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A GAUSSIAN MODEL OF EXPERT OPINIONS FOR SUPPORTING DESIGN DECISIONS

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1. Introduction

Decision making in design is of great importance, resulting in success or failure of a system. This paper describes a robust decision support tool for engineering design process, which can be used throughout the design process. The tool is graphical and designed to communicate efficiently with different fields of expertise. It takes into account the Gaussian form of expert lack of certainty and generates the concept or model uncertainty which is necessary for a robust design.

Design can be described as a journey that starts from a very abstract level and finishes with a product. It presents a transition from the abstract level of ideas and plans to the detailed level of products by following certain specific steps. The information given in this level is often known as the "design brief and is quite limited. Because of the highest amount of uncertainty in this level, a designer is thirsty for the relevant information [Rajabalinejad and Spitas 2011b]. Type of information and decisions made in this phase can influence the whole design and often it is costly to modify decisions made in this phase later in the design process. To proceed to the next level, a designer seeks information that could reduce the uncertainty [Roozenburg and Eekels 1995], [Spitas 2011]. Any type of information can be helpful in this phase, but a designer needs to make a distinction between the non-informative and informative data. In general, a designer combines creativity, relevance (pertinence) of information with the experience to develop different design concepts. With availability of several options for different concepts, a preferred choice (or target concept) would help to maintain the focus and efficiency of design process. Each concept should address the design briefs, and the designer has to select the most robust and preferred concept in order to further develop and refine the concept. Since all the concepts at this level are acceptable to a certain extent, a robust design methodology or similar methods may have to be used to accelerate the selection of design process more efficiently. Once a preferred concept is selected, the designer can proceed to further develop that concept by collecting detailed design information necessary for making rational decisions to develop designs specs and engineering plans. The focus of this paper is on development of a novel method for decision making process. Decisions play a major role at all stages of the design process. Here we propose to use a new decision making tool for the design process. This method helps designers to account for all uncertainties [Hatchuel and Weil 2009] involved by appropriately factoring them into the decision making process. Because this method is rather new, numerical examples are presented for clarification to demonstrate the application of the method. This method with a uniform probability distribution function has been applied to the Cold Facts project [Rajabalinejad and Spitas 2011a] and further developments are presented in this paper.

2. Decisions in design and necessity of structured decisions

Decisions in the design process should follow a logical or chronological order. Decisions through a systematic design process produce the end products, and well-developed products are demanded by

society. Good decisions depend on the quality of available information. Many decisions are influenced by past experience, intuition and also personal preferences rather than by facts and scientific analyses. Consequently, it is necessary for designers to integrate the experience and intuition with knowledge and insight [He 2010]. This may require many years of evidence and data from past experiences.
The importance of structured decisions becomes evident when the product risk is high. Risk is directly related to cost and consequences. Therefore, a high product risk is often either due to production of a large number of inexpensive products or production of a limited number of expensive products. In either of these cases, it is important for a designer to be aware of uncertainties which increase product development risk. This awareness must be recognized a priori and reflected in decisions made through the design process. Design teams should be aware of such uncertainties and use them in the decision making process. Having a framework for this purpose provides a basis to use the associated information [Sharma and Agrawal 2010]. This information is sometimes of great value and may change certain aspects of a design. Experts can provide most informative information, called "judgmental information" that can be of great value to the design process. Insufficiency or absence of factual information usually is used as an excuse for not seeking information upfront. Judgmental information should not be underestimated by the designer. For example, expert judgment has proved to produce accurate forecasts [Arunkumar et al. 2011], and such information should be sought and used in the design process.
As a matter of fact, decisions in the front-end of the design process usually influence the complete design cycle. In this stage of design, concepts must be defined, be technically coherent, fulfil the set of requirements and be socially acceptable. All conceptual alternatives in consideration in a design process must meet the need of stakeholders and ultimate users.
There are different sources of uncertainties that complicate the design process. These uncertainties are more probable in large design projects. From the decision making perspective, there are three main reasons a decision process can become increasingly more complex [White et al. 1994]. The first is the "push the envelope" objective that goes beyond the current practice of societal or technical boundaries (or limits). The second is an unclear demand by stakeholders. The third is the dynamic of the environment where the product is ultimately targeted for. These three factors can sometimes collide in certain ways, have competing interests which are difficult to meet and their goals are incompatible. In such cases, the prioritization of these demands and associated consequences must be considered in the design process for reaching an optimal resolution of contradictions or competing interests involved [Abt et al. 2010].
On the other hand, judgments made by humans are not perfect, and even experts make mistakes. Most decisions involve some uncertainties with respect to the outcomes. Uncertainties always lead to risk as well as unexpected opportunities. To reduce the risk and increase opportunities, it is important to not only be aware of the uncertainty of different sources, but also be able to consider them. Only then it may be possible to anticipate reasonable outcomes. Furthermore, in the design process, it is easy to overestimate how much work has been done by individuals, and equally easy to underestimate how much of the design-brief has been addressed or how much of the user's expectations have been addressed.
In making decisions, there are specified requirements, inputs and outputs for different components of the final product the design team is trying to develop. Many of these inputs and requirements are unknowns (uncertainties) and data/information for these contains errors. It is important that all the uncertainties affecting the design process are factored into the decisions made during the course of design process.

