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Design for excess capability to handle uncertain product requirements in a developing world setting

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Abstract Products designed for the developing world often go unused or underused by the intended customers. One cause of this problem is uncertainty regarding the actual requirements of customers in the developing world. This can result when designers, with experience in technologically advanced countries, apply their own value structure to the products they design. Because of the designers' lack of experience in the culture and environment of the developing world, the actual requirements are only partially known to them. This problem can be mitigated by (i) optimizing product flexibility and adaptability to react to uncertain requirements, and (ii) reducing the most critical uncertainties. The flexibility of a product to adapt to new or changing requirements has been shown to extend the service life of large complex engineered systems (e.g., aircraft carriers, aircraft, communication systems, and space craft). These systems must remain in service for extended periods of time, even though the environments and requirements may change dramatically. Applying these proven techniques to products designed for the developing world can alleviate the problem of uncertain requirements. This paper presents and demonstrates a technique aimed at improving the success of developing world engineering projects. Flexibility and adaptability minimize the impact of uncertainties, and are enabled by numerically optimized amounts of designed-in excess. A sensitivity analysis performed on the system model helps the designer prioritize the set of uncertain requirements and parameters for refinement. The technique is demonstrated in the design of a cookstove intended for use in the developing world.

Keywords Developing world · Excess · Evolvability · Adaptability · Reconfigurability · Reconfigure · System design · Improved cookstove

List of symbols

k	Known requirements
u	Uncertain requirements
d	Design parameters
x	Excess
ζ	Known requirement function
η	Uncertain requirement function
b	Benefit of uncertain requirements
F	Benefit factors
p	Probabilities of uncertain requirements
β	Benefit function or uncertain requirements
c	Cost of excess capabilities
M	Cost factors
γ	Cost function of excess capabilities
V	Value function for optimization
g	Constraints for optimization

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1 Introduction

Today many of the world's inhabitants struggle to survive in a state centuries behind that of the most advanced societies (Lall 1998). Products and systems that improve the health and well-being of the end users, such as products that deliver clean water, medical care, and clean energy, are desperately needed. Unfortunately attempts to provide these products and systems are hampered by low long-term adoption rates (or premature obsolescence) (Free 2004; Hammond 2004). While there are a variety of issues that influence the success of a product including social, political, engineering, and environmental issues, one of the most significant is uncertainty regarding the requirements (Campbell and Vainio-Mattila 2003; Chavan et al. 2009). There are three causes of uncertain requirements (i) inadequate understanding, (ii) incomplete information, and (iii) conflicting performance alternatives (Lipshitz and Strauss 1997). These uncertainties can result in products that fail to be adopted initially or suffer prematurely obsolescence. Some historical examples include primary health care systems, clean water delivery systems, and improved cookstoves (Free 2004; Pine et al. 2011).

In search of potential solutions, we can turn to complex engineered systems. Avoiding premature obsolescence has been a topic of interest for large complex systems (i.e. aircraft carriers, warplanes, etc.) (Saleh and Hastings 2000). As an illustration, consider the C-130 aircraft, which was originally designed in the early 1950s as a military cargo and troop carrier (Smith 2001; Tackett et al. 2014; Bowman 1999). Since its first flight in 1954 it has undergone over 55 adaptations, including maritime patrol and rescue, electronic warning and control system, aerial refueling, and even a gun ship. Today, with over 2000 aircraft in service, the C-130 remains a vital military aircraft. Because of its ability to apply excess capability to address new and changing requirements, the C-130 has exceeded service-life expectations. By contrast the F-117, which was introduced in 1983 for a very specific type of mission, was retired just 25 years later in 2008. Unlike the C-130, the F-117 did not demonstrate the ability to adapt to new and changing missions (Ireton 2006).

Examining large complex engineered systems, we can see that the addition of strategically placed excess capability can enable a design to adapt to new, changing or uncertain requirements (Hu and Cardin 2015). The authors of this paper have written three previous papers regarding evolvability and excess capability in complex engineered systems. Those papers address two aspects of evolvability: (i) that evolvability can be numerically evaluated by considering the usability of excess within a design (Allen et al. 2016; Tackett et al. 2014), and (ii) that excess can be optimized to increase the evolvability of a product (Watson et al. 2016). While the current paper utilizes the concept that excess can be designed into a product to increase the flexibility of the design, it is unique because it presents a technique that identifies for the designer which assumptions must be refined in the context of optimizing the product for uncertain requirements.

Given the work, by the authors and other researchers, directed at complex engineered systems, two research questions come to mind. The first question is: how can the presence (location and quantity) of excess be added to a *simple design*, targeted at users in the developing world, with the intent of improving its success and long-term adoption? A second question is: can numerical search and sensitivity analysis be used to analyze and provide insight into identifying and resolving the most critical uncertainties? This paper seeks to answer these questions by presenting a numerical technique that is shown to improve the long-term adoptability of products designed for the developing world. The technique efficiently identifies a path to prioritize for refinement the uncertain requirements and parameters. The impact of uncertainties are further mitigated by flexibility and adaptability that are optimally designed-in by the addition of excess. While this technique is not limited to developing world applications, it is well suited to address issues resulting from a geographic or cultural separation between designers and customers.

2 Review of related work

We begin this section by reviewing literature specifically directed at creating products for the developing world. Then we transition to the more general topics of flexibility and uncertainty in engineered designs.

The developing world represents a large percentage of the world's population. The United Nations has developed the Millennium Development Goals to highlight the needs of this portion of the world. A report by Annan (2005) describes these goals and the current barriers to achieve them. The inability to transfer technology and innovation from developed countries has been identified as a main barrier (Binagwaho and Sachs 2005). Studies indicate that only a small percentage of products introduced into the developing world succeed (Austin-Breneman and Yang 2013) as compared to a much larger success rate in more advanced countries (Cooper and Kleinschmidt 2011).

Why does this difference in success rates exist? Mattson et al. (2016) indicate these differences stem from the socioeconomic and technical differences between the societies. These differences can result from deeply held assumptions by engineers regarding what is needed in the developing world, such as that only simple solutions are needed or that the need for an inexpensive solution eliminates the opportunity for companies to make an attractive profit. Even when the basic need area is simple, the specific requirements regarding the engineered solution may be and often are complex. Mattson and Winter further point out that modern development methods have been shaped by the kinds of problems faced in the developed world. New evolutionary paths may be needed to arrive at development methodologies suitable for solving the problems facing the developing world. To that end, several new techniques and methodologies can be found in the literature.

In the business literature, the market represented by the developing world has been described as the "Bottom of the Pyramid" (Prahalad and Hart 2002). It has been shown that there is a "potential of serving" this "unserved market and alleviating the level of global poverty while still earning a profit" if the adoption barriers can be overcome (Pitta et al. 2008). Many methodologies and proposals have been introduced in an effort to increase the acceptance of new products and technologies by those in the developing world. These methodologies include (a) "Customer Value Chain Analysis" (Donaldson et al. 2006), (b) a product service system approach (Schafer et al. 2011), (c) design for emerging markets guidelines (Chavan et al. 2009; Kang et al. 2014), (d) design for sustainable development guidelines (Ngai et al. 2007), and (e) design for the base of the pyramid (Whitney and Kelkar 2004). The main focus of these methods is to identify requirements. They do not identify nor analyze uncertainties and as is often the case in design tasks, uncertainty remains and the problem of new products and technologies failing to meet the needs of the developing world continues to exist (Bell and Pavitt 1997). This problem is not necessarily an indication that these methods have failed. Determining requirements is an expensive process, the cost of which is proportional to the accuracy of the information. As noted in Sect. 1, this paper presents a technique to guide the designer to the requirements needing the highest level of attention. This enables the designer to focus on the most critical requirements resulting in an improved product while minimizing development costs.

