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SIMULATING VARIABILITY OF REWORK COST AND MARKET PERFORMANCE ESTIMATES IN PRODUCT REDESIGN

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ABSTRACT
When considering the redesign of an existing product, designers must consider possible engineering and marketing ramifications. Ideal changes capture a large portion of the market and have a low risk of change propagation that results in reduced cost to the manufacturer. Engineering change tools such as the Change Prediction Method and market research models such as Hierarchical Bayes Mixed Logit allow designers to estimate the cost of the redesign process and market shares of preference. Variability in the inputs of the Change Prediction Method (impact and likelihood values) results in a range of redesign cost values. Assumptions regarding model form and the randomness used in model fitting also lead to variations when estimating market performance. When the variability associated with these techniques is considered, focus should shift from a point-estimate to a region-estimate. This paper explores the region-estimate produced for proposed redesigns when considering rework cost and market share of preference.

INTRODUCTION
In response to customer heterogeneity, designers may be tasked with the redesign of an existing product. Depending on the designers and the existing product, a large number of redesign options may be generated. The ideal candidate may cost the least to manufacture and be the most popular in terms of market performance. Predicting cost and market share requires the combination of existing design tools. The Change Prediction Method (CPM) [1] quantifies the risk of a change propagating through a system. This risk value is a term in the formula used to estimate product cost. Discrete Choice Analysis (DCA) can be used to predict the market response to a redesigned product. Through the implementation of these tools, the selection of the ideal redesign option may appear straightforward.

Figure 1 provides a sample tradeoff plot for 5 hypothetical redesign options for the existing product. As an ideal case, the clear redesign option for embodiment is Option A as it diverts the greatest amount of market preference and costs little to redesign. Conversely, Option E diverts little of the competitor market share of preference and is the most expensive option to produce. Option D and Option C provide an example of a tradeoff between cost and market share of preference.

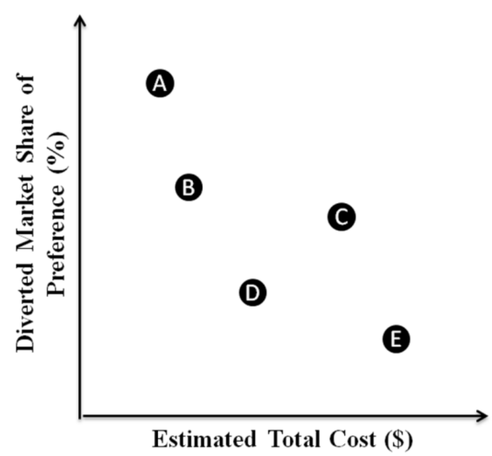

Figure 1: Redesign Option Tradeoff Plot

Unfortunately, Figure 1 does not tell the entire story. The CPM requires a designer to provide estimates of impact and likelihood values. As subjective estimates, the risk profile of the expert may lead to more conservative or liberal input estimates. Further, no formal method exists to verify the accuracy of the input values and the resultant combined risk value.

From a market analysis perspective, the estimated market preference calculation is subject to the accuracy of survey responses and the estimation technique used to fit the coefficients of the market model. When variability in input values to the CPM and of the part-worth estimates for the market model are considered, the point estimates from Figure 1 transition into range estimates shown in Figure 2.

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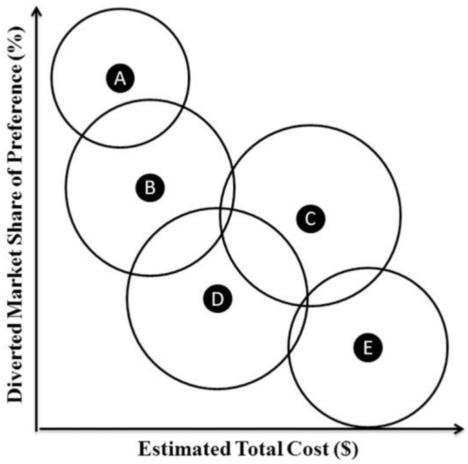


Figure 2: Redesign Option Variability Tradeoff Plot

In Figure 2, Option A is no longer the clear redesign option for selection and embodiment. While the potential exists for Option A to cost the least and capture the market share from the competitor, there is a chance that Option B may cost less and capture more share. Once again, Option E can be discarded as even the cheapest cost and highest diverted market share of preference is beat by the most expensive and smallest diverted market share of the other options.

This paper expands on the basic example provided in Figure 2 by considers the effects of variability in engineering redesign and market analysis when exploring redesign option selection. Further, implementing the market analysis and engineering tools are considered in the context of the validation criteria introduced by Olewnik and Lewis for design decision support frameworks [2].

BACKGROUND

Prior work conducted in [3] provides a procedure for exploring the tradeoffs associated with a set of redesign options in terms of market desirability and engineering cost. As an extension of the work in [3] this research occurs at the intersection of engineering redesign and market analysis. The following subsections provide the relevant background information for each of the subject areas.

Engineering Redesign

Engineering change is defined as 'changes to parts, drawings or software that have already been released during the product design process, regardless of the scale of the change' [4]. The study of engineering change is increasing in importance as nearly all 'new' products stem from earlier designs [5] [6]. Studies involving engineering change have determined changes later in the design process impact projects to greater extent [7]. Therefore, it is important to identify possible changes as early as possible.

Several tools exist for identifying changes during a redesign. Early work in engineering change management involved the use of Design Structure Matrices (DSMs) [8] [9]. When using a DSM designers must decompose a system into subsystems that become the titles of the rows and columns. The column headings depict initiating subsystems and the row headings indicate affected subsystems. An interaction between subsystems is marked, generally with an 'X'. A DSM depicts the direct interactions between subsystems and possible paths in which a change may travel and affect other subsystems, or propagate.

Formally, change propagation is defined as the process in which a change to one part of an existing system results in a change to another part of the system that would not have otherwise occurred [10]. Often, change propagation is studied in terms of risk, as a change does not necessarily propagate to each and every possible subsystem. Several techniques to quantify the risk of change propagation have been proposed including: Change Favorable Representation (C-FAR) [11], Change Prediction Method (CPM) [1], a Matrix Based Algorithm (MBA) [12] and RedesignIT [13].