3. A new visual tool for decision-making

In the early stage of the design process, the SWOT analysis is used. The SWOT is a simple strategic analysis technique. The purpose is to create awareness of the forces that will impact the design process. The SWOT is meaningful only for analysing the merits of an overall design. In this respect, a more meaningful analysis can be performed to identify strength, weakness, and threats for each alternative concept. This will allow the design team to realize the specific threats (e.g., major concerns or roadblocks and issues) facing each of different concepts in consideration. Similarly, this analysis can also inform the design team which factors are most beneficial to a concept.

Uncertainty analysis is another tool commonly used to consciously monitor the risks and opportunities involved in a design [Eddy 1989]. This analysis is justified especially in the early phases of the design for simply considering the likelihood of the possible events and their consequences. The multiplication of the likelihood by consequences defines the collective risks. In a system design, the goal is to develop strategies for avoiding occurrence of negative elements (risk) and increasing the likelihood of positive elements (opportunities). This analysis is important to the design process because it furnishes the information required for the SWOT analysis. The uncertainty analysis can also be used to improve the understanding of the uncertainties in each concept design and for refinement of the final concept.

In addition, sensitivity analysis is a suitable tool for determining how sensitive different estimates are in terms of changes in the controlling parameters and effect of these changes on the overall concept. Therefore, this tool is closely related to uncertainty analysis, and both analyses are always used together [Coleman and Steele 1999]. Numerical methods are used in engineering designs to compare, rank and select among alternative design concepts. The information about comparison of concepts can be provided in the tables or matrices. In system design process, a different method, called spider chart, is used for comparing different concepts [Gadallah 2011]. Another numerical tool is the criteria testing is useful for multiple goal analysis [King and Sivaloganathan 1999]. In this method, one can model the impact of different design alternatives on a set of different objective functions. It can be a difficult task to select one of the concepts among many design alternatives. This method performs a paired comparison two candidate alternatives to select the preferred alternative [Borup and Vanderborgh 1995].

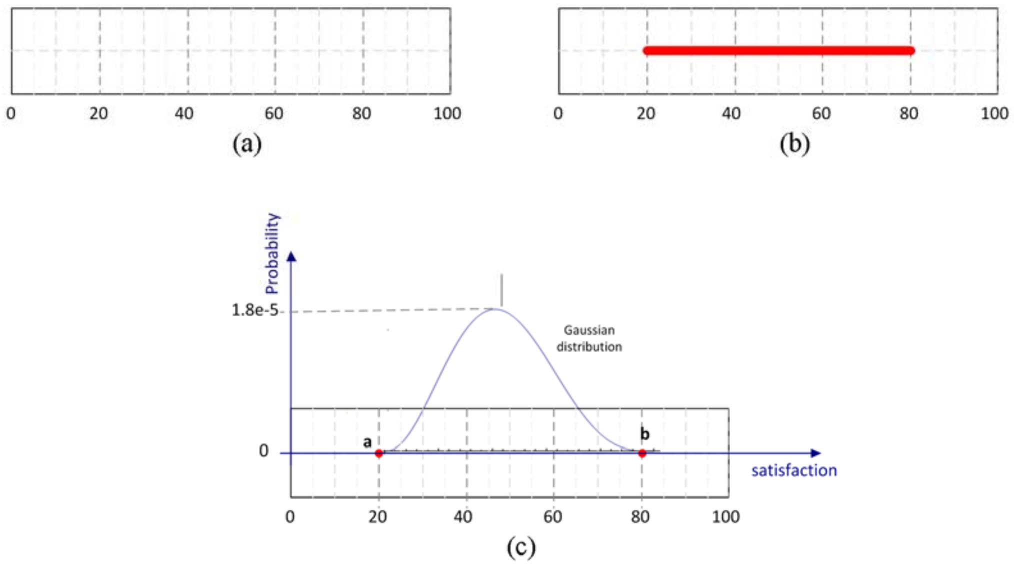


Figure 1. (a) The form that is to be offered to an expert to present his opinion within a confidence interval. (b) The confidence interval presented by the expert. (c) The Gaussian distribution is used to analyze the expert opinion