Uncertain requirements have been highlighted as a key contributor to the technology transfer or adoption barrier (Bell and Pavitt 1997; Campbell and Vainio-Mattila 2003; Chavan et al. 2009; Kang et al. 2014; Ramamurti 2009). Separation, both geographically and culturally, between the designers and customers has been identified as the most significant cause of uncertainty (Donaldson 2009; Fathers 2003). When designers are geographically or culturally separated from customers, important preferences regarding requirements can be misunderstood, or omitted. It should also be noted that even designers living in the developing world might misunderstand or be unaware of important requirements (Sheffield and Lin 2013). The premise of this paper is that the impact of these uncertain requirements can be mitigated by an efficient technique to identify, resolve, and adapt to the most critical uncertainties (Li et al. 2008).

Again turning to similar conditions, designers of large complex engineered systems have utilized adaptability to prolong their systems' service life (Bloebaum and McGowan 2012). Examples of systems that employ some type of adaptability to increase their success rates and prolong their service life include communication networks, commercial aircraft, ocean vessels, telecommunication satellites, and military weapon systems. While these systems are generally complex and expensive (in terms of development and production), it is possible to employ the same techniques on simpler less expensive products.

Many methodologies are used in the development of large complex systems to increase success rates and extend service life. Commonly used terms to describe these methodologies include: changeable, reconfigurable, transformable, adaptable and flexible. These terms have been defined and differentiated in a paper by Ferguson et al. (2007). Changeable is defined as the most general of these terms, referring to systems, which undergo any type of change, for any reason. Reconfigurable and transformable are used to describe systems, which are capable of undergoing repeatable and reversible change. Adaptable is used to describe systems that change in response to varying conditions or requirements while in service. Adaptable systems are not restricted to making only repeatable or reversible changes. Systems that do not require a change to accomplish multiple requirements are referred to as flexible systems. This paper focuses on developing flexible and adaptable systems to address requirement uncertainties.

Engel and Browning have presented a "model to assess the value of architecture adaptability" known as Architecture Option (AO) theory (Engel and Browning 2008). It has recently been refined by Engel and Reich (2015). The model is based on a financial analysis of the product design alternatives. It utilizes *real options theory* to assess the alternatives. The model can incorporate a wide variety of financial inputs and is, therefore, an excellent tool to determine the degree to which adaptability is appropriate and generally how can it be achieved.

Change is critical to adaptive systems (Siddiqi et al. 2011). Jarratt et al. have presented an overview of published material on engineering change (Jarratt et al. 2011). They categorize key aspects, methods and tools for managing change. Keese et al. (2006, 2009) have presented several papers outlining methods to characterize the flexibility of a system based on impact of change throughout the system, using "Enhanced Change Modes and Effect Analysis" (CMEA). In a similar vein, several papers have been written on the propagation of change through a system (Pasqual and de Weck 2012; Hamraz et al. 2013, 2012; Giffin et al. 2009). These papers provide valuable insight into the impact of change (during the design, manufacturing and in-service phases). However, they do not present a direct method to construct a numerical model of the product based on part and subassembly parameters. The numerical model presented in this paper is a direct translation of the requirements in terms of product parameters. It enables the optimization of the product based on the customer's values and the analysis of the uncertainties.

Change and adaptability require flexibility in a product or system (Niese and Singer 2014; Luo 2015). There are a number of papers proposing frameworks, guidelines and methodologies to manage the design of flexibility within a system. Saleh and Hastings (2000) and Olewnik et al. (2004) focus on determining when and how to embed flexibility. The authors of this paper (Allen et al. 2016; Tackett et al. 2014; Watson et al. 2016) use the concept of designed-in excess to provide systems with increased flexibility. Tilstra et al. have presented several papers on the value of system flexibility and associated design guidelines (Tilstra et al. 2009, 2012, 2015). They incorporate "High Definition Design Structure Matrix" (HDDSM) and "Change Modes and Effect Analysis" as tools to accomplish this. The HDDSM and the CMEA tools provide an excellent visualization of the impact of adaptability and change, but they do not lead directly to a numerical model of the product suitable for optimization.

Robustness is another import attribute sought by designers of complex engineered systems. Robustness methodologies are often used to desensitize a product to uncontrolled variations, such as manufacturing tolerance or changes in environmental conditions (Du and Chen 2000). Recognizing that robustness is often limited to resilience to noise, Ziv Av and Reich have presented a method for dealing with the broader perspective of robustness including customer requirements and market conditions. Their method, known as Subject Objective System (SOS) was presented in Ziv-Av and Reich (2005) and refined in Reich and Ziv Av (2005). The SOS method uses a scalable structure similar to the Quality Function Deployment—House of Quality approach presented by Akao (1994). Because of its scalable nature and ability to include many types of inputs, SOS can be used at several points in the design process. It is especially appropriate during the conceptualization phase. However, as with other approaches, it does not lead directly to a detailed numerical model of the system based on design parameters.

From the literature we see that flexibility, adaptability, change, and robustness are important topics related to engineered systems. The methodology and guidelines presented provide excellent visualization of design alternatives and their impacts, but generally do not provide a simple method to develop a numerical model of the product nor do they identify critical uncertainties. There is a common message from the published material that flexibility and future adaptability are often very desirable product attributes. In this paper, a technique utilizing a numerical model is employed to strategically design-in excess capabilities while dealing with uncertain requirements. Thus, enabling product flexibility and adaptability and as a result improving the probability of adoption by the customer.

3 A new technique to optimize a product with uncertain requirements

Designers faced with creating products for the developing world can benefit from a technique that increases the success rate and long-term utilization of their products. Two objectives of this technique are to provide a process for (i) optimizing excess capability included in the product for flexibility, or adaptability and (ii) dealing with the uncertainty of the requirements and assumptions. The following technique allows the designers to make gross approximations in creating a preliminary numerical model. The process then analyzes these assumptions in terms of their impact on the value of the design. Through the recursive process critical assumptions are refined and improved.

Once a numerical model of the product is created, designed-in excess capabilities are optimized and a sensitivity analysis is performed on the assumptions to determine their suitability. The assumptions are categorized into four groups as shown in Fig. 1. Assumptions in quadrants 1–3 either are accurate (i.e., high confidence) or do not appreciably affect the value of the product (i.e., low sensitivity). The sensitivity analysis identifies the assumptions in quadrant 4 (i.e., high sensitivity and low confidence) thus providing guidance as to which assumptions require further study (i.e., higher confidence levels). Once the confidence level of indicated assumptions has been improved, the process is repeated.

Six steps are used to perform this process (see Fig. 2).

