Durham University
Insights
Institute of Advanced Study

Guiding the Engineering Design Process: Path of Least Resistance versus Creative Fiction

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Volume 2 2009 Number 6
ISSN 1756-2074

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GUIDING THE ENGINEERING DESIGN PROCESS: PATH OF LEAST RESISTANCE VERSUS CREATIVE FICTION

The engineering design process represents a highly creative process that is decision rich. Due to the immature nature of the design information during the earliest phases of the design process, these decisions are frequently taken with incomplete or uncertain information leading to risk exposure. Engineering designers may use their own subjective experience to direct them through this process. This paper explores support methodologies that are able to complement this decision making process and thus propose a conceptual Bayesian-based decision framework. Based on the literature, two variants of this framework are presented: one which will lead the designer 'down the path of least resistance' and one that will encourage creativity.

Introduction

The engineering design process is heavily influenced by subjectivity in decision making. For this reason, this process has been the subject of many studies investigating the effect that context has on the human engineer and how this in turn affects the final product. The early (conceptual) engineering design process represents the most creative domain within engineering. Designers are typically encouraged to think boldly in search of novel solutions during this phase. Once the nature of the solution has been determined, a significantly more routine form of problem solving takes place for the remainder of the design process.

The impact that human direction has upon the engineering design process is partly governed by behavioural aspects. Engineering design methodologies must balance the need for an objective decision process with the important, but subjective, nature that is brought by human intuition in search of novel solutions. At the same time, it is still important to maintain some control over this subjectivity, either to maintain the customer's original need for the product or ensure that the final designs are feasible given the manufacturer's capabilities.

This paper will initially present a more detailed review of the fundamental aspects of engineering design. This will be followed by a review of a selection of decision making processes from a diverse set of disciplines, with a view to informing the engineering design decision process further. A note on creativity from the engineering design process will then be presented. These ideas are then used to construct a stochastic decision support methodology that aims to respect the needs of the design process; specifically, two perspectives are presented: (1) a support tool that directs the designer to a solution that is likely to be readily implementable, and (2) a support tool that directs the designer to be creative. The paper is then concluded with some comparative remarks between these two perspectives.

Engineering Design

Engineering design represents the process that transforms a, frequently incomplete, specification for a product or system into an implementable description for that product or system. For example, there could be a need to toast a high volume of bread rapidly. Bread toasters already exist, but in this case there is an emphasis placed on the volume of bread to be toasted. Solutions to this design problem could include using higher power heating elements to reduce the time required per slice through to a conveyor system that would provide for a continuous stream of toasted bread. These two solutions represent fundamentally different design concepts that will require significantly different detailed models to estimate the various performance criteria. The construction of these models will be costly, and therefore will only be undertaken once the conceptual design has been decided upon.

The design process transforms the initial, vague, specification into a detailed set of instructions for manufacturing the final product through what is fundamentally an iterative search and refine process (Pahl and Beitz, 1996). During the earlier stages of this process there is little objective information about the design's performance. This is due to the incomplete definition of the design and the amount of flexibility that remains with its completion. As the design matures, its definition is enhanced and it becomes possible to use objective evaluation methods to gain information regarding the potential performance indices of the design. However, by the nature of completing the design, this reduces the amount of significant structural change that can be easily done to it. Hence, the latter stages of the design become ever more prescriptive and tend to be reduced to 'completing the details' of it. This is an increasingly mechanical process, which at the very last stages can frequently be left to an optimiser to finalise the design.

This paper will be primarily concerned with the earlier, conceptual, stage of the design process. The challenges at this stage are considerable and are knowledge intensive. The designer must have the relevant knowledge to be able to identify suitable design alternatives and be able to construct rapidly an adequate model for evaluating each design alternative. This information is needed at the time when the alternatives are being created. Should the information be presented too early, there is the risk of information overload; should it be presented too late, there will be a delay in completing the design.

The conceptual design stage is costly in terms of expert time used and commitment to future costs. Although, from a global cost perspective, the total costs expended during the conceptual design phase are minor in comparison to the total project costs, there remain reasons why this aspect should not be ignored. First, there are real economic pressures to reach the market first with a high specification product. Therefore, it is important that the design process is as swift as possible – any delay represents an opportunity lost. Second, as noted above, the design process considers alternative solutions as part of the initial design search process. Each of these solutions requires an intellectual investment, yet only a small portion will be taken through for further development. Those designs not being taken forward represent a form of largely wasted effort, albeit necessary to ensure that the design solution space was suitably searched. The effort is not completely wasted, as it will have contributed to the designer's understanding of the domain. Finally, where the next stage of the design process is to refine the design through the use of an optimiser, there are real benefits from seeding the optimiser with good designs. This is often the case in re-design, where a previous product has been used as a starting point for a variant design. In such cases, an optimiser will be able to converge on the global optimum more rapidly if it is initiated with a design that is close to that optimum point.