The CPM is the risk quantification tool of choice for this research. In change propagation research, risk has been defined as the probability or likelihood of occurrence times the impact of occurrence [14]. When using the CPM, likelihood is defined as the average probability that a change in one subsystem results in a change in another subsystem through a direct connection. Impact is the average portion of the design rework that must be redone upon change propagation occurring [1].

There are four general steps required to implement the CPM. The first step requires decomposing the subsystem into no more than 50 subsystems as recommended by [1] to balance the level of detail and computational complexity. In the second step, the DSM is generated to depict direct interactions between subsystems. Third, each 'X' in the DSM is replaced with an impact and likelihood value. Generally, system experts are called upon to generate these values. The average of the likelihood values is used to replace the 'X' in the likelihood matrix and the average of the impact values is used to replace the 'X' in the impact matrix. Finally, Eq. (1) is used to calculate the combined risk matrix which gives the risk of a change propagating between two systems regardless of whether or not a direct connection exists. In Eq. (1), $R_{b,a}$ is the combined risk of a change propagating from subsystem A to subsystem B, $\rho_{b,u}$ is the risk of a change propagating from Subsystem U to Subsystem B where Subsystem U is the penultimate subsystem in the path from Subsystem A to Subsystem B, $\sigma_{u,a}$ is the likelihood of a change reaching Subsystem U from A, $l_{b,u}$ is the direct likelihood of a change propagating from Subsystem U to Subsystem B and $i_{b,u}$ is the direct impact of a change propagating from Subsystem U to Subsystem B.

$$R_{b,a} = 1 - \prod (1 - \rho_{b,u})$$

Where (1)

$$\rho_{b,u} = \sigma_{u,a} l_{b,u} i_{b,u}$$

Figure 3 depicts the general process of the CPM. The system is broken down into 4 distinct subsystems and the direct interactions are marked in the DSM. After building the DSM, the 'X's are replaced with expert provided average impact and likelihood values. Once both the direct likelihood and direct impact matrices are generated, the combined risk matrix is calculated using Eq. (1) or a software tool such as the Cambridge Advanced Modeller [15].

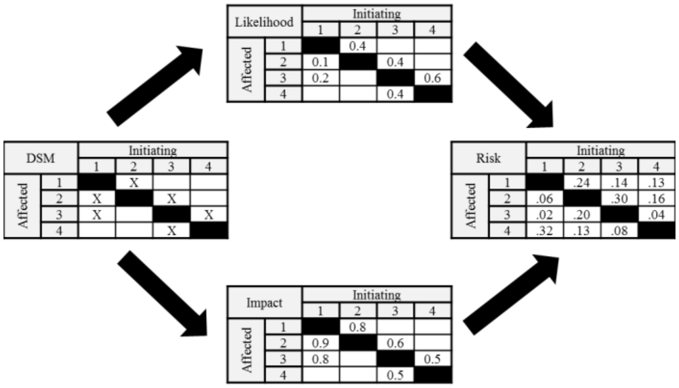


Figure 3: CPM Process

Prior work exploring the sensitivity of the CPM has produced mixed results. In [5], Clarkson et al. perturb each impact and likelihood value by 20%. They note the subsystems with the highest risk do not change in terms of rank ordering and remaining subsystems that change rank position do so in small groups. Further work applies a standard deviation of 0.05 to compare the use of the CPM with the use of Monte Carlo methods. The results indicated that in an actual product redesign, the CPM accurately predicted propagation of changes in the highest ranked subsystems [7]. However, in [16], the conclusions suggest the variability in rank is dependent on the number of uncertain interactions and the range of uncertainty within those interactions.

The combined risk matrix can be used to calculate the estimated total cost of a redesign. A redesign that produces a high risk of changes in multiple subsystems will cost more than a redesign option that affects only one subsystem. The documented changes in the combined risk matrix that are a result of changed input values to the CPM will vary the estimated total cost.

Market Analysis

The overarching goal of product family design is to "design and develop a family of products with as much commonality between products as possible with minimal compromise in quality and performance" [17]. This design methodology arose in response to the desire to offer products that meet the ever changing [18], heterogeneous needs of the market [19] while maintaining a competitive advantage. Another design method is the match-to-order approach, where consumers select the product from a set that most nearly meets their needs. This approach removes the ability of the consumer to select the desired options as is present in product family design [20].

A challenge associated with the use of product family design and match-to-order approaches is the task of obtaining consumer needs and selecting the redesign most capable of fulfilling those needs. Ideally, a product will meet the needs of the consumer on a functional, emotion and anthropological level [21]. Broadly stated, there are 4 different approaches to meeting and gathering consumer needs. The first involves an open dialog between a company and consumers in which consumers express needs and select products to identify their stated needs. The second allows consumers to alter the product themselves. Third, the same product is represented differently to consumers. The fourth and final approach monitors the use of products and uses that information to produce redesigned products without explicitly notifying the consumer that the product is redesigned to meet his or her needs [22].

Methods for using the open dialog approach to gathering customer needs involves searching though previously collected data, conducting focus groups or personal interviews, mail or phone surveys and conjoint analysis/discrete choice analysis [23] [24]. Discrete choice analysis provides a survey-taker with a set of choice task questions to answer. In each choice task, a set of product profiles and a 'none' option are presented [23]. A respondent then chooses the product that they prefer the most for each choice task question. These results are then aggregated across the population of respondents, and market research models forms – multinomial logit, hierarchical Bayes mixed logit, etc. – can be selected as a foundation for estimating respondent part-worths for the features and attributes considered in the survey. From these part-worth estimates, the market-level share of preference for a product can be estimated using a market simulator [25].

The Hierarchical Bayes mixed logit (HB) model allows for respondent-level part-worths to be estimated from the choice task questions answered. In this work, Sawtooth Software's CBC/HB Model is used to estimate the part-worths [26]. The HB model assumes individual part-worths are characterized by a multivariate normal distribution, and the probability of choosing a particular product configuration is governed by a multinomial logit model [25]. The distribution for calculating the individual part-worths is given in Eq. (2) where β_i is the vector of part worths for respondent i, α is a vector of means of the distribution of part-worths of the individuals and D is a matrix of variances and covariances of the distribution of part-worths.

$$\beta_i \sim Normal(\alpha, D) \tag{2}$$

To obtain values for β, α and D, an iterative approach is used where each iteration consists of a 3 step process. First, the current estimates of β and D are used to generate a new estimate for α where α is assumed to have a normal distribution with the mean equal to the average of β and a covariance matrix equal to D divided by the number of respondents. Second, using the inverse Wishart distribution a new estimate of D is gathered from the present estimates of α and β. Third, using the Metropolis Hasting Algorithm, a new estimate of β is generated using the present estimates of α and D. This process repeats for several thousand iterations to ensure convergence. After convergence, the process continues. Estimations are saved and averaged to produce the final part-worth estimates for each individual [25].