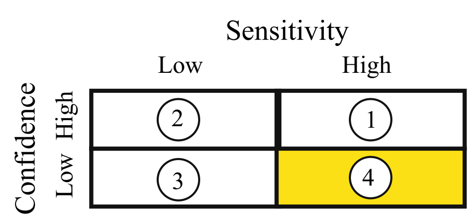


Fig. 1 The relationship between the confidence and sensitivity of assumptions is presented. Assumptions with low confidence and high sensitivity are highlighted in quadrant 4 (in *yellow*) and are the focus of this paper. (Color figure online)

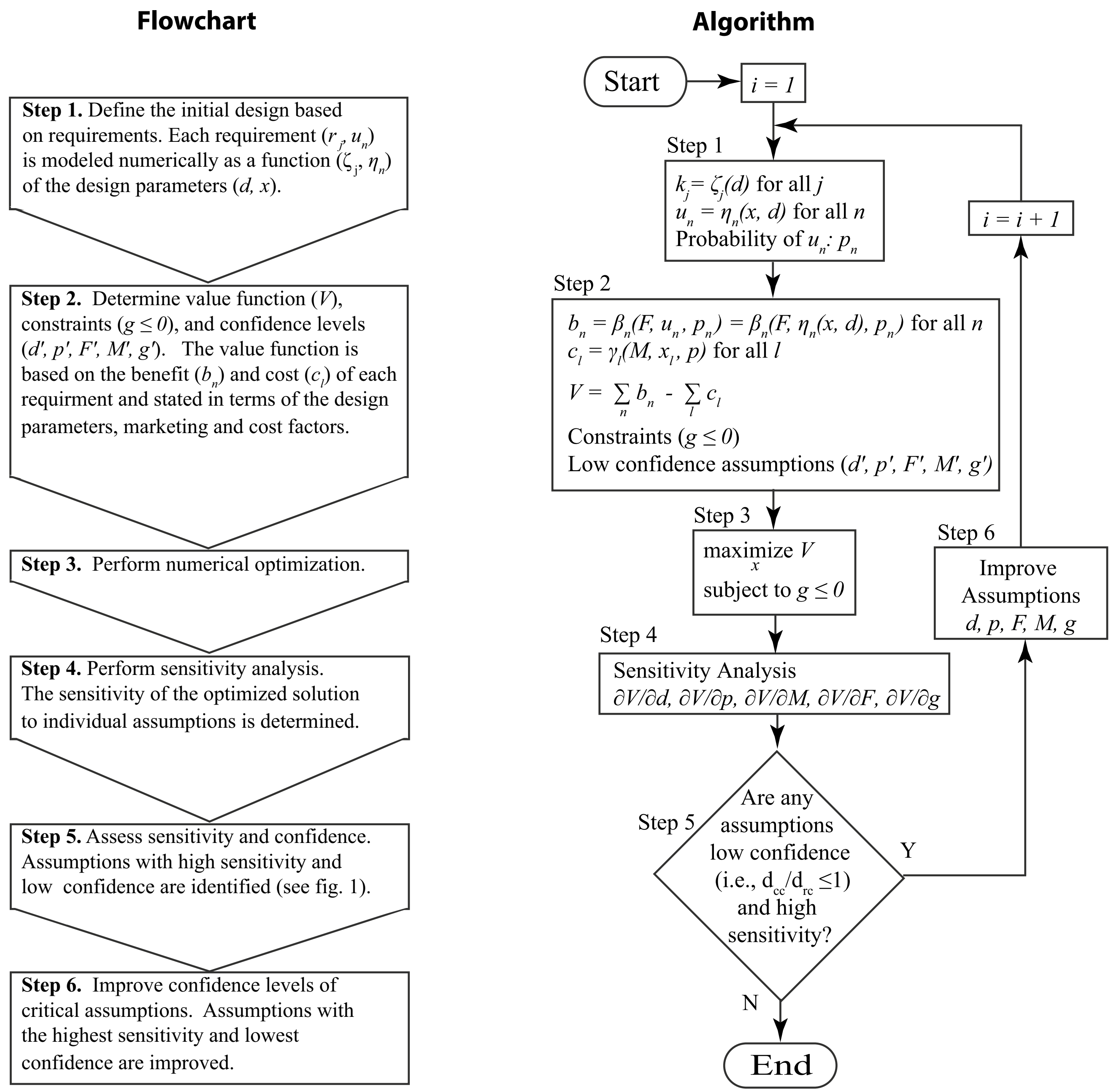


Fig. 2 Flowchart and corresponding algorithm to optimize excess capability in a product with uncertain requirements

Step 1	Define the design based on known and uncertain requirements
Step 2	Determine the value functions, constraints, and confidence levels of assumptions
Step 3	Perform optimization
Step 4	Perform sensitivity analysis
Step 5	Assess the sensitivity and confidence levels
Step 6	Improve the confidence levels of critical assumptions (in quadrant 4 of Fig. 1). Then repeat steps 1–6 until adequate confidence levels are achieved

In this section, each of these steps is explained in detail.

3.1 Step 1: Define the initial design based on requirements

The first step in Fig. 2 is to define the initial design based on the requirements of the product. Those requirements that are virtually certain are referred to in the paper as known requirements (k_j). Other requirements, with more uncertainty, are referred to as uncertain requirements (u_n).

If available the probabilities (p_n) that the uncertain requirements will actually be required are also noted.

The next step is to determine what design parameters (d) are necessary for each requirement. These design parameters may be geometric positions, material properties or other design properties. Excess (x) associated with each design parameter is used as the design variable for the uncertain requirements. In the optimization step described in Sect. 3.3, the optimization variables are the elements of the excess (x) array, and the design parameters are the elements of the d array. Each known requirement (k_j) is modeled as a function (ζ_j) of the design parameters. Similarly each uncertain requirement (u_n) is modeled as a function (η_n) of the design parameters (d), and corresponding excess (x).

Each of the arrays noted above (k_j, u_n, p_n, d, and x) are of one dimension, the length of which is dependent on the number requirements and parameters being used. There is a one to one relationship between the elements of u and p and between the elements of d and x. The functions ζ_j and η_n can be considered as one-dimensional arrays of functions with each element ζ_j associated with a known requirement and each element η_n associated with an uncertain requirement. When the designer does not have high confidence in some of the parameters used to create the numerical model of the product, it is part of the technique to use estimates. The impact of these estimates is assessed in steps 4 and 5 (Sects. 3.4 and 3.5). If necessary these estimates are improved in step 6 (Sect. 3.6).

3.2 Step 2: Determine the value functions, constraints, and confidence levels

The second step in Fig. 2 involves the overall value of the product (V), constraints used in optimization, and confidence levels of the assumptions. The overall value of the product (V) is a function of the customer-perceived benefit obtained from the product when the uncertain requirements are satisfied minus the cost to include each excess capability. The equation for each customer-perceived benefit (b_n) can be written as

$$b_n = \beta_n(F, u_n, p_n) = \beta_n(F, \eta_n(x, d), p_n) \tag{1}$$

where F is a matrix of the market factors necessary to define the benefit.

If the customer-perceived benefit is expressed as a power or Fourier series then all possible curves can be expressed by appropriate selection of the coefficients. This is useful if the shapes of the curves are uncertain. For example, if the benefit of a particular excess capability is believed to increase as the quantity of the excess increases, then b_n could be expressed as a first-order power series, that is, a straight line, with a slope and intercept defined by the market. In this case F would contain the slope and intercept constants for the line. Higher order coefficients would be set to 0 until further study indicates a need for a higher order approximation of customer-perceived benefit.

There is generally a cost associated with each excess capability. This cost can be calculated based on the design parameters, material and manufacturing (or fulfillment) costs. An equation for the cost of including each excess capability (c_l) is written as

$$c_l = \gamma_l(M, x, p) \tag{2}$$

where M is a matrix containing the costs factors necessary to define the cost of the excess capability.