To summarise, there is a need for timely design decision support in an information-poor environment. This support must provide the designer with the means to search the design solution space broadly, while imposing a minimal effort to be able to construct or generate the designs. These designs should contain sufficient information to be evaluated, even if that evaluation is only relative to the other designs under consideration. Finally, although there is an overall aim to reduce subjectivity from the decision process, it is important to remember that this subjectivity contains the designer's expertise. Therefore, any decision support methodology must allow for this through some means of the designer overriding the algorithmically determined decision. To inform the agenda on design decision support, the next section will consider decision support methods from non-engineering domains.

Decision Making Across Domains

The engineering design process represents a rich and varied decision making environment. The type of decision ranges across a spectrum of highly prescribed and quantitatively based decisions, where high quality utility functions exist, to decisions based on the engineer's domain understanding and creative instincts. In the latter case, the challenge lies in the ill-formed statement of the problem (Courtney, 2001). The engineer must further specify the problem and attempt to resolve any internal conflicts that exist within the original problem.

To enable robust support for the engineering decision support process, a review of the decision support methodologies in a disparate sample of other domains is provided. Initially, classic decision making processes are considered. Then, a sample of medical decision making methodologies is reviewed. Next, a discussion on policy decision making is given. Finally, the implications of the framing problem are presented in the context of engineering design.

Classic decision making

Basic decision making can be reduced to considering the case of a one-dimensional utility function. This provides a mapping of the decision space onto some totally ordered space, typically the set of real numbers, and the decision can be reduced to selecting the option that leads to the smallest (or largest) utility value. Under this paradigm, the various options that are to be selected from can have significantly different structures. For example, consider the hypothetical investment decision: an investor has \$100 available, either to (a) deposit in a savings account with 5% interest, or (b) go to the casino. The utility function in this case is simply the expected return on the investment. With (a) there is very little further structure to this decision, namely the return is \$105. With (b) there is greater structure: three outcomes are possible. The investor can (1) lose the initial stake (return \$0); (2) break even (return \$100); or (3) double the stake (return \$200). To obtain the expected return in this case requires the probability distribution across these outcomes. For example, if the respective probabilities for the three outcomes are 0.1, 0.7 and 0.2, then the expected return is:

$$E(\text{return}) = 0.1 \times \$0 + 0.7 \times \$100 + 0.2 \times \$200 = \$110$$

In this case, given that the investor appears to be a skilled gambler by the nature of the probability distribution function, the decision should be to select the casino option, as it maximises the expected return.

This classic approach is made significantly more complex when the utility function becomes multi-dimensional. By the nature of mapping into a multi-dimensional space, there is in general a loss of total ordering. However, it is in general possible to create a partial order, i.e., to identify when the utilities of one option are all 'better' than the respective utilities of another option, versus the case where this is not possible and the options are non-comparable. In the case where there are a finite number of options, there will be a set of options that are non-dominated, the Pareto-optimal set. Each member of this set represents the 'best', and in this instance the decision maker must bias their decision in some manner to determine where within the Pareto set they should focus. The shape of the Pareto set can also be of interest. This shape represents the rate of trade-offs between the various utility dimensions. Depending on the robustness requirements, or otherwise, a decision maker might wish to identify an area of the Pareto set that does have significant trade-offs, e.g. an area where change in one objective does not have a great impact on any of the other objectives.

Medical decision support

There is significant literature on the area of computational medical decision support. Within this domain there are shared challenges with the engineering design domain, in particular the vagueness of the observations and incomplete information (Simic et al., 2006; Akbarzadeh and Moshtagh-Khorasani, 2007).