Some commonly used methods in the design process were mentioned above. These tools are used for making decisions when there is a major amount of uncertainty in design. In this respect, designers need to use a consistent method to accurately implement the information for decision-making. In the above mentioned methods, it was noted that the opinions of a designer or expert can provide a basis for decisions. However, the confidence in these opinions has not been explicitly addressed. For this purpose, we provide a method for addressing designer's confidence or uncertainty in the decision-making process.

The proposed method must be easy to implement and readily adaptable by different users. In the design process, decision makers are not comfortable to comment on uncertainties in a formal manner by coefficient of variation [Glickman and Jensen 2005]. Having said this, graphs and drawings can be used to clearly and more effectively communicate with different users. Because designers are usually strong in visual communication, we decided to communicate visually with designers to present the uncertainties or confidence visually. In our proposed method, we used a simple table for this purpose with a scale factor ranging from 0 to 100% as shown in Figure 1. Values of 0 and 100% represent two extreme limits respectively for no satisfaction and absolute satisfaction for a certain criterion. Figure 1(b) represents a concept that satisfies a certain criterion between 20% and 80%. Figure 1 (c) shows the Gaussian probability distribution of an expert opinion.

4. Mathematical formulation

Given the decision criteria, we provide two different metrics to evaluate the total score and total uncertainty of concepts. The Gaussian distribution may be used to assess the information used in uncertainty reduction and decision making. Gaussian distribution is a widely used type of distribution used where different independent variables are added together based on the Central Limit Theorem [Jaynes and Bretthorst 2003]. Therefore, it is advisable to use this distribution for variables which are dependent on multiple variables [Williams 2003]. The probability distribution function of Gaussian distribution is defined as

$$f_X(x) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(\frac{(x-\mu_X)^2}{2\sigma^2} \right) \tag{1}$$

where μ and σ are the mean value and standard deviation of variable x, respectively.

4.1 Gaussian score function

Assume that there are a number of concepts j and criteria i present, where i and j are integers. Given these, we wish to make a rational decision by choosing between the j competing concepts. The expert opinion for j-th concept is given by a set of random variables with Gaussian distribution, $s_j = \{s_j^{(1)}, s_j^{(2)}, \ldots, s_j^{(i)}\}$. On the basis of the rational frame work, we consider the first moment of these random variables as the scoring function [Cover and Thomas 2004], [Rajabalinejad 2009]. Assuming different weight factor for each criteria, we use the following equation to rank the candidate concepts and select the concept with the highest score:

$$\begin{aligned} S_j &= \frac{1}{\sum_{k=1}^{i}\lambda_k}\left[\int \lambda_1 \frac{1}{\sqrt{2\pi}\sigma_j^{(1)}} \exp\left(\frac{\left(x-\mu\left(s_j^{(1)}\right)\right)^2}{2\left(\sigma_j^{(1)}\right)^2} \right) x\,dx + \cdots + \int \lambda_i \frac{1}{\sqrt{2\pi}\sigma_j^{(i)}} \exp\left(\frac{\left(x-\mu\left(s_j^{(i)}\right)\right)^2}{2\left(\sigma_j^{(i)}\right)^2} \right) x\,dx \right] \\ &= \frac{1}{\sum_{k=1}^{i}\lambda_k}\left[\lambda_1\,\mu\left(s_j^{(1)}\right) + \lambda_2\,\mu\left(s_j^{(2)}\right) + \cdots + \lambda_i\,\mu\left(s_j^{(i)}\right)\right] = \frac{1}{\sum_{k=1}^{i}\lambda_k}\sum_{k=1}^{i}\lambda_k\,\mu\left(s_j^{(k)}\right) \end{aligned} \tag{2}$$

where S_j is the given score (rank) to the j-th concept, i is the total number of criteria, λ_i is the weight factor of criterion i, and $\mu(\ )$ is the first moment function. The first moment (mean value) of individual criterion i for concept j is defined as follows:

$$\mu\left(s_j^{(i)}\right) = \frac{b_j^{(i)} + a_j^{(i)}}{2} \tag{3}$$

where $a_j^{(i)}$ and $b_j^{(i)}$ are respectively the lower and upper confidence limits of the i-th criterion for concept j. For instance, μ in Figure 1(b) is equal to $(80+20)/2$.