The overall value is written as

$$V = \sum_n b_n - \sum_l c_l \tag{3}$$

Note that the summation is taken separately on the benefit and cost terms. This enables issues associated with redundant costs or coupled benefits to be addressed within the c_l and b_n equations, respectively.

There are often important limitations on a design, such as cost, weight, or power consumption. These limits define the constraints ($g \leq 0$) of the analysis. Care should be taken to ensure that these limits are required. Their inclusion can severely limit the design options to be identified by this analysis (Wassenaar and Chen 2003). The constraints ($g \leq 0$) are used in step 3, the numerical optimization.

Up to this point, the designer has made a number of assumptions in formulating the design problem and in representing the overall value of the product. These assumptions include the design parameters, the probabilities that uncertain requirements will be used, market and cost factors used in the M and F matrices and the constraints. The confidence levels may be very high on some of these assumptions (e.g., material costs, and material properties), but others can have lower or even very low confidence levels.

Confidence levels can be determined by several methods. For example, in a study on assessing confidence and prediction accuracy of designers from different cultures and experience levels, Zhang (2015) presents a method of determining confidence levels using a Likert scale (e.g., 1 = 'not at all confident' and 7 = 'very confident') (Likert 1932). Interestingly, Zhang found that both experienced and novice designers are more confident when designing for their home market than for a foreign market. In a sense the algorithm presented this paper is an extension to the work by Zhang. It provides a systematic method to determine which areas of low confidence should be prioritized for further study.

For the purpose of this paper, low confidence assumptions are defined as assumptions where the current confidence level is lower than the required confidence level. For example, this can be expressed for a design parameter (d) as:

$$\frac{d'_{cc}}{d'_{rc}} \le 1 \tag{4}$$

where d'_{cc} is the current confidence of the design parameter and d'_{rc} is the required confidence of that design parameter. If $d'_{cc} = 50\%$ and $d'_{rc} = 90\%$, then $d'_{cc}/d'_{rc} = 0.56$ and the assumption is considered low confidence. Similar expressions can be written for each of the assumptions (d, p, F, M, and g) used in the numerical model.

The low confidence assumptions are recorded in arrays (d', p', F', M', and g'). It is often impractical or very expensive to achieve high levels of confidence for all of the assumptions. This process will aid the designer in selecting which of these low confidence assumptions should be studied to improve the confidence level and achieve a more accurate result.

3.3 Step 3: Perform the numerical optimization

The third step in Fig. 2 is to perform the numerical optimization. The optimization problem is written as

$$\begin{aligned} &\underset{x}{\text{maximize}} \quad V(x,d) \\ &\text{subject to} \quad g(x,d) \le 0 \end{aligned} \tag{5}$$

where x are the design variables (excess), and d are the fixed design parameters. V and g are the value function and constraint equations defined above. Note the objective of this optimization is to determine optimal amounts of designed-in excess to achieve the highest possible value to the customer. The designed-in excess provides flexibility and adaptability to respond to uncertain requirements.

3.4 Step 4: Perform the sensitivity analysis

A sensitivity analysis is performed in step 4 of Fig. 2 to determine the degree to which the optimized design is sensitive to the low confidence assumptions (d', p', F', M', and g'). The sensitivity analysis can be performed in a number of ways. Plots can be made of the overall value (V) as a function of perturbation in the assumptions. Changes in the value (V) as a function of the assumption under consideration indicates sensitivity to that assumption. This provides the designer with a visual understanding of the impact of variations in the assumption. Other approaches include calculating the partial derivative or gradient of the value function with respect to the low confidence parameters (d', p', F', M', and g'). This can quickly indicate to which parameters the value function is most sensitive.

3.5 Step 5: Assess the sensitivity and confidence levels

In step 5 of Fig. 2 a comparison is made between the confidence levels of the assumptions (d', p', F', M', and g') and sensitivity of the overall value (V). Assumptions with low confidence levels and high sensitivity occupy the fourth quadrant of Fig. 1. These are the assumptions that should be considered for further study. Improving them with higher confidence replacements provides the designer with a higher level of confidence in meeting the customer's requirements through optimal flexibility and adaptability. Because changing the low sensitivity assumptions does not noticeably affect the product's value, the designer does not need to invest in improving them.

3.6 Step 6: Improve the confidence level of critical assumptions

The purpose of the last step of Fig. 2 (step 6) is to improve the assumptions identified in step 5. This technique provides the designer with guidance in determining which assumptions require further study and which can be accepted as they currently exist. This saves time and resources by focusing on improving only assumptions that are critical to the value of the product. These assumptions can be improved by basic market methodologies (e.g., focus studies, surveys, interviews, adjacent product comparisons). The technique has pointed the designer toward the most useful areas of study. This is especially beneficial when gathering market information is time consuming or expensive as it is in a developing world setting.

Once high-confidence assumptions have replaced the earlier low confidence assumptions, the algorithm can be repeated to see if other assumptions should be reviewed. This process is repeated until the designer is satisfied with the confidence levels of the high-sensitivity assumptions.

4 Demonstration of the technique applied to a cookstove

Over the past decade, the topic of improved cookstoves has steadily received attention in both peer-reviewed literature and other media sources. The reason for such attention is that approximately 3 billion people throughout the world still cook over an open fire or with other traditional forms of biomass cookstoves (IEA 2004). The smoke and pollution from these fires cause nearly 1.6 million deaths every year, contribute to global warming (Edwards et al. 2003), require women to spend long hours gathering fuel (Smith et al. 1993), and in some cases cause local deforestation (Gill 1987). One attempted solution to this problem has been the design and distribution of improved cookstoves.

When designed correctly, these improved cookstoves are capable of reducing emissions by 90% and reducing fuel consumption by nearly 50% (Charron 2005).

However, as with many other products designed for the developing world, the majority of these improved cookstoves have not been adopted and have only been used at surprisingly low rates. Such low rates can be due to the improved cookstoves not meeting the current, or future requirements of the users (Garcia-Frapolli et al. 2010; Pine et al. 2011; Simon et al. 2012). The technique described in this paper can potentially help resolve these issues.

4.1 Step 1: Define the initial cookstove design based on requirements

A cookstove can be a significant advancement from cooking over an open fire. It can be more efficient in terms of temperature control, heat containment and fuel consumption (Ballard-Tremeer and Jawurek 1996; Boy et al. 2000). An example of this type of cookstove is the Proleña Ecofogon cookstove pictured in Fig. 3. As noted by Terrado (2005) Proleña is “an active NGO specializing in fuel wood issues that has had a long presence in Nicaragua, Honduras and other parts of Central America”. The Proleña cookstove has been successfully manufactured and sold in Central America since the year 2000. A simplified model of the Proleña cookstove is used in this paper to illustrate the algorithm outline in Sect. 3. The requirements and parameters, while realistic and consistent with Proleña stoves are selected to illustrate specific points for this example. Note that the purpose of this paper is to demonstrate a design technique not to present a new cookstove design.

To be adopted and used over time a cookstove must provide for the basic cooking needs of a family. These needs can vary from family to family and for a single family, they can vary over time. For example, the available cooking utensils, such as pots and pans can vary from family to family and over time. Similarly, cooking time and temperature can vary from meal to meal. Ergonomic needs (e.g., work surface height) may be different from one family to the next or even over time for a single family. The size of the family is also likely to change over time, increasing or decreasing pot size and time spent cooking (Thacker et al. 2014). The cookstove must be easy to use and capable of meeting these varying needs. If it is adopted and used consistently over time, even a simple cookstove design can have an impact on a family’s health and economic well-being (Albalak et al. 2001; Romieu et al. 2009).