VARIABILITY

The basis for this work involves exploring how the combination of outputs in the CPM (used to calculate rework cost) and the HB model (used to calculate market share of preference) vary due to the information used as inputs or the approximation methods used to estimate the outputs. This section discusses the sources of variability and highlights the possible impact.

Rework Cost

The equation for calculating the estimated total cost (ETC) of a redesign is given in Eq. (3) [27].

$$ETC_{k,i} = \sum_{j=1}^{N} fix_j + rework_{k,i} + \sum_{\substack{j=1 \\ j \neq i}}^{N} rework_j (E_{k,i\to j})(r_k(i \to j)) \tag{3}$$

In Eq. (3), N is the total number of subsystems, fix_j is the cost of subsystem j, $rework_{k,i}$ is the cost to change subsystem i to offer redesign option k, $rework_j$ is the estimated cost to change subsystem j, $E_{k,i\to j}$ is the estimated number of changes initiated by subsystem i on subsystem j in order to offer redesign option k and $r_k(i \to j)$ is the risk of a change in subsystem i creating a change in subsystem j as a result of offering redesign option k. For the purposes of this work, $E_{k,i\to j}$ is held at 1 for all changes as is consistent with [3]. With the exception of the $r_k(i \to j)$ term, all terms in Eq. (3) are held constant. Annex A contains each of these values.

The CPM produces a combined risk matrix that depicts the risk of a change propagating from one subsystem to another [1]. When calculating the estimated total cost of a product with redesign option k, the $r_k(i \to j)$ term is extracted from the combined risk matrix of the CPM [3]. However, the impact and likelihood matrices, which are used to calculate the combined risk matrix, are subject to variability in input as the values are collected from product experts. These values range between 0 and 1 in increments of either 0.1 or 0.05. For the purposes of this study, the impact and likelihood values are rounded to the tenths place as is consistent with existing literature on the CPM [3] [1] [5] [7].

Figure 4 is an outcome of prior work using a Monte Carlo simulation to analyze the change in combined risk values and the associated rank ordering of the cells within the combined risk matrix. The baseline combined risk value was 0.18 when expert input data was assumed for the impact and likelihood matrices. When these inputs were slightly varied, the mean and standard deviation of the combined risk value was 0.18 and 0.03, respectively. As the percentage of uncertain impact and likelihood matrix elements and level of uncertainty associated with the input value increased so too did the standard deviation of the combined risk values [16].

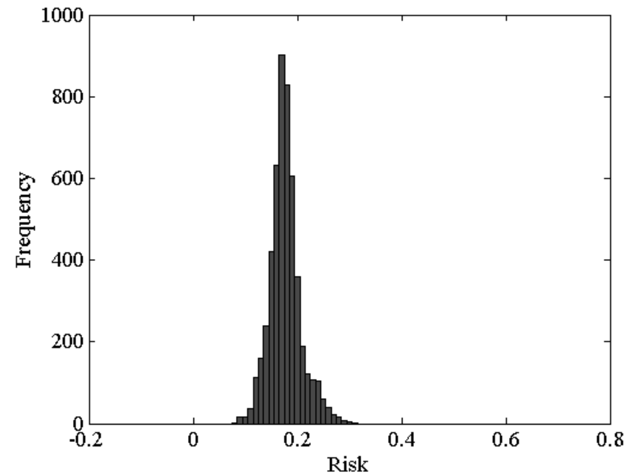


Figure 4: Frequency of Combined Risk Value when 50% of Impact and Likelihood Values are Altered by 0.1 [16]

To demonstrate the effect of variability in the impact and likelihood values on the estimated total cost, Table 1 displays the change in estimated total cost stemming from different values in the combined risk matrix. Three variability cases are depicted and the estimated total cost associated with each set of values for the desk fan case study introduced in the next section. From Table 1 a decrease in combined risk value is associated with a smaller estimated total cost. The variability in estimated total cost from the three evaluations poses a problem for designers and manufacturers. Given that the overall objective is increased profit, one method to accomplish this is to reduce manufacturing cost [28]. For the example given in Table 1, the approximately $0.50 difference between the highest and lowest estimated total cost may or may not be significant to manufacturers. However, when considered on a larger scale and combined with the profit margin associated with the product, the difference in estimated total cost may become significant.

Table 1: Effect of CPM Variability on Estimated Total Cost

		Initiating Subsystem		
		2	2	2
Affected Subsystem	1	0.06	0.02	0.12
	2			
	3	0.05	0.03	0.10
	4	0.03	0.01	0.03
	5	0.04	0.02	0.05
	6	0.03	0.02	0.07
	7	0.02	0.01	0.04
	8	0.03	0.02	0.06
	9	0.04	0.02	0.07
Estimated Total Cost		$15.83	$15.63	$16.10

Table 2: Part-worth Estimates for a Selected Respondent

	Brand				Performance			Price			
Draw	High Flyer Pro	Magnum Force	Eclipse	Long Shot	+5 yards	+10 yards	+15 yards	$4.99 for 3	$6.99 for 3	$8.99 for 3	$10.99 for 3
1	1.4585	0.8736	-1.2453	-1.0868	-1.4946	0.2725	1.2221	2.6544	0.54299	0.5428	-3.7402
2	1.3394	0.8562	-1.1751	-1.0205	-1.5586	0.3412	1.2174	2.0755	0.53922	0.5390	-3.1538
3	1.9169	0.2574	-0.7032	-1.4711	-1.4301	0.2215	1.2086	2.1646	0.48437	0.4842	-3.1332

Market Share of Preference

To calculate the market share of preference of a given product or set of products, Eq. (4) is used [23].

$$MSP_l = \frac{\sum_{i=1}^{N} p_i^l}{N} \tag{4}$$

In Eq. (4), MSP_l is the market share of preference for product profile l, N is the number of respondents and p_i^l is the individual share of preference of the i^{th} respondent. Before calculating the market share of preference, the share of preference at the individual level p_i^l, must be calculated. To obtain these values, part-worth estimates from Sawtooth Software's CBC/HB Module are generated and a market simulator must be created [26].

