable of interest at each time step in the solution. The average value of the sensitivity was then found and normalized with respect to a 1% change in the design parameter. For example, in Table 5 a 1% increase in the value of the variable X3 results in an average .0655% increase in overall efficiency. The coefficient of variation of each sensitivity curve was also calculated and appears in the tables below.

Crank Spring	**Change Rot. E.**	**X_3**
	S (1%)	0.0655%
	Cv	54.98%

Table 5 – Change Rotational Energy Sensitivity Results

The values of S and CV were calculated for each design variable within each function for all three concepts. The results of this sensitivity analysis were then used to identify various classes of functions. Tables 6 and 7 show functions that are on average more sensitivity and less sensitivity respectively. The lowest sensitivity to variation in the Convert Rot. E. to Elec. E. function is two orders of magnitude higher than the most sensitive variable in the Convert Hum. E. to Rot. E. function. It is also shown in Table 6 and 7 that these two functions have comparative sensitivities across the different concepts. The values for the average sensitivity of similar design variables (the values of R for example) are similar.

Crank	**Rot. E. /Elec. E.**	**J_3**	**B_3**	**K_3**	**R_3**
	S (1%)	-0.1068%	-0.0231%	0.27%	0.09%
	Cv	13.13%	57.62%	19.20%	79.57%
Crank Spring	**Rot. E. /Elec. E.**	**J_4**	**B_4**	**K_4**	**R_4**
	S (1%)	-0.0250%	-0.0136%	0.143%	0.069%
	Cv	7.88%	56.44%	36.75%	79.57%

Table 6 – Convert Rotational Energy to Electrical Energy Sensitivity

Crank	**Convert Hum. E. to Rot. E.**	**J_1**	**B_1**
	S (1%)	-0.00010%	-0.00010%
	Cv	11.57%	57.60%
Crank Spring	**Convert Hum. E. to Rot. E.**	**J_1**	**B_1**
	S (1%)	0%	0%
	Cv		

Table 7 – Convert Human Energy to Rotational Energy Sensitivity

During the sensitivity analysis it was also found that some functions exhibited large fluctuations in sensitivity across concepts. Table 8 shows the sensitivity analysis results for the Store Elec. E. function. The largest value of sensitivity is three orders of magnitude greater than the smallest value. In addition, the values of the coefficient of variation for the capacitance is much greater than one for the Crank and Crank-Spring systems and less than one for the Shake system.

Crank	**Store Elec. E.**	**C_4**
	S (1%)	0.04%
	Cv	216.43%
Shake	**Store Elec. E.**	**C_3**
	S (1%)	-1.40%
	Cv	73.67%
Crank Spring	**Store Elec. E.**	**C_5**
	S (1%)	0.0017%
	Cv	4776.00%

Table 8 – Store Electrical Energy Function Sensitivity

The overall effect of each function on the efficiency of a concept is shown in Table 9. This table contains the sensitivity analysis for each function in the crank concept. The large relative values of S for the design variables in the Convert Rot. E. to Elec. E. function show that this function deserves the most attention during the design process. Uncertainty in the design parameters of this function result in large changes in the overall efficiency of the system. This also means that tweaking these parameters results is the largest gains in overall efficiency. The low relative values of CV for the J3 and K3 parameters show that adjusting these parameters has a more consistent effect on efficiency across the 30 second charging time.

Hum. E. / Rot. E.	**J_1**	**B_1**		
S (1%)	-0.00010%	-0.00010%		
Cv	11.57%	57.60%		
Change Rot. E.	**X_2**			
S (1%)	0%			
Cv	32.34%			
Rot. E. / Elec. E.	**J_3**	**B_3**	**K_3**	**R_3**
S (1%)	-0.106800%	-0.0231%	0.27%	0.09%
Cv	13.13%	57.62%	19.20%	79.57%
Store Elec. E.	**C_4**			
S (1%)	0.04%			
Cv	216.43%			

Table 9 – Crank Concept Sensitivity

3.5 Discussion of Results

The results of the sensitivity analysis of the three flashlight concepts provide key information when designing a new flashlight or a device with similar functionality. The high sensitivity of the Convert Rot. E. to Elec. E. function means that great care should be taken when using this function to reduce variation in design variables. This also means that the greatest gains in efficiency can be found by optimizing this function. The values of CV for the design parameters allow a designer to choose which variables to modifying based on how their effect on the overall performance varies with time. Since the probability that a human powered flashlight is going to be charged for exactly 30 seconds is small, a consistent effect on performance over time is desirable. Keying the results of the sensitivity analysis to functionality allows this knowledge to be directly applied during the design of a new flashlight or any system that requires similar functionality. To store and reuse the sensitivity information generated from previous designs, an engineering design knowledge repository is required. An explanation of such repository can be found in Bohm et al, 2003 [17].