4.1.1 *Identify the known requirements of the cookstove*

This example uses a very simple cookstove design. The use of a simple, though realistic, design is intended to allow the reader to focus on the algorithm. The cookstove design has three well-understood requirements.

Fig. 3 The Proleña Ecofogon is an example of a cookstove currently manufactured and sold in Central America. Reproduced by permission of the non-governmental organization (NGO) Proleña

k_1: cooking surface supports pots, which are 0.3048 m (12 in.) in diameter (k_1: d_1 and $d_2 \geq 0.3048$)

k_2: cooking surface temperature is suitable for general cooking (k_2: cooking surface temperature equal to or greater than 478 K or 400 F)

k_3: combustion chamber is large enough to hold sufficient fuel to cook for 30 min without adding fuel (k_3: $d_1 \times d_2 \times d_3 \geq 0.0566$ m^3).

To model the cookstove for these known requirements several design parameters must be specified. The design parameters can be divided into two groups. The first group shown in Table 1 and depicted in Fig. 4 define the geometries of the stove. The second group, shown in Table 2 includes the thermal and material properties of the design. These parameters are used later in this section, in conjunction with excess capabilities, to create a numerical model of the cookstove.

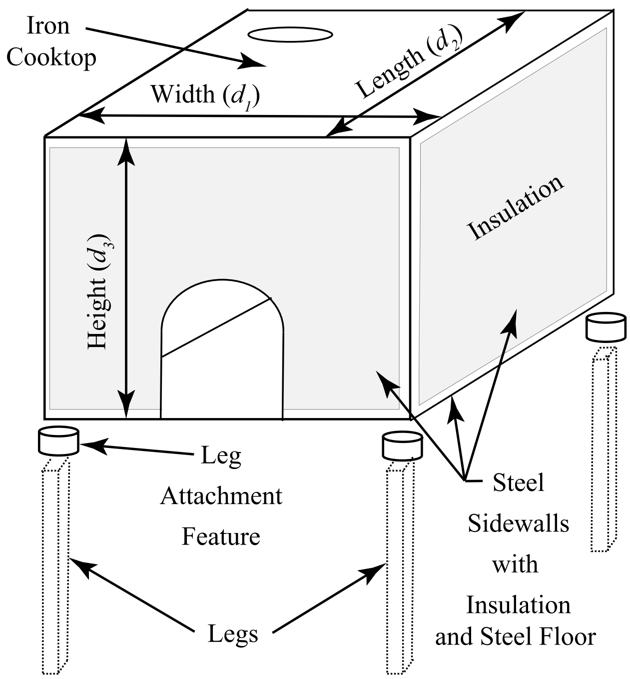


Fig. 4 Simplified model of the cookstove that will be optimized for flexibility and adaptability

4.1.2 Identify the uncertain requirements of the cookstove

The cookstove design described above, in Fig. 4, Tables 1 and 2, meets the known requirements. However, there is uncertainty in some assumptions and the future needs of the customers. Even if these requirements are adequate for the initial use of the stove, it is possible that the customers' needs may change in the future, and the cookstove will need to provide additional capability. If cookstove designers knew exactly what these future requirements were, they could simply redesign the entire stove to optimally meet those requirements. But in reality there is a large amount of uncertainty in predicting future requirements. Therefore, it would be advantageous to the designers if they could develop a sound base design that meets the current requirements, and then explore how excess could be added to enhance the cookstove's flexibility and adaptability. Thus, increasing the cookstove's chances of meeting both current and possible future requirements.

Four additional (potential) customer requirements have been selected to demonstrate the use of uncertain requirements in this example.

u_1: a larger cooking surface area
u_2: an ability to cook at higher temperatures
u_3: a larger combustion chamber, in which greater amounts of fuel can be inserted at one time
u_4: an ability to add legs to the cookstove.

These uncertain requirements can be described numerically using the design parameters (d) noted above and corresponding excess (x). Excess is not applied to most of the design parameters; however, excess will be required as follows

x_1: excess width of the cookstove
x_2: excess length of the cookstove
x_3: excess height of the cookstove
x_4: excess thickness of insulation
x_5: excess thickness of steel
x_6: excess material and attachment features to allow for the addition of legs (to elevate the stove off the ground).

Table 2 Thermal, material and cost properties of the cookstove

Thermal properties	
Energy of combustion (w)	2000
Temperature ambient (K)	303
Conduction	
Iron (w/m-K)	55
Steel (w/m-K)	35
Insulation (w/m-K)	0.04
Convection/radiation	
Cook surface (w/m^2 K)	20
Stove sides (w/m^2 K)	10
Stove bottom (w/m^2 K)	11
Densities	
Iron (kg/m^3)	7300
Steel (kg/m^3)	7850
Cost factors	
Iron ($/kg)	1.248
Steel ($/kg)	2.819
Insulation ($/m^3)	10.000

Table 1 Original cookstove dimensions

Original stove dimensions				
Width (d_1)	Length (d_2)	Height (d_3)	Insulation thickness (d_4)	Steel structure thickness (d_5)
0.3048 m (12 in.)	0.6096 m (24 in.)	0.3048 m (12 in.)	0.0 m	1.519e−3 m (16 ga. 0.060 in.)

For the remainder of this article, these six excesses are referred to as the design variables. It is important to note that all of these elements of excess are continuous variables except x_6, which is a discrete variable that can exist only in certain states. These states are described later in this section.

4.1.3 *Determine the probabilities associated with the uncertain requirements*

Probabilities are used in a numerical model of requirements that can be achieved through a change in the product during its service life. In this case, the addition of legs are a good example of an adaptation, which can be partially included during the initial design, and completed at some time after the product has been sold. It is an uncertain requirement. Therefore, the probability that legs will be required is set, as a rough estimate or starting point, at 70%. This assumption will be assessed and refined if necessary during Sects. 4.4–4.6.

4.1.4 *Develop the numerical model of the cookstove*

The equations for the uncertain requirements are determined using well-understood geometric or thermal relationships. To maintain focus on the technique presented herein the equations are summarized without derivation.

The first uncertain requirement is for a larger cook surface area (to accommodate a larger number or size of pot). It is a function of the cookstove width, length and the associated excess as shown below

$$u_1 = (d_1 + x_1)(d_2 + x_2) - (d_1)(d_2) \tag{6}$$

where u_1 is the increase in cook surface area. The original cookstove width and length are d_1 and d_2, respectively. The excess width and length are x_1 and x_2.

The equation for increasing the combustion chamber volume is similar.

$$u_2 = (d_1 + x_1)(d_2 + x_2)(d_3 + x_3) - (d_1)(d_2)(d_3) \tag{7}$$

where d_3 and x_3 are the original and excess cookstove height, respectively.

The equation for increasing the cook surface temperature (u_3) is much more complicated. It is a recursive function of the design parameters (d) including geometric, thermal, and material properties and the excess quantities (x). The actual equations used in the optimization and sensitivity analysis are presented in Sects. 4.3 and 4.4. However, because developing thermal models is not the focus of this paper and for brevity they are referred to here simply as

$$u_3 = \eta_3(x, d) \tag{8}$$

The last uncertain requirement, presence of legs (u_4), is discrete, as mentioned previously. This requirement is expressed as states of the cookstove as originally sold:

$$u_4 = \begin{cases} \text{State 0: no leg features} \\ \text{State 1: only increased steel structure thickness} \\ \text{State 2: increased steel structure thickness} \\ \qquad\quad\;\; \text{and mounting features} \\ \text{State 3: full leg implementation (increased steel} \\ \qquad\quad\;\; \text{structure, mounting features and legs)} \end{cases} \tag{9}$$

To attach legs to the cookstove, the states must occur in the order outlined above.