4.2 Gaussian uncertainty function

In this section, we aim to calculate the total uncertainty of each design concept. Again, we assume that there are a number of concepts j and criteria i present. The expert opinion for the j-th concept is given by the same set of random variables $s_j = \{s_j^{(1)}, s_j^{(2)}, \dots, s_j^{(i)}\}$. The total uncertainty of the j-th concept [Rajabalinejad et al. 2010] is defined as

$$U_j^2 = \frac{1}{\sum_{k=1}^{i} \lambda_i^2} \sum_{k=1}^{i} \left(\int \left(\lambda_i\, \mu\left(s_j^{(k)}\right) - \lambda_i x \right)^2 \frac{1}{\sqrt{2\pi}\sigma_j^{(k)}} \exp\left(\frac{\left(x - \mu\left(s_j^{(k)}\right)\right)^2}{2\left(\sigma_j^{(k)}\right)^2} \right) dx \right) \tag{4}$$

where the probability distribution function is localized for each variable based on Equation (1). Integration of Equation (4) using Equation (1) gives

$$U_j^2 = \frac{\sum_{k=1}^{i} \lambda_k^2 \left(\sigma_j^{(k)}\right)^2}{\sum_{k=1}^{i} \lambda_k^2} \tag{5}$$

Here, we assume that the expert opinion can be presented by 95% accuracy. This concludes that

$$\sigma_j^{(i)} = \frac{b_j^{(i)} - a_j^{(i)}}{4} \tag{6}$$

Equation (5) provides the measured uncertainty of the j-th concept. Therefore, design subjects with similar scores obtained from Equation (2) can be ranked according to their uncertainties. In general, a more robust design comes along a smaller amount of uncertainty. In fact, a robust design methodology focuses on designs with a smaller amount of uncertainties [Williams 2003].

5. A case study: cold facts project

The Cold Facts is a program of the Dutch World Wide Fund (WWF Netherlands) established on the topic of climate change in the Polar Regions. The purpose of this project is to build a reliable and lightweight weather station to be deployed at the sea ice surface to measure and record temperature, barometric pressure and position data. The measured data will be added into the database of International Arctic Buoy Program (IABP). In order to promote scientific data collection in the Polar Regions, the instrument will be portable, easily deployable and include a weather station and GPS locator. The program requirements for this project are that the device should be lightweight, compact and easy to carry, plug and play, durable in extreme weather conditions, sustainable and have a satellite uplink.

The design team is composed of 15 students from different faculties of TUDelft, and is an interdisciplinary team coached by the authors of this paper. The team started with a reformulation of the design brief to identify a set of important design criteria. The modularity and sustainability are two main aspects of this design that can lead to a unique design, provided that they are well implemented in design. Furthermore, the design team has to pay utmost attention to the electronics and make sure of its reliability. Because of several electronics components involved, the device has to be waterproof and tightly secured (well fixed) to the ground. The structure should be light, efficient in distribution and handling of external and internal loads. The device has to be collapsible, and this indicates its ease of deployment requires a careful attention because of the harsh nature of the North Pole.

Decision-making in the design process was a challenge in its nature and at the managerial level because of the experience level and the diversity of designers' knowledge. This challenge was explicitly addressed through a series of reports and presentations. Here, we focus on one important decision which was made by the team to select the final concept. We use this as an example of decision challenge to describe the method which was used at each stage of design process. The design team developed three different concepts. To overcome the challenge of choosing the most preferred concept, team members were tasked to use our novel method to select the most successful concept. Team members incorporated their thoughts and experts' opinions into decisions by considering the uncertainties involved. Each member of the design team was free to independently assess all the concepts based on his/her opinion and by taking into consideration all known uncertainties. Based on our robust design methodology, the preferred concept would be the one with the highest score and the lowest uncertainty [Arvidsson and Gremyr 2008].