Within the medical domain, there is a tradition of adopting case-based reasoning (CBR) and rule-based reasoning (RBR) approaches to decision support. To an extent, this is a reflection of clinical physician practice. Wang et al. (2007) note the differences between these two approaches from within the clinical community as follows: 'CBR and RBR are always applied separately. Usually, RBR is applied first; when it fails to provide a reliable solution, CBR is then applied to retrieve similar solutions [...].' This reflects that where there is sufficient information to be able to identify a suitable rule, then this rule should be followed. Where this is not the case, a practitioner is encouraged to identify with a previous similar case and use this previous case as guidance for action in the current situation.

Stochastic methods have been developed for medical decision support. Examples include diagnosis support for diseases based on observations. For instance, Nakamura et al. (2006) generated a single rule to predict the presence of a potentially fatal blood bacterium. The approach generated a score (utility) based on a set of clinical observations, which in turn mapped onto a probability of the bacteria being present. The result of this system was that physicians changed their treatment decisions in 28% of cases. The significant element of such systems is that the human decision maker is provided with stochastic information that they can use in addition to any other observations, but, most critically, the final decision rests with the (human) expert. However, Sadatsafavi et al. (2007) provide a note of caution where Bayesian decision support is deployed in clinical environments. This study found that where there was relatively high agreement in post-test diagnosis, the variability of the post-test probabilities was also relatively high. From this it can be concluded that there is significant uncertainty in the Bayesian decision support in the first instance.

Organisational decision support

Organisational decision support relates to the design, or structuring, of organisations and systems so that effective decisions can be taken within these contexts. Lakats and Paté-Cornell (2004) use the design of an aircraft control system as an example of organisational support. Within the cockpit, the pilots are provided with various signals from the aircraft systems and external environment. These signals are assumed not to be fully accurate, in the sense that they can convey incorrect information (e.g. an oil temperature warning arises even though the oil is within nominal temperature). Based on this information, action might need to be taken, or the signal needs to be identified as false. This information must be processed by someone, and this is where the organisation design becomes important: the decision can be taken by someone who is 'close' to the system (a 'low ranking' operative) or it can be taken by a higher placed manager. This leads to a trade-off between a rapid decision (taken by the operative) against a decision with greater latency that considers the wider aspects of the problem. In the case of the faulty oil temperature reading, the 'low operative' is the pilot who could decide to divert the aircraft (at some significant cost), versus a fleet technician who has access to wider information and is aware that there is a high failure probability in the gauge and can direct the aircraft to continue. Both of these options have different latencies and implications to the system as a whole. These effects are not deterministic and therefore a stochastic approach should be adopted to assist in organisational design.

The overall organisation structure can also be designed to promote 'adequate' decisions (Allen and Strathern, 2005). These are decisions that are of a suitable quality, without expending additional effort for unnecessary higher quality. Specifically, the new product development process is considered from a strategic perspective. An organisation must be able to understand their competitor's strategies to enable them to anticipate what the competitor is likely to develop and thus be able to respond in an adequately competitive manner. It is argued that to create and develop good novel ideas successfully, an organisation must contain a sufficient diversity to ensure that there is a sufficient source of randomness from within the organisation.

Inducing bias

Decisions are made within a context of some desired outcome. This could relate to the nature of the implementation of the solution (e.g. a forging company will be biased towards solutions that use forging as a key process) or the market profile (e.g. a high-end audio-visual manufacturer targeting young affluent professionals with significant disposable incomes). Depending on these biases, decisions where there would otherwise be little to discern between certain options can be provided with additional support. For this reason, bias represents an important factor in decision support.

Bias can be introduced through a variety of methods. A simple and relatively direct method is to 'frame' the problem, aligned with the desired bias. Framing is the process of presenting what would ordinarily be a rational choice problem but focusing the attention of the (human) decision maker towards some, potentially non-rational, outcome. Human decision makers are known to bias their decisions subsequently according to this framing (Tversky and Kahneman, 1981; Kahneman and Tversky, 1982). Within a product development process, this bias can be introduced as part of the brief or specification for the product.

Engineering design

Decision support tools within engineering design are primarily aimed at removing or reducing subjectivity from the designer's part. In the case of conceptual design, the availability of objective evaluation tools is scarce. This tends to reduce the engineering designer to their own subjective expertise to evaluate designs. The decision support tools that exist tend to support relative assessment of designs through direct comparison. The evaluation methodologies are based on dividing the design into smaller components and then channelling the designer's subjective assessment accordingly with the aim of minimising subjectivity.