The formulation of the HB model is built around an assumption that the part-worth estimates of the survey respondents resemble a multivariate normal distribution using a covariance matrix and a vector of means. The HB model further assumes individual respondent preferences are governed by a multinomial logit model [25]. Individual respondent preferences are estimated at the attribute level. That is, each level within each attribute is given a part-worth value where the sum of the part-worths for each attribute is equal to 0 [26]. Equation (5) is used to calculate the individual share of preference where the $\sum_j x_{ijk}\beta_j$ term represents the summing of the individual part-worths corresponding to the attributes and levels within a given product configuration.

$$p_i^l = \frac{e^{\sum_j x_{ijk}\beta_J}}{\sum_{k=1}^{K} e^{\sum_j x_{ijk}\beta_J} + e^{V_{i,none}}} \tag{5}$$

When sampling repeatedly from an HB estimation, the recommended procedure involves using the draws [25]. After the recommended number of iterations to estimate the β, α and D values, further iterations are completed and saved. In opposition to averaging the saved iterations to get a set of point estimates (where the standard deviation and covariance between the part-worths can be used to explore variability in estimation), the individual draws themselves can be used. Since each draw or iteration is an estimation at the market-level, slight variability exists within the part-worth estimates for each respondent. For example, Table 2 depicts the part-worth estimates for three consecutive draws using a golf ball as an example.

To demonstrate the variability in market share of preference for each draw, two product configurations are generated. Eq. (5) is used to calculate the individual share of preference for each draw and Eq. (4) is used to calculate the market share of preference. Table 3 depicts the variability in market share of preference resulting from the use of draws. While only a small example, the average market share of preference for product 1 and product 2 across the draws is 37% and 69%, respectively. The corresponding standard deviations are 7% and 12%. The wide standard deviations within the market share of preference values suggest there exists significant variability within the market wide preference of a given product configuration. Designers and manufacturers must consider these standard deviation values when deliberating between which product configurations to offer. The smaller the standard deviation, the better chance manufacturers have of producing a product with the average market share of preference. The risk profile of the manufacturer plays a large role in the product configuration decision making process. Risk averse manufacturers will select options with smaller standard deviations while risk prone manufacturers will take chances with larger standard deviations.

Table 3: Sample Product Configurations

	Configuration	Draw 1 MSP	Draw 2 MSP	Draw 3 MSP
Product 1	Eclipse, +5 yards, $6.99 for 3	45%	33%	34%
Product 2	High Flyer Pro, +10 yards, $10.99 for 3	55%	77%	76%

DEVELOPING AN EXAMPLE PROBLEM

To demonstrate the effect of variability in the outputs of CPM and the Hierarchical Bayes mixed logit model, the Lasko desk fan case study from [3] is used. The initial step in risk quantification requires the decomposition of the fan into 9 subsystems as shown in Figure 5.

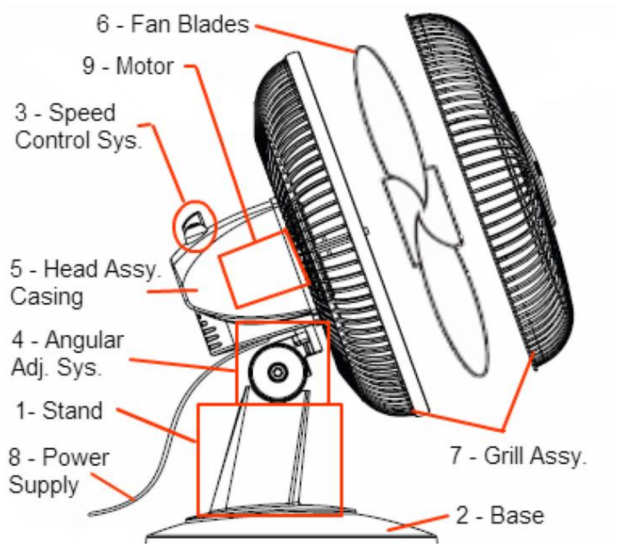


Figure 5: Desk Fan Decomposition

Following the steps of the CPM, after decomposition into subsystems, interactions were depicted using a DSM and are displayed in Table 4.

Table 4 : Desk Fan DSM

DSM		Initiating Subsystems								
		1	2	3	4	5	6	7	8	9
Affected Subsystems	1		X		X			X		
	2	X						X		
	3					X			X	X
	4	X				X		X		
	5			X	X			X	X	X
	6							X		X
	7	X			X	X	X			
	8			X		X				X
	9			X		X	X		X	

The associated impact and likelihood values are given in Table 5 and Table 6.

Table 5: Desk Fan Likelihood Matrix

Likelihood		Initiating Subsystems								
		1	2	3	4	5	6	7	8	9
Affected Subsystems	1		0.3		0.4			0.2		
	2	0.4						0.3		
	3					0.2			0.8	0.6
	4	0.1				0.4		0.4		
	5			0.2	0.2			0.4	0.4	0.8
	6							0.6		0.8
	7	0.2			0.3	0.3	0.6			
	8			0.2		0.2				0.6
	9			0.4		0.5	0.8		0.6	

Table 6: Desk Fan Impact Matrix

Impact		Initiating Subsystems								
		1	2	3	4	5	6	7	8	9
Affected Subsystems	1		0.2		0.3			0.3		
	2	0.3						0.2		
	3					0.2			0.8	0.5
	4	0.2				0.3		0.3		
	5			0.2	0.2			0.3	0.4	0.6
	6							0.5		0.6
	7	0.2			0.2	0.2	0.2			
	8			0.4		0.5				0.5
	9			0.6		0.7	0.6		0.6	

Using Eq. (1), the combined risk matrix was calculated and is given in Table 7. The values in Table 7 are substituted into Eq. (3) to produce the estimated total cost. The diagonal of the combined risk matrix is marked out as the risk of a change propagating to itself is 1.