State 1 can only be designed-in as excess during the initial manufacturing of the stove, but states 2 and 3 can either be initially designed-in or retrofitted at some later time. If the additional steel thickness is not included initially in the design, then there is no possible way to retrofit at a later time and evolve to having legs.

Equations (6)–(9) represent a numerical model for the uncertain requirements of the cookstove.

4.2 Step 2: Determine the value functions, constraints, and confidence levels for the cookstove

The value of the excess capabilities applied to the cookstove is a function of the benefit perceived by the customer of the uncertain requirements minus the cost of the excess required to achieve them, as indicated in Eq. (3).

4.2.1 *Determine the benefit of the uncertain requirements*

Typically, the benefit of a particular uncertain requirement is determined from market studies or designer intuition. For this example, three types (or shapes) of benefit functions (or curves) are presented as representative typical of benefit functions. These equations are generally the result of some type of market research.

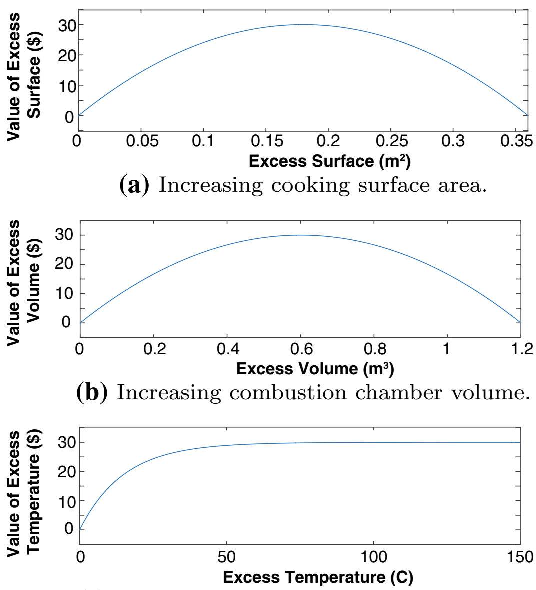
The benefit of increased cook surface area (b_1) is represented by an inverted parabola, which is translated upward and to the right (see Fig. 5a). The apex is the maximum benefit of increased cook surface area. The parabola is translated to the right until it intersects the origin (no benefit if no increase in cook surface area exists). A familiar parabolic form of the equation follows:

$$b_1 = -925.9(u_1 - 0.180)^2 + 30.00 \tag{10}$$

In this form the apex is easily located at (0.180, 30.00). This curve can also be expressed as a power series, which may be more convenient if the shape of the curve must be changed.

$$b_1 = 30.00u_1 - 925.9u_1^2 \tag{11}$$

The shape of the customer-perceived benefit curve for increased combustion chamber volume (b_2) is similar to



(a) Increasing cooking surface area.

(b) Increasing combustion chamber volume.

(c) Increasing cooking surface temperature.

Fig. 5 Customer-perceived benefit curves for **a** increased cooking surface area, **b** combustion chamber volume, and **c** cook surface temperature

that of increased cook surface area as shown in Fig. 5b. It can be expressed in the familiar parabolic form, with the apex at (0.600, 30.00):

$$b_2 = -83.33(u_2 - 0.600)^2 + 30.00 \tag{12}$$

It can also be expressed in the form of a power series as:

$$b_2 = 100.0u_2 - 83.33u_2^2 \tag{13}$$

The benefit of increasing cook surface temperature is represented for this example as a different shape. It is shown, in Fig. 5c as an exponential curve, which begins at the origin and proceeds up and to the right toward an exponential maximum.

$$b_3 = (-e^{-u_3/7.5} + 1)(30) \tag{14}$$

A power series approximation of the equation for the benefit of increased cook surface temperature is

$$\begin{aligned} b_3 =& 4u_3 - 2.667e^{-1}u_3^2 + 1.185e^{-2}u_3^3 - 3.951e^{-4}u_3^4 \\ &+ 1.053e^{-5}u_3^5 - 2.341e^{-7}u_3^6 \end{aligned} \tag{15}$$

The benefit of legs is represented by a relatively simple function. The expected value of legs is the product of the value of legs and the probability that they are required.

$$b_4 = p * \$30 \tag{16}$$

where p is the probability that legs will be required. In this example an estimate of $p = 70\%$ is used as a starting point. Sensitivity analysis discussed in Sects. 4.4 and 4.5 is used to evaluate if this estimate is sufficient.

In this example, the capability of having fully functional legs has a value of \$30. This is regardless of whether the legs are designed-in during the initial manufacturing, or if they are added on later during the cookstove's service life. But the expected benefit of having legs is dependent on the probability that the legs will actually be needed. Therefore, when optimizing the value of the cookstove, the benefit of having legs is computed using the Eq. 16.

As mentioned earlier, if the designer is uncertain about some of these factors, estimates can be used. These estimates are assessed in steps 4 and 5 (Sects. 4.4 and 4.5) to determine if they are adequate, or if they must be refined in step 6 (Sect. 4.6).

4.2.2 Determine the cost of the excess capability

There are trade-offs that come with increasing the amount of excess capability in any system. These trade-offs come in the form of increased costs required to implement the excess. In this example, the costs associated with increased cook surface (c_1), combustion volume (c_2) and cooking temperature (c_3) are modeled based on the increase in steel, iron, and insulation. The increase in material cost is calculated based on the design parameters (d), associated excess (x) and cost per unit mass of the material. The cost per unit of mass of these materials is presented in Table 2. Though this is a major simplification, it is well suited for demonstration purposes.

The cost of adding legs is dependent on whether each element of the legs is initially designed-in or retrofitted. It can cost more to retrofit the attachment features and leg extensions than it would be to include them in the initial design. The cost of adding legs is also dependent on the probability (p) that legs will be needed, and is described by the following equation:

$$c_4 = (c_e) + (p)(c_r) \tag{17}$$

where c_4 is the expected cost of legs, c_e is the cost of the designed-in elements and c_r is the cost of retrofitted elements. In this example, the cost to include the attachment features in the initial design is \$4 and to retrofit is \$8. The cost of the designed-in leg extensions is \$8 while purchasing them as a retrofit is \$12. The optimization performed in Sect. 4.3 determines the optimal state of the leg addition, based on the parameters and probability used in the model. Sensitivity analysis (Sect. 4.4) of the probability of legs being required provides insight into the probability at which the additional cost of retrofitted legs is justified.

The overall value of the product is determined using Eq. (3). The sum of the cost equations described above is subtracted from the sum of the benefit equations. The result is used as the value function in the optimization discussed in Sect. 4.3.

4.2.3 Determine the constraints that are applied to the optimization problem

For this cookstove example, the only constraint is that the maximum cost of adding the excess capabilities must be less than \$75 (i.e., $g \leq \$75$).

4.2.4 Determine confidence levels of assumptions

Many of the assumptions used in this example could be of low confidence. The designer must identify which factors (design parameters, constraints, benefit and cost factors) are based on low confidence assumptions. For this example, the following are identified as representative low confidence level assumptions.