To enable FUNdesign, the values of the average sensitivity and coefficient of variation for each design variable would be stored in the repository along the performance models and variable ranges used to calculate the measures. Information about the range used to evaluate the sensitivity is required to insure that the measures are applicable to the system being designed. If the range of the system being designed is greater than that of the systems with stored information, there is no guarantee that the sensitivity measures explain the behavior outside of the investigated range.

4 FUNDESIGN

The flashlight example demonstrates that the sensitivity of functions to uncertainty in design variables can be classified during the design process and stored for use in future design efforts. Certain functions in a system, such as the Convert Rot. E. to Elec. E. function, exhibit much higher sensitivity than other functions the system. With these functions, certain design variables exhibit more a consistent effect on the performance of the system. Additionally, functions that exhibit large variation in sensitivity across applications in different concepts can be identified. These functions can be classified as noisy and their use can be reduced or modified in order to satisfy design goals. To enable FUNdesign for new systems, the results of the sensitivity analyses should be stored in an engineering design repository.

By performing these function-based sensitivity analyses and storing the results, significant knowledge about the sensitivity to design variable uncertainty can be retained and reused though common functionality. To apply this knowledge, a functional model must be created for the system to be designed. For each function in the model, the design repository should be searched for matching functions. If solutions containing similar functions are found, the knowledge associated with these functions should be applied to the new design to prioritize modeling and resource allocation. If no matching functions are found in the repository, the information must be generated as shown in the flashlight example. Generating and applying sensitive information is the basis for the FUNdesign technique (Figure 14).

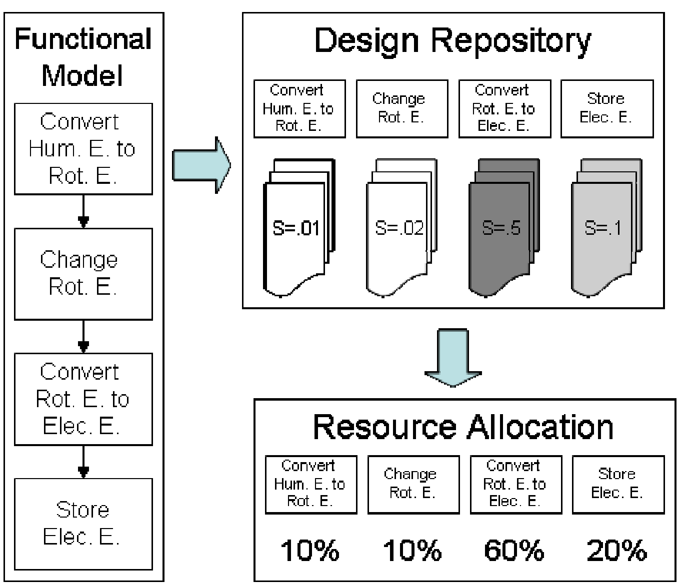

Figure 14 –FUNdesign

The sensitivity measures developed to date are applicable to functions with discrete or continuous models that demonstrate ranged or nominal valued outputs. The measures generated from a solution to a function can be applied to identify potential solutions to the same function in a new design. However, the method is limited to analyzing the sensitivity of the performance of a system one variable at a time. During the sensitivity analysis, these variables are assumed to be independent. Further research must be conducted into a method of combining the individual sensitivities of a system to create a single set of measures that describe the overall sensitivity of a function. By applying such measures to multiple solutions for a function, it will be possible to create a sensitivity history that is less dependant on the specific form of the model used to represent the function. Additionally, differences between the range of the system being designed and systems that have been modeled limit the applicability of the ranged measures. The range used to calculate the sensitivity of a system must be stored along with the measures and compared to the expected range of the system to be designed before the sensitivity knowledge can applied.

Additional areas of research include populating a design repository with performance models and associated sensitivities for a variety of functions as well as multiple solutions for particular functions and applying the results from the knowledge storage phase of FUNdesign to the design of a new system. The first task requires the identification of a set of existing design solutions that possess a variety of functionality in addition to multiple common functions. In addition to the presented human-powered flashlight solutions, several other human-powered devices, such as a human-powered radio or certain types of watches, exist that could be used as sources for design knowledge. Specific solutions for functions could also be used to increase the knowledge stored in the repository. For example, a chemical battery could be modeled for the Store Electrical Energy function instead of a capacitor or a flywheel could be used to store rotational energy before being converted to electrical energy.