Table 7: Desk Fan Combined Risk

Risk		Initiating Subsystems								
		1	2	3	4	5	6	7	8	9
Affected Subsystems	1		.06	.11	.15	.13	.17	.16	.19	.18
	2	.13		.08	.09	.10	.12	.12	.14	.13
	3	.15	.05		.31	.52	.60	.50	.74	.64
	4	.07	.02	.16		.19	.24	.23	.27	.26
	5	.10	.03	.34	.19		.50	.38	.55	.59
	6	.11	.04	.37	.24	.43		.42	.57	.57
	7	.05	.01	.13	.10	.16	.20		.22	.20
	8	.09	.03	.27	.19	.34	.39	.32		.42
	9	.13	.04	.39	.27	.52	.56	.45	.62	

To implement the HB model, 10 attributes were determined for the desk fan and the levels within the attributes were further identified. A complete breakdown of the attributes and levels is given in Annex A. Using the redesign options generated in [3], a discrete choice survey was fielded and the individual part-worths for each redesign option and respondent were estimated. Annex A contains the entire list of potential redesign options developed. Note, the noise, weight and price attributes are not considered in the suggested 23 redesign options. Weight and noise are functions of the other attributes levels and price is a function of redesign cost.

METHODOLOGY

An initial step in the evaluation of the effect of variability within the market analysis and engineering redesign models is identifying the product configurations/systems for exploration. After market scenario selection, the variability within the estimated total cost and market share of preference calculations can be considered. Figure 6 outlines the general procedure for investigating the variability within the individual respondent part-worths and the expert provided impact and likelihood terms.

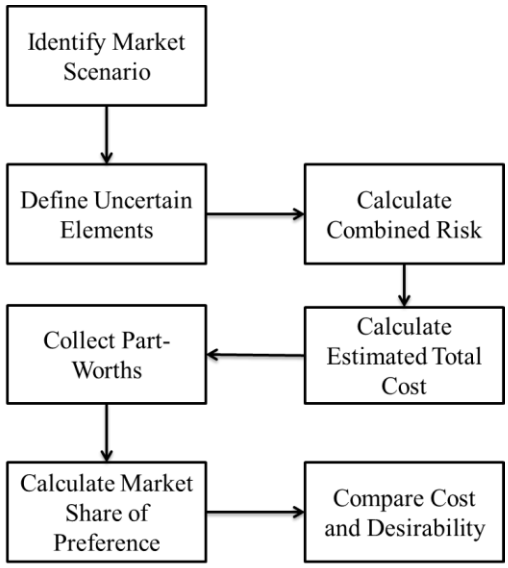


Figure 6: Sensitivity Analysis Procedure

Identify Market Scenario
A common strategy for market analysis suggests the removal of the "none" option and the insertion of competitor products in its place. For this reason, we introduce 3 competitor products to the study. The first competitor product is the MaxxAir 8" USB Desk Fan. In terms of the attributes developed in [3], the MaxxAir fan has 8" blades, a flat base, 1 speed setting, a 3.6 foot power cord, weighs 2 pounds, moves 0 degrees in the horizontal direction, moves 90 degrees in the vertical direction, is considered a custom color, produces 46 decibels and is retail priced at $22.99 [29]. Keystone's 6" USB Desk Fan is selected as the second competitor product. The fan has 6" blades, a flat base, 5 speed settings, has a 6 foot power cord, weighs 1 pound, moves 0 degrees in the horizontal direction, moves 15 degrees in the vertical direction, is black, produces 44 decibels and is priced at $44.99 [30]. The third and final competitor product is Ozeri's Brezza 10" Oscillating High Velocity Desk Fan. The fan has 10" blades, a flat base, 3 speed settings, has a 6 foot power cord, weighs 5 pounds, moves 90 degrees in the horizontal and vertical directions, is black, produces 48 decibels, and is priced at $37.95 [31]. Since typical installation guides do not provide noise levels for the competitor products, the noise level guide in [3] is used to calculate the noise levels. A static market is assumed to demonstrate variability effects stemming from the tools implemented.

Estimated Total Cost
To calculate the estimated total cost, the number of uncertain interactions in the DSM must be determined. For the purposes of this study, 50% of the DSM interactions are deemed uncertain. The uncertain values are allowed to vary by ±0.1. This value stems from the belief that experts are unlikely to provide impact and likelihood values to more than one decimal place. From the altered impact and likelihood matrices, an updated combined risk matrix is calculated. Given the remaining values in the estimated total cost equation are constant and can be found in Annex A, the estimated total cost can be calculated for each redesign option.

Market Share of Preference:
To obtain part-worth values for each attribute level on a respondent basis, Sawtooth Software's CBC/HB Module is implemented [26]. To account for potential sources of error within the HB model, 50,000 iterations are completed prior to the part-worths output by Sawtooth Software. After completion of the initial 50,000 iterations, an additional 500 iterations are completed in which every 5th "draw" or set of respondent level part worths is saved. These draws are used to calculate the market share of preference for each redesign option. When determining the respondent part-worths for price, the estimated total cost value produced in the previous step is doubled. This assumption is carried over from [3]. Once the respondent level part-worths have been estimated, Equation (4) is used to calculate the market share of preference for the baseline product, redesigned product and competitor products.

Comparison
After calculating the estimated total cost and market share of preference, the results can be compared graphically. Ideally, small perturbations in the inputs of CPM and slight variability in the part-worths would not produce different results and the redesign option with highest market share of preference and the lowest estimated total cost is selected.

RESULTS
To demonstrate the effect of variability in estimated total cost and market share of preference, baseline values are first calculated. Table 8 depicts the market before the introduction of a redesigned product where product cost is assumed to be half the market price. Competitor 1 possesses the largest market share of preference with the Standard Desk Fan, Competitor 2 and Competitor 3 having less, but nearly equal market shares of preference.

Table 8: Cost and Market Share of Preference Before Introduction of Redesigned Product

Product	Cost	Market Share of Preference
Standard Desk Fan	$15.00	21%
Competitor 1	$11.50	37%
Competitor 2	$22.50	22%
Competitor 3	$18.98	20%

With the market scenario defined prior to the introduction of a redesigned product, the baseline values for the market scenario with each redesign option must be calculated. Table 9 gives the baseline values for the estimated total cost and market share of preference diverted from competitor products for each redesign option. In Table 9, the baseline values consider the addition of only one product modification to the market at a time.