Table 1. Different weight factors are given for different design criteria

Criteria	Weight
Light weight	0.8
Aesthetics	0.3
Reliable	1.0

To clarify the implementation aspect of our method, we selected three criteria used in selection of the final concept. These criteria are: reliability, aesthetics, and light weight. These requirements of the model are given in Table 1. It provides the weight factors of each criterion. In the next step, Concept 1 and Concept 2, were presented to an expert asking for his opinion. The expert opinion is collected as shown typically in Table 2. The score function, described in this paper, is applied to Concepts 1 and 2 and is calculated as

$$S_1 = \frac{\sum_{k=1}^{3} \lambda_k \, \mu\left(s_1^{(k)}\right)}{\sum_{k=1}^{3} \lambda_k} = \frac{1\times 50 + .3\times 70 + .8\times 40}{1 + .3 + .8} = 49, \quad S_2 = \frac{\sum_{k=1}^{3} \lambda_k \, \mu\left(s_2^{(k)}\right)}{\sum_{k=1}^{3} \lambda_i} = 45 \tag{7}$$

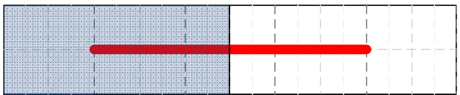
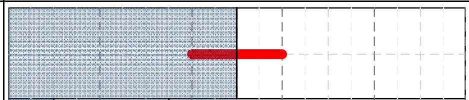
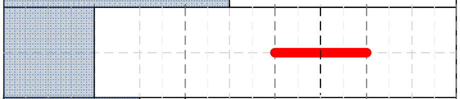
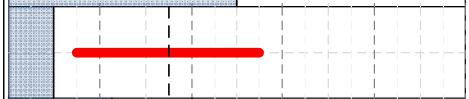
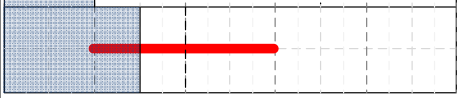
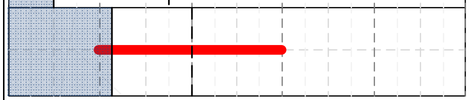
As a result, $S_1 > S_2$ and we again conclude that the Concept 1 is preferred to Concept 2. Total uncertainty for Concepts 1 and 2 whose features are calculated using Equation (5) can be obtained as

$$U_1 = \sqrt{\frac{\sum_{k=1}^{3} \lambda_k^2 \left(\frac{b_1^{(k)} - a_1^{(k)}}{4}\right)^2}{\sum_{k=1}^{i} \lambda_k^2}} = \sqrt{\frac{(1\times 15)^2 + (.3\times 5)^2 + (.8\times 10)^2}{1^2 + .3^2 + .8^2}} = 13, \qquad U_2 = 7.5 \tag{8}$$

Having different ranking of design criteria influences the calculated model uncertainty. The results show more uncertainty for Concept 1 than Concept 2.

Since the aim of this research is to communicate the results visually and robustly, we present the results of the score function and uncertainty function in Table 2. This table presents expert opinion for either concept. It can be easily shown that the dark area communicates the total score. Meanwhile, the total score is numerically calculated and presented in the table together with the total uncertainty of concepts. The influence of weight factors is visualized by reduction of the area proportional to each weight factor. Numerical results for each concept are presented in this table. The total score and total uncertainty are, therefore, calculated.

Table 2. Different weight factors are given for different design criteria

Criteria	Weight	Concept 1	Concept 2
Reliable	1.o		
Aesthetics	0.3		
Light weight	0.8		
Total Score		49	45
Total Uncertainty		13	7.5

6. Conclusions

This paper provides the principles and application of a novel graphical tool developed to support decision-making in the design process. The proposed method is not application-specific, is robust, at can be used in either of the concept space or knowledge space [Arvidsson and Gremyr 2008]. The method has been implemented in an easy-to-use graphical tool, with the associated mathematical formulation. This formulation enjoys from Gaussian modelling of the input information. The application of graphical tool is demonstrated in numerical examples for the Cold Facts project. This project was chosen because of an interdisciplinary team of students and experts who had different level of experience and expertise. The team was tasked to use the proposed method for decision making. The elements of a design process are described for selection of the final concept for a project. The method relies on experts' and designers' knowledge, and integrates these uncertainties into the decision-making process. The application of method to the Cold Facts project is demonstrated in this paper both graphically and numerically. We believe that our proposed method offers an easy-to-use graphical implementation tool to help designers by integrating different sources of information required for a robust design and by combining the collected information efficiently and incorporating into the decisions the uncertainties involved. The current method relies on deterministic weight factors which is indeed a limitation. Further research is required to address this issue.

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