It was discovered during the flashlight example that the most time consuming part of extracting the desired sensitivity information from a system design was performance modeling. FUNdesign relies on the availability of good performance models. If these models are not available, as in the flashlight example, they must be created. Once the models have been generated, the process of actually calculating the sensitivity measures can be processed automatically through the use of scripts (the measures for the flashlight example were calculated automatically using a Matlab script). For systems with closed-form models or simple differential equation models, the computational burden is light (the flashlight example would complete in a few seconds). However, the computational burden of extracting the sensitivity information is proportional to the complexity of the model. For very complex models such as finite element analyses and Monte Carlo simulations, the time required to compute the measures increases drastically (the models must be solved across the range at least twice for each design variable).

The second task, applying the stored knowledge, involves identifying a design problem that requires specific functions that are represented in the knowledge base. This could involve a design for a product that doesn't exist or an improvement on a specific solution that occurs in the repository.

REFERENCES

[1]Otto, K. and Wood, K. (2001), Product Design: Techniques in Reverse Engineering, Systematic Design, and New Product Development, New York, Prentice-Hall.

[2]Ullman, D. (2002), The Mechanical Design Process 3rd Edition, McGraw-Hill, Inc., New York, NY.

[3]Hundal, M. (1990), "A Systematic Method for Developing Function Structures, Solutions and Concept Variants," Mechanism and Machine Theory, 25, pp. 243-256.

[4]Hubka, V. and Ernst Eder, W. (1984), Theory of Technical Systems, Springer-Verlag, Berlin.

[5]Murdock, J., Szykman, S., and Sriram, R. (1997), "An Information Modeling Framework to Support Design Databases and Repositories," Proceedings of DETC'97, DETC97/DFM-4373, Sacramento, CA.

[6]Lai, K. and Wilson, W. (1989), "FDL - A Language for Function Description and Rationalization in Mechanical Design," Journal of Mechanics, Transmissions, and Automation in Design, 111, pp. 117-123.

[7]Iwasaki, Y., Vescovi, M., Fikes, R., and Chandrasekaran, B. (1995), "Casual Functional Representation Language with Behavior-Based Semantics," Applied Artificial Intelligence, 9.

[8]Umeda, Y. and Tomiyama, T. (1997), "Functional Reasoning in Design," IEEE Expert Intelligent Systems and Their Applications, 12, pp. 42-48.

[9]Akiyama, K. (1991), Function Analysis: Systematic Improvement of Quality Performance, Productivity Press.

[10]Collins, J. A., Hagan, B. T., and Bratt, H. M. (1976), "The Failure-Experience Matrix: A Useful Design Tool," Journal of Engineering for Industry, 98, pp. 1074-1079.

[11]Modarres, M. (1997), "A Functional Classification Based on Conservation Principles," Proceedings of the Fifth International Workshop on Functional Modeling of Complex Technical Systems, Paris-Troyes.

[12]Szykman, S., Racz, J., and Sriram, R. (1999), "The Representation of Function in Computer-Based Design," Proceedings of the ASME Design Theory and Methodology Conference, DETC99/DTM-8742, Las Vegas, NV.

[13]Hirtz, J., Stone, R., McAdams, D., Szykman, S. and Wood, K. (2002), “A Functional Basis for Engineering Design: Reconciling and Evolving Previous Efforts,” Research in Engineering Design, 13(2): 65-82.

[14]Stone, R. and Wood, K. (2000), "Development of a Functional Basis for Design," Journal of Mechanical Design, 122(4):359-370.

[15]Ulrich, K. and Eppinger, S. (1995), Product Design and Development, McGraw-Hill, New York, NY.

[16]Hutcheson, R., Donndelinger, J., McAdams, D. and Stone R. (2004), “Applying Functional Modeling as a Unifying Basis for Design for Six Sigma Execution,” Proceedings of the ASME International Mechanical Engineering Congress and RD&D Expo, IMECE2005/62312, Anaheim, CA.

[17]Bohm, M., Stone, R. and Szykman, S. (2003), “Enhancing Virtual Product Representations for Advanced Design Repository Systems,” Proceedings of DETC2003, DETC2003/CIE-48239, Chicago, IL.