Table 9: Basline Estimated Total Cost and Market Share of Preference per Redesign Option

Redesign Option	Baseline Cost	Share of Preference Diverted from Competitor
Fan blade diameter to 4”	$18.35	22%
Fan blade diameter to 6”	$18.54	9%
Fan blade diameter to 8”	$18.73	13%
Fan blade diameter to 12”	$19.11	4%
Mount type to clip	$15.80	10%
Mount type to wall mount	$15.47	9%
Number of speed settings to 1	$17.09	2%
Number of speed settings to 2	$17.29	2%
Number of speed settings to 4	$17.75	5%
Number of speed settings to 5	$17.95	2%
Horizontal adjustment to 0°	$16.93	1%
Horizontal adjustment to 60°	$17.04	9%
Horizontal adjustment to 150°	$17.09	6%
Vertical adjustment to 0°	$16.93	2%
Vertical adjustment to 30°	$17.04	3%
Vertical adjustment to 90°	$17.09	14%
Power supply to 3ft cord	$19.04	8%
Power supply to 10ft cord	$19.63	10%
Power supply to battery	$20.14	1%
Color to red	$15.98	6%
Color to blue	$15.98	5%
Color to white	$15.98	8%
Color to custom	$15.98	4%

When introducing a redesign option without considering variability, all of the options listed in Table 9 are viable as they divert market share of preference from the competitor to the redesigned product. A result not depicted in Table 9 is the cannibalization that occurs when introducing a redesigned product to the market. In all cases, the redesign option cannibalizes some amount of market preference from the standard product. While any amount of cannibalization is not ideal, the introduction of the redesigned product provides the manufacturer with a larger portion of the market despite the reduction in share of preference of the standard product.

From Table 9, total product costs range from nearly $16.00 to just over $21.00. This range is the result of differences in cost between redesign options. For example, the cost of switching to battery power is $0.94 while the cost of switching the horizontal or vertical adjustment to 0 degrees is $0.02. However, within an option, variability in costs were found to be no more than $3.00. For example, given the redesign option “Reduce Blade Diameter to 4 Inches”, the maximum estimated total cost is $19.51 and the minimum estimated total cost is $17.55. These values suggest that when considering risk in terms of cost, the variability in inputs to the impact and likelihood matrix has a much smaller impact than when considering only the rank ordering of the risk values. However, the ultimate decision of whether $2.00-$3.00 is significant falls into the hands of the manufacturer.

Without considering the variability in the part-worths and CPM, Table 10 displays the baseline cost and market scenario of the redesign option “Reduce Blade Diameter to 4 Inches”. The price values for the standard product and the competitor products remain constant. With the introduction of the redesigned product, the manufacturer increases his total market share of preference to 44%. However, 12% of the market share of preference gained by the manufacturer is cannibalized from the standard product.

Table 10: Baseline Market Scenario for "Reduce Blade Diameter to 4 Inches' Redesign Option

Product	Price	Market Share of Preference
Standard	$30.00	9%
Customized	$36.70	35%
Competitor 1	$22.99	31%
Competitor 2	$44.99	19%
Competitor 3	$37.95	6%

Continuing with the “Reduce Blade Diameter to 4 inches” redesign option, Figure 7 depicts the frequency in which each estimated total cost value appears. Using the Anderson-Darling test [32], the estimated total cost of the redesign option does not fit a normal distribution. However, the average estimated total cost is $18.38 which is $0.03 more than the baseline value given in Table 9 and the standard deviation is $0.25.

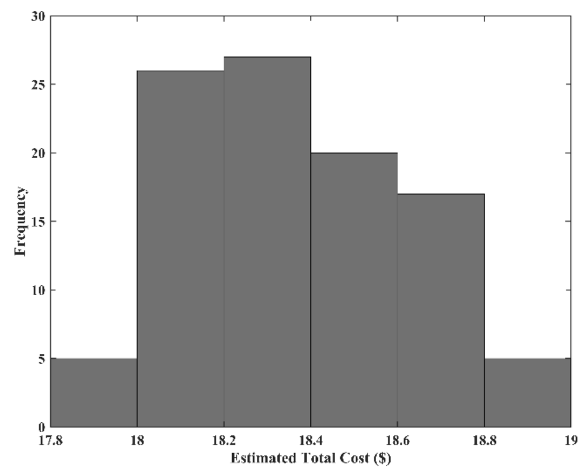


Figure 7: Reduce Blade Diameter to 4 Inches Estimated Total Cost

The consideration of the variability in the CPM produces a range of cost values for the redesigned product. Variability in part-worth estimations for each respondent leads to changes in the individual share of preference and overall market share of preference for each product. In calculating the market share of preference, the estimated total cost value is doubled and used as the price value for the redesigned product. Figure 8 displays the frequency of each diverted market share of preference value for the “Reduce Blade Diameter to 4 inches” redesign option to the nearest percent excluding cannibalization. The mean market share of preference diverted from the competitor is 21.53% and the standard deviation is 1.68%. This is a slight decrease in diverted market share of preference from the baseline value and indicates the variability in cost does not play a significant role in the capture of competitor market share of preference.

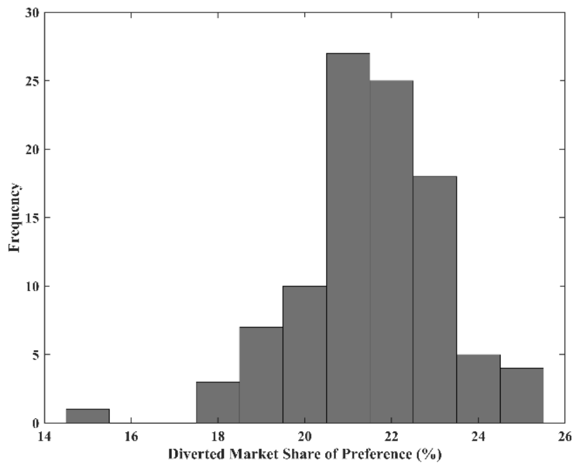


Figure 8: Reduce Blade Diameter to 4 Inches Market Share of Preference

To demonstrate the movement from a point estimate to a region estimate, Figure 9 graphically displays the estimated total costs and the corresponding market share of preference for 100 draws. The shaded circle in Figure 9 depicts the baseline values estimated for the redesign option. The baseline value falls in the middle of the total cost and diverted market share of preference estimates. The variability within the inputs causes output variability in the standard deviation only, as the average nearly equals the baseline (no variability) estimates.