A classic example of this approach is given by the Pugh chart (Hollins and Pugh, 1990). The design is assessed against an agreed set of objectives, which can be functional, market-informed, aesthetic, etc. However, these objectives are not assessed absolutely, rather they are assessed relative to some datum design. The 'best' design is then selected based on the highest score. Therefore, this approach has effectively constructed a one-dimensional utility function from the set of objectives and the datum design. Other similar approaches include Voice of the Customer/Voice of the Engineer and Quality Function Deployment (Dawson and Askin, 1999; Vanegas and Labib, 2001; Raharjo et al., 2006).

Another aspect of engineering design decision support is to enable efficient search of the solution space. This search process provides the set of conceptual design solutions that provide the basis for further detailed investigation. Due to the variety of methods for solving typical engineering problems, the conceptual solution space tends to be very large. A full search of this space is prohibitive, not necessarily because generating the design concepts is costly, but rather that evaluating them is. Therefore, methods exist for channelling the designer's search into generating designs that (1) sufficiently explore the space and (2) are likely to be good candidates for further analysis. The morphological matrix is an example of such a design search method. Here, the design is initially divided into functionally independent modules. Each module then represents a sub-design problem. The designer then generates a set of solution principles (or similar) against each functional module. The (full) design space can now be explored by generating designs through selecting one solution against each functional module and combining these to create a complete design concept.

Summary

Clearly, where good single objective utility functions exist, decision support is a straight-forward process. However, this becomes more complex as the number of objectives increases and the certainty of the underlying model and/or the input data decreases. This is then further complicated where a controlled amount bias is desired to achieve a decision that is aligned in some prescribed manner. These are typical conditions within the early stages of the engineering design process. For these reasons, it can be argued that a stochastic route is appropriate for supporting the early stages of the engineering design process. However, as noted from the medical case, there are certain dangers of following the stochastic decision support route, typically that the reported probabilities are inaccurate. Hence, there is an important 'supervisory' role that the practitioner must undertake as part of the decision process, and the practitioner must understand where the weaknesses of the support tool lie.

Creativity

A key aspect of engineering design is the creative nature of the process and the final outcome. It is this creativity that results in novel products, which represents an important aspect for industry to ensure that individual organisations operating in a common market can create significant differences between themselves based on product innovation. Therefore, it is important that when supporting a designer that this creativity is encouraged.

As described in previous sections, there are several design methodologies to help guide a designer through the solution space. There is a real danger with these support tools that they constrain creativity by not encouraging the designer to explore ideas beyond those presented. In some cases, for example with the morphological matrix, the design has the opportunity to be creative while constructing the matrix: the designer can introduce novel functional solutions as part of the design, and then use these when constructing complete designs through the morphological matrix approach. Therefore, it is critical that any decision support system provides a mechanism for the designer to follow their own creative route as appropriate.

In light of this need to be creative, Cross has reported some key characteristics of highly creative designers (Cross and Clayburn Cross, 1998; Cross, 2004). This work considered the differences between how novice and expert designers approached design problems. Novice designers, with their limited engineering experience, would follow a prescriptive process to direct their work. Where they were offered support, this would be followed in mostly an unquestioning manner. As these novices gained experience, they formed two types of designers: those who would gather information for the sake of gathering information (effectively avoiding design work) and those who would strategically gather information and, once sufficient information was available, use it to further their design. The most significant contribution of Cross's work was the analysis of the approach of expert designers to the design process. The experienced designer was shown to *seek conflict* within the design. By seeking conflict, the designer forces themselves to create novel solutions which would not have come about by following the 'path of least resistance.' Further, the expert designer is able to identify suitable conflicts where there is a high likelihood of the solution providing novelty for the product.

From this it can be concluded that a successful engineering design decision support tool requires that at some points within the process, the suggestions provided by the decision support tool must either be countered or, better, that the support tool must be able to identify areas of conflict that the designer might wish to explore.

Stochastic Design Decision Support

The design search process prescribes a wide and deep search of the solution space. To implement this, the designer must be able to promote a number of designs simultaneously through the design process. Such approaches are not readily possible with rule-based systems which promote a linear progression based upon the outcomes of the rules which have been triggered. The case-based reasoning methodology represents an improvement on the rule-based approach, in the sense that a set of completed designs can be presented based on the similarity of the current design specification to those within the case database. However, the CBR approach provides complete solutions rather than support in how the solution could develop.