1. Expressions for the benefits of uncertain requirements (b_1, b_2, b_3, and b_4), specifically the coefficients on each of the terms (12 assumptions—2 each in Eqs. (11), (13), and (16), and 6 in Eq. (15)). For example, p in Eq. (16), the probability that legs are required.
2. Initial stove dimension (3 assumptions—width, length, and height)
3. Combustion Energy (1 assumption, the energy supplied by the fire)
4. Maximum cost constraint (1 assumption, \$75).

These four sets (totaling 17 assumptions) illustrate a variety of low confidence assumptions. They can be categorized as low confidence in the: (i) perceived benefit of uncertain requirements, (ii) design parameters, (iii) operating or environmental conditions, and (iv) constraints. Several of these are used later in this example to show how sensitivity analysis can be used to identify the most critical low confidence assumptions.

4.3 Step 3: Perform numerical optimization on the cookstove

Now that the value function has been determined (based on the benefit and cost functions discussed in Sect. 4.2), the optimization can be performed to determine optimal excess capabilities using Eq. (5).

The optimization resulted in the addition of excess capability to address all four uncertain requirements (see Table 3). To achieve this excess capability the cookstove width, insulation thickness, and steel thickness are increased, and legs are added to the design (see Table 4). Figure 6 presents the original parameters of the cookstove and the optimized excess to be added. These results are typical of a variety of different original cookstove geometries.

At this point, two observations can be made. The graphical representation (Fig. 6) illustrates both of these observations. From the figure it can be seen that

1. Excess tends to be added to move the cookstove to a square footprint
2. Excess height is not added.

The tendency toward a square footprint is primarily the result of the thermal equations, which are attempting to maintain or increase the cook surface temperature, while minimizing heat loss through the other surfaces (i.e., minimizing the overall surface area of the cookstove). Thus, a square footprint is more thermally efficient.

The absence of excess height results from the fact that increasing width or length provides both cooking surface

Table 3 Optimization results for new capabilities

	Capability	Increase (%)
Optimized excess capability (maximum cost: \$75)		
Cooking surface area	$0.0921\ m^2$	49
Combustion chamber volume	$0.0281\ m^3$	49
Cooking surface temperature	62.5 K	30
Legs	Provided	n/a
Value (V)	\$42.64	

Table 4 Optimization results and the associated design parameters for the cookstove

	Optimal excess	Original dimension
Optimal design variable excess (maximum cost: \$75)		
Width (m)	0.1511	0.3048
Length (m)	0.0000	0.6096
Height (m)	0.0000	0.3048
Insulation thickness (m)	0.0094	0.0000
Legs attributes		
Steel thickness (m)	2.278e−3	1.519e−3
Attachment feature	Yes	No
Legs provided	Yes	No

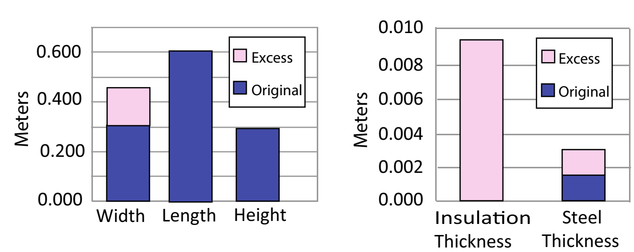


Fig. 6 Original and excess design parameters optimized for value

and combustion chamber benefit, while increasing the height only provides combustion chamber volume benefit. It also negatively impacts the cook surface temperature. The value of increasing width and length is greater than the value of increasing height. Clearly all six design parameters are tightly connected in this example.

4.4 Step 4: Perform sensitivity analysis on the cookstove

Sensitivity analysis provides additional insights into the optimization. It identifies which assumptions have the greatest affect on the optimized value of the cookstove. Assumptions with high sensitivity and low confidence can be targeted for further study to improve the confidence level. Assumptions in quadrants 1, 2, and 3 of Fig. 1 do not merit further study at this point. This sensitivity analysis is especially valuable when gathering information about assumptions is difficult or expensive, as it is in the developing world. It allows the designer to strategically invest in only improving the most critical assumptions. Sensitivity analysis can be performed by several techniques (e.g., gradients, partial derivatives or sensitivity curves). In practice sensitivity analysis is performed on all low confidence assumptions. In this example, 17 assumptions are identified as low confidence. To clearly illustrate the algorithm and for brevity only five of these assumptions are analyzed in detail here. These five assumptions represent each of the four types of assumptions described in Sect. 4.2. They are:

1. Perceived benefit of uncertain requirement:
   - Maximum benefit of increased cooking surface area
   - Probability that legs are required (p)
2. Design parameters: initial cookstove dimensions (width and length)
3. Operating condition: combustion energy
4. Constraint: maximum added cost.

In this example, sensitivity curves are plotted for the high-sensitivity, low confidence assumptions. The sensitivity analysis revealed that the optimization is not sensitive to

1. Combustion energy (energy supplied by the fire). 50% change in the combustion energy assumption results in ≤0.7% change in the value
2. Initial cookstove dimension (width, and length). 20% change in the initial cookstove dimensions results in ≤1.7% change in the value (see Fig. 7).

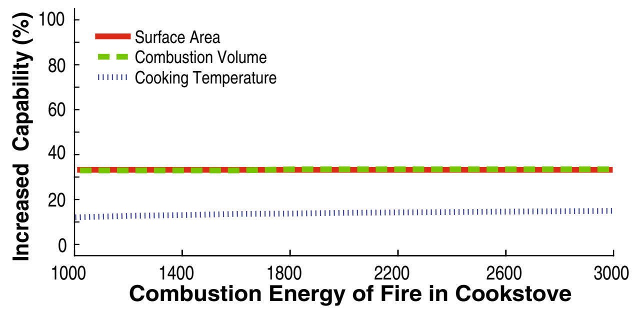


Fig. 7 Combustion energy assumption. To observe the sensitivity of the optimization to the combustion energy, the assumption is varied by ±50%. Changes in the normalized increase in cookstove capabilities are indicated by the *vertical axis*

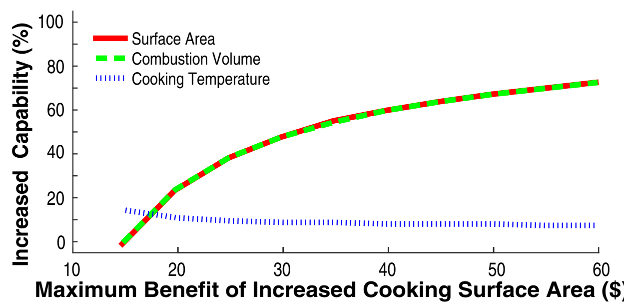


Fig. 8 To observe the sensitivity to maximum of the benefit of increased cooking surface area, the maximum benefit is varied from $15 to $60. Changes in the normalized increase in cookstove capabilities are indicated by the *vertical axis*

However, the value of the optimized product is sensitive to

1. Maximum benefit of increased cooking surface area
2. Maximum cost constraint
3. Probability that legs are required

which are discussed below (see Figs. 8, 9, and 10).

4.4.1 Determine the sensitivity to the maximum benefit of increased cooking surface area

The sensitivity of the optimization to the assumed maximum benefit of increased cooking surface area is depicted in Fig. 8. The analysis indicates that the optimized excess cooking surface area and combustion chamber volume are sensitive to this assumption. The excess cooking surface temperature is much less sensitive to this assumption. Therefore, the assumption of the maximum benefit of increased cooking surface area has been identified as a candidate for further refinement.