As another example of the movement from a point estimate to a region estimate, the redesign option of changing the mount type from a flat base to a clip is explored. From Table 9 the baseline estimated total cost is $15.80 and the market share of preference diverted from the competitor is 10%. Figure 10 depicts variability in the estimated total cost resulting from altered impact and likelihood values in the CPM and the market share of preference due to part-worth estimations from the HB model. As opposed to the blade reduction redesign option, the baseline market share of preference value falls toward the lower end of the diverted market share of preference values, but in the middle of the estimated total cost estimates. The average market share of preference of the variability study is 11.29% and the standard deviation is 1.22%. This gives an increase of 1%, on average, when compared to the baseline value. In terms of estimated cost, the average estimated cost of the variability study is $15.79 and the standard deviation is $0.13.

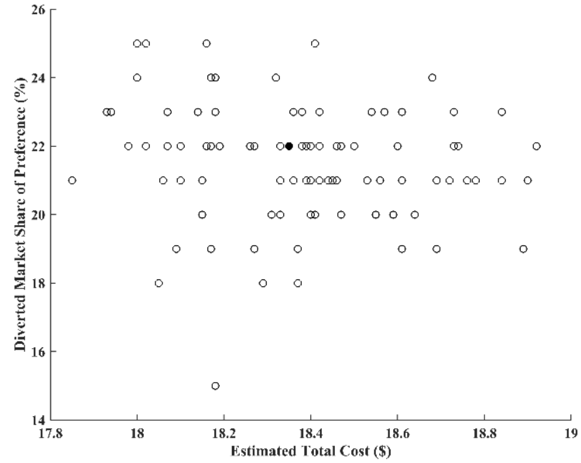


Figure 9: Variability in Estimated Total Cost and Market Share of Preference for 4 inch Blade Diameter

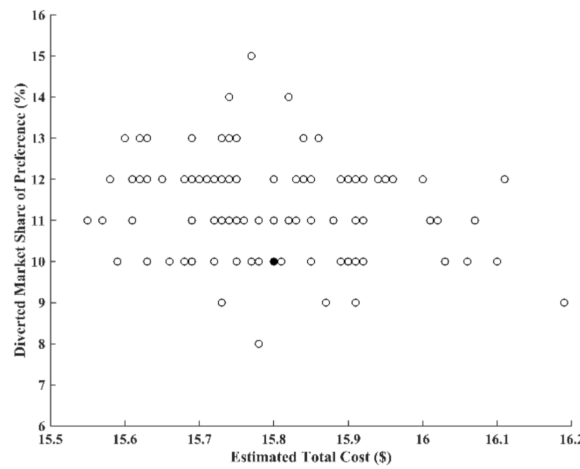
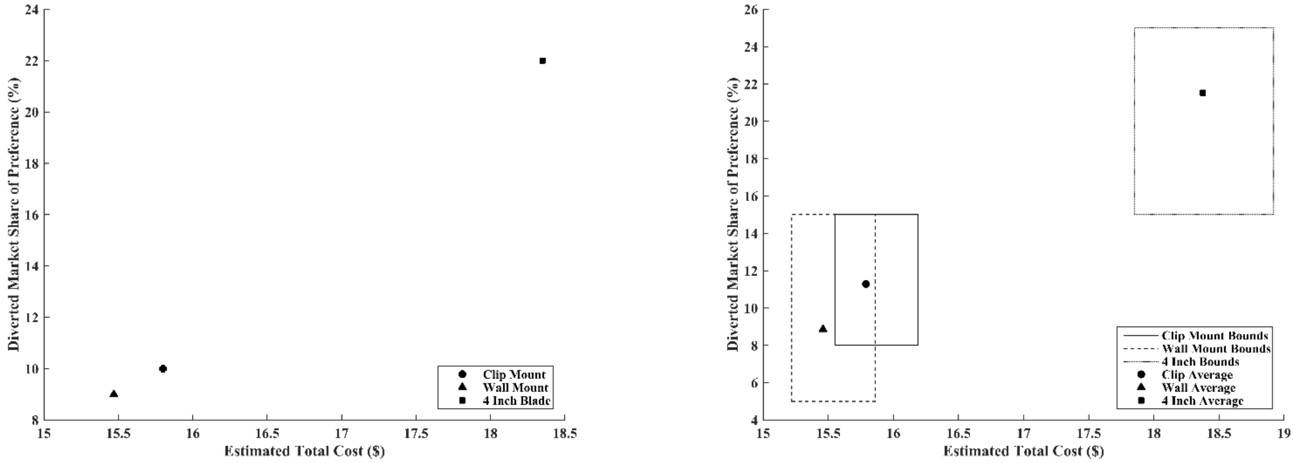


Figure 10: Variability in Estimated Total Cost and Market Share of Preference for Clip Mount

To demonstrate the effects of variability in total estimated cost and market share of preference when evaluating multiple redesign options, Figure 11(a) depicts the original baseline (no variability) point estimates for three different redesign options. Figure 11(b) shows the associated region estimates where the data points depict the average values and the surrounding boxes indicate the maximum and minimum values produced in the variability study.



(a) **(b)**

Figure 11: Multiple Redesign Options (a) Baseline and (b) Variability Consideration Estimated Total Cost and Diverted Market Share of Preference Tradeoff

In Figure 11(a), the choice of redesign option becomes a decision between reducing cost and increasing market share of preference depending on the desires of the manufacturer. If a reduction in cost is the main goal, the redesign option of changing the mount from a flat base to a wall mount is the best choice. However, if increasing market share of preference diverted from competitors is the objective, the manufacturer should elect to decrease the blade diameter to 4 inches.

However, when considering the variability in results, the process of determining the redesign option to implement becomes much more complicated. There exists overlap in both market share of preference diverted from competitors and total estimated cost among the redesign options shown in Figure 11(b). This variability removes the ability to simply discuss the tradeoffs between cost and diverted share of preference. The estimated total cost of each of the redesign options increases from changing the mount to a wall mount to changing the mount to a clip mount to reducing the blade diameter to 4 inches. The diverted market share of preference values span large ranges with the clip mount option having the smallest range and the wall and 4 inch blade diameter options larger. The upper diverted market share of preference value for the clip and wall mount equal the lower diverted market share of preference value for the 4 inch blade diameter option.

To more accurately interpret Figure 11(b), the mean and standard deviation of the estimated total cost and market share of preference diverted from the competitor are given in Table 11. The average values for both the estimated total cost and market share of preference diverted are nearly equal to the baseline values shown in Table 9. This indicates that the tools used to generate these values are capable of handling small amounts of variability. The difficulty in redesign option selection lies with the standard deviations. The market share of preference standard deviations are all within 0.50% of one another, but the standard deviations of the estimated total cost range from $0.13 to $0.25. A large standard deviation demonstrates the possibility that an evaluation of the estimated total cost run only one time has a higher chance of being on the extreme ends of the ranges shown in Figure 11. The risk profile of the designers and manufacturers as well as the current profit margin of the company will help to determine whether or not the company can risk the estimated total cost or market share of preference value landing on the lesser end of the spectrum.

Table 11: Mean and Standard Deviation of Selected Customization Options

	Clip Mount	Wall Mount	4 Inch Blade Diameter
ETC Mean	$15.79	$15.46	$18.38
ETC Standard Deviation	$0.13	$0.13	$0.25
MSP Diverted Mean	11.29%	8.86%	21.53%
MSP Diverted Standard Deviation	1.21%	1.86%	1.68%

CONCLUSION

The effect of variation in the combined risk matrix of the CPM through altered impact and likelihood values produces a range of estimated total costs for a product redesign. The result of calculating the market share of preference using the HB draws gives a range of preference values. The inclusion of both sources of variability results in a region estimate for each redesign option instead of a point estimate.

When considered in the context of the validation criteria introduced by Olewnik and Lewis [2] for design decision support frameworks, details of the CPM and HB model must be discussed with respect to two criteria: use meaningful, reliable information and provide a sense of robustness in results. Concerning the CPM, the challenge of having meaningful information arises when considering the impact and likelihood matrices. The first aspect of this challenge is selecting the appropriate resolution of the values used to populate the matrices as small amounts of variability can change the output.

A second challenge lies in the inherent belief structure associated with each designer. As the impact and likelihood scores are subjective, the overall risk values are expected to be larger for a designer that is inclined to magnify possible ramifications and smaller for a designer inclined to downplay the ramifications. The difficulty associated with the HB model stems from the survey fielded with a series of choice-task questions and the estimation technique used in fitting the model. Flawed market predictions can result from a survey with too many or too few questions and/or responses that do not accurately reflect consumer preferences. Yet, if more information is provided by each respondent, then the model estimate may be more accurate.

In terms of robustness in results, when only a single scenario of input variables is considered, no statements about solution robustness can be made. When possible variations are accounted for and used in computer simulations a better understanding of outcome robustness can be obtained. These distributions can give a designer insight into the extent of variability in the output as well as the range of risk and share of preference values that a particular redesign option is assigned.

Several avenues for future work involve the exploration of other sources of uncertainty within the market analysis and engineering rework realms. Market model fit and part-worth estimates are impacted by the number of iterations completed before saving draws as well as the number of respondents. Decreased accuracy due to over-fitting of the model can stem from large amounts of insignificant interaction terms within the draw data [33]. Sources of error within the market formulation also exist, such as uncertainty in competitor product specifications. Within the CPM, other areas of uncertainty exist beyond the variability of the expert provided impact and likelihood values. Flawed assembly of the DSM may miss direct interactions between subsystems or may incorrectly identify non-existent connections. Reducing the length of the change propagation path may affect the results of the CPM.

Expansion of the role of variability in other choice models and risk quantification tools is another avenue for future work. For example, Randomized First Choice [34] allows for the calculation of market share of preference. In terms of the estimated total cost calculation, the matrix-based algorithm for risk quantification produces a combined risk matrix in the same manner as the CPM. For this reason, implementing the matrix-based algorithm requires no reformulation of the estimated total cost function.

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ANNEX A

Table A1 displays the attributes and corresponding levels developed for the HB model estimation. Part-worth estimates for each attribute level are collected and used to calculate the market share of preference values.

Table A1: Attributes and Levels for Desk Fan Case Study

		Attributes									
		Blade Diameter (in)	Mount Type	Number of Speed Settings	Horizontal Adjustment Range	Vertical Adjustment Range	Power Supply	Noise (dB)	Color	Weight (lbs)	Price ($)
Levels	1	4	Flat Base	1	0°	0°	3ft cord	20	Red	0.5	10
	2	6	Clip	2	60°	30°	6ft cord	40	Black	1	20
	3	8	Wall-mount	3	90°	60°	10ft cord	60	Blue	2.5	40
	4	10		4	150°	90°	Battery-powered	70	White	5	60
	5	12		5					Custom		

The total cost of the standard desk fan is $15.00. After decomposition of the fan into subsystems, the percentage of the overall system which the subsystem makes up is quantified. Using the total cost of the system and the percentage over the all system, fix_j is the cost of subsystem j. The estimated cost to redesign subsystem j is estimated and represented by $rework_j$.

Table A2: Estimated Rework and Cost per Subsystem

Subsystem	Percentage	fix_j	$rework_j$
1	7%	$1.05	$0.70
2	6%	$0.90	$0.60
3	12%	$1.80	$1.20
4	8%	$1.20	$0.80
5	14%	$2.10	$1.40
6	19%	$2.85	$1.90
7	10%	$1.50	$1.00
8	11%	$1.65	$1.10
9	13%	$1.95	$1.30

Table A3 displays the redesign options, the subsystem affected by the option and the $rework_{k,i}$ term. In Table A2, $rework_{k,i}$ is the cost to change subsystem i to offer redesign option k, where i is listed in the subsystem column.

Table A3: Estimated Rework Cost to Change Subsystems

Redesign Option	Subsystem	$rework_{k,i}$
Fan blade diameter to 4”	6	$0.19
Fan blade diameter to 6”	6	$0.38
Fan blade diameter to 8”	6	0.57
Fan blade diameter to 12”	6	0.95
Mount type to clip	2	0.47
Mount type to wall mount	2	0.14
Number of speed settings to 1	3	-0.28
Number of speed settings to 2	3	-0.08
Number of speed settings to 4	3	0.38
Number of speed settings to 5	3	0.58
Horizontal adjustment range to 0	4	0.02
Horizontal adjustment range to 60	4	0.13
Horizontal adjustment range to 150	4	0.18
Vertical adjustment range to 0	4	0.02
Vertical adjustment range to 30	4	0.13
Vertical adjustment range to 90	4	0.18
Power supply to 3ft cord	8	-0.16
Power supply to 10ft cord	8	0.43
Power supply to battery powered	8	0.94