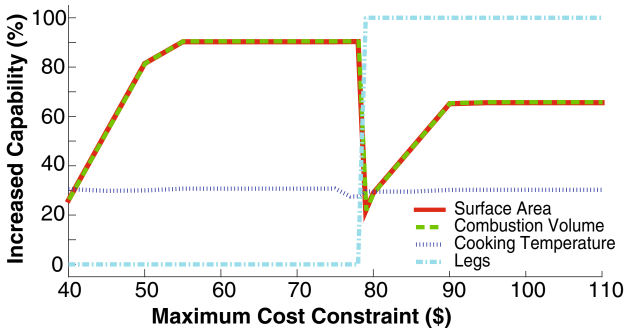


Fig. 9 To observe the sensitivity to maximum cost constraint, the constraint is varied from \$40 to \$110. Changes in the normalized increase in cookstove capabilities are indicated by the *vertical axis*

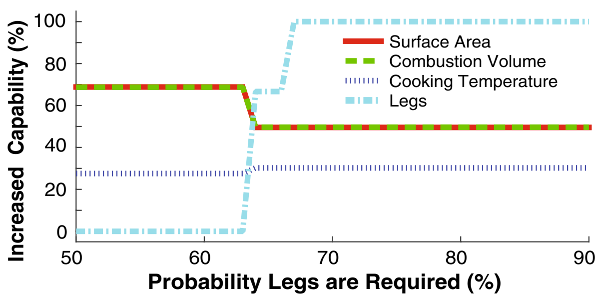


Fig. 10 To observe the sensitivity to the probability that legs are required, the probability is varied from 50 to 90%. Changes in the normalized increase in cookstove capabilities are indicated by the *vertical axis*

4.4.2 Determine the sensitivity to the maximum cost constraint

A sensitivity analysis of the maximum cost constraint provides interesting results regarding discrete variables (see Fig. 9). Observe the variation in the increased capability as a function of the maximum cost constraint. As the maximum cost constraint increases (from \$40), the cooking surface area and combustion chamber volume also increase, reaching a constant level of \$90 at \$55. The discrete leg capability is excluded until the maximum cost constraint is sufficiently high to accommodate its cost. Once the maximum cost constraint reaches \$79 state 3 of the leg option becomes possible and the optimization shifts to enable it. States 1 and 2 of the leg option are not included because the probability of legs being required is set high enough (70%) that the incremental cost of retrofitting legs is not justified (see Fig. 10). As a result of the addition of legs, at \$79 the cooking surface area and combustion chamber volume drop from 90 to 18% of increased capability. As the cost constraint continues to increase, the area and volume begin to increase, ultimately reaching a constant level of 66% at \$90 . Beyond \$90, the constraint is not active and the maximum value is \$48.43. This is 13% greater than the \$42.64 value achieved when subject to a \$75 cost constraint.

4.4.3 Sensitivity to the probability that legs are required

A study of the sensitivity to the probability that legs are required reveals that the optimization is sensitive to this assumption. Figure 10 illustrates that the optimization is sensitive to the probability that legs are required in the range from $63\% \leq p \leq 68\%$. However, outside this range there is no sensitivity to the probability that legs are required.

4.5 Step 5: Assess the sensitivity and confidence levels on cookstove

Comparing the sensitivity results discussed in Sect. 4.4 with the confidence levels recorded in Sect. 4.2, reveals that two assumptions should be considered for further study to achieve higher confidence levels.

1. Maximum benefit of increased cooking surface are
2. Maximum cost constraint
3. Probability that legs are required.

4.6 Step 6: Improve confidence of specific cookstove assumptions

Once the confidence levels have been improved on the low confidence assumptions, the steps are repeated. This process is continued until no assumptions are detected with high sensitivity and unacceptably low confidence level (see Eq. (4)). The result is a cookstove optimally designed for flexibility and adaptability based on known and uncertain requirements.

The sensitivity analysis identified critical assumptions for further study. It also provided insight into what might be done to alleviate the impact of these assumptions. For example, as seen in Fig. 10, the optimization is only sensitive to the probability that legs are required between 63–68%. If the designer is confident that the probability falls outside this range the assumption can be removed as a concern and no further study is required. An important part of improving the confidence level of the assumptions is often to note the ranges in which the optimization is insensitive to a particular assumption.

4.7 Concluding observations of the cookstove example

This example demonstrates that the technique presented in this paper can be applied to a product (cookstove) to increase its flexibility and adaptability, in the presence of uncertainty. The optimization for excess capability is performed using estimates for the uncertain parameters and assumptions. Sensitivity analysis identifies the most critical assumptions for further study and refinement. In this example, all four of the uncertain requirements are achieved by including some level of excess capability (see Tables 3, 4). Sensitivity analysis determines that the optimization is sensitive to two of the uncertain requirements, i.e., maximum cost constraint, and the probability that legs are required. In addition to identifying these two uncertain requirements as critical, regions are identified where the optimization is not sensitive to either of them. Once these requirements (as well as other low confidence assumptions) have been studied and refined the algorithm is repeated until the current confidence level of the critical requirements is greater than the required confidence level (see Eq. (4)). The result is a flexible and adaptable design.

5 Concluding remarks

In this paper, a technique is presented for designing products in the presence of uncertainty. It is specifically aimed at improving the success of products designed for the developing world. The technique optimally determines the amount of designed-in excess and resulting flexibility and adaptability necessary to respond to uncertain requirements and design parameters. The impact of these uncertainties is further reduced by a prioritization and refinement process which utilizes sensitivity analysis.

An important aspect of the technique is that it provides a time- and resource-efficient technique for dealing with uncertainty. It is recognized that designers face many uncertainties during the design process, especially when working in a developing world setting. Uncertainties frequently exist with the product requirements and the evaluation of users perception of benefits. Other areas of uncertainty are the product design parameters. This technique allows designers to begin a design with estimates for unknown or uncertain parameters. The most sensitive of these estimates are identified and refined. As a result of the technique designers focus time and resources only on refining the assumptions that will have a significant impact on the value of the product.

There are several ideas presented in this paper that merit further study. First, the idea is presented that excess capability can contribute to increased success rates and prolonged service life of a product in two distinct ways. It can be used to increase the flexibility and adaptability of the product to meet unforeseen requirements as designed. It can also be employed to enable in-service adaptations of the product to address changing requirements. There are two questions for further study. How should these two different types of excess capability be employed? What factors determine which type of excess should be employed in a particular design?

A second area involves the coupling between benefits. For example, two benefits may be mutually exclusive or one benefit may depend on the presence of another. The question then follows, what impact do coupled benefits have on the value function, benefit or cost equations? Do they need to be modified to facilitate analysis of coupled benefits?

A study of the application of the technique to actual development projects is a third candidate for further study. The cookstove example presented in Sect. 4 is a simplified example intended to demonstrate the technique. While it is based on parameters similar to stoves being produced in the developing world, it is not a case study. An extensive case study with comparative data would be an excellent opportunity for further study.

The last area for further study involves uncertainty in functions, which are used in the numerical model of the product (e.g., customer-perceived benefits). It has been proposed that expressing these functions in the form of power or Fourier series allows the shape of the functions to be completely altered by adjusting the coefficients of the individual terms. In the example, the benefit functions are represented using a power series. Further study should address the question; what form should be used when expressing completely uncertain functions, a power series, Fourier series or some other form? Answers to these questions will strengthen this technique.

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