A stochastic representation of the design solution space provides a means for multiple options to be natively presented. Rather than representing solutions, or solution variables, as a point in design space, they are represented as a distribution which the design process narrows as more information becomes available. The solution space is spanned by some representative set of the design domain, for example the functional dimensions or the parameter set. Within each of these dimensions, the set of possible values that the dimension can take are listed, either as a continuous interval (e.g. length), ordinal value set (e.g. number of doors) or some other unordered set (e.g. list of possible colours). Multiple outcomes can now be represented natively using a probability distribution function (PDF) on each dimension. Multiple outcomes are represented through the possible values that can be taken on that have non-zero probabilities within the PDF. These probabilities represent the frequency that a certain design value has been taken in previous history. Further, by imposing a causal structure between the design variables that represents how the state of one design variable affects others. Therefore, these PDFs will dynamically change depending on the status of other parts of the design. It therefore becomes possible for the designer to specify aspects of the design partially and visualise the impact of this specification on other (unspecified) aspects of the design. The details of this process are given below.

Bayesian engineering design

The fundamental aspects of stochastic engineering design support are based on an interpretation of the basic definitions of probabilistic measures. These are best illustrated through example. For illustration purposes, the standard and well-known UCI machine learning car design database provides a suitable design domain (Blake and Merz, 1998). This domain represents a car design using the following variables for a typical passenger car: the comfort level of the car (Comfort) and the number of passenger doors (Doors) of the car. These will be taken to be discrete values. It is possible to express a measure of the probability of achieving a certain design variable value using basic probabilistic notation, for example if the probability of the comfort of a car being 'good' is 80%, then this can be expressed as:

$$P\ (\text{Comfort} \geq \text{good}) = 0.8$$

Where relevant information exists, this can be used to update the probability through a Bayesian approach. For example, if within the car design it has already been determined that there will be two passenger doors, the probability that the comfort level can obtain the level 'good' is now given by:

$$P\ (\text{Comfort} \geq \text{good} \mid \text{Doors} = 2) = 0.67$$

Using these concepts, it is possible to investigate the design space with the aim of identifying high probability areas, or designs that are likely to result in successful (saleable) products.

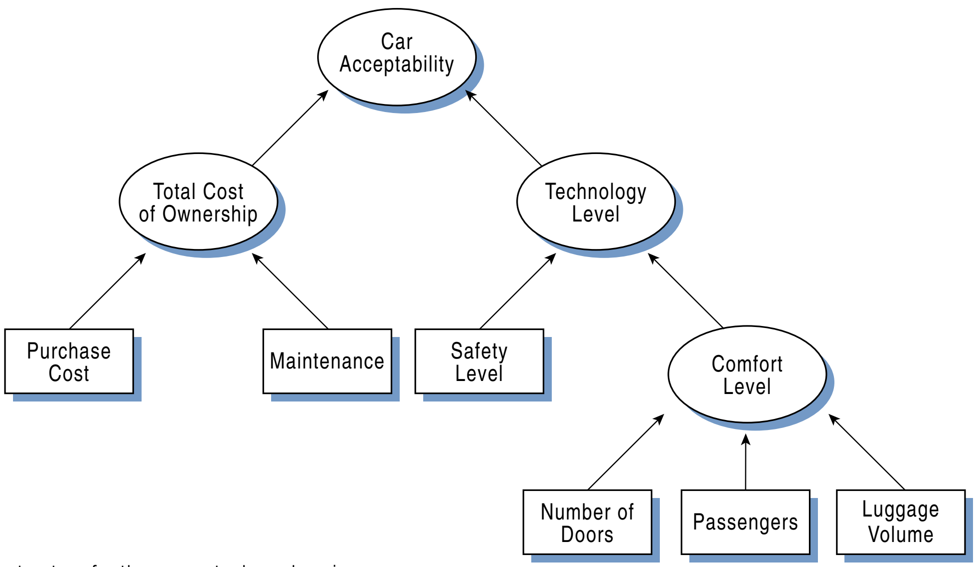

Figure 1: Rule structure for the conceptual car domain.

The car design domain has a causal structure (Matthews, 2008), given in Figure 1. Using the above Bayesian form, there are two variables that can be tested, in the case of the above example they are the Comfort variable and the Doors variable. This provides two distribution functions: *f(x)*, a conditional PDF, and *g(x)*, a likelihood distribution function:

$$f(x) = P\ (\text{Comfort} = x \mid \text{Doors} = 2)$$
$$g(x) = P\ (\text{Comfort} = \text{good} \mid \text{Doors} = x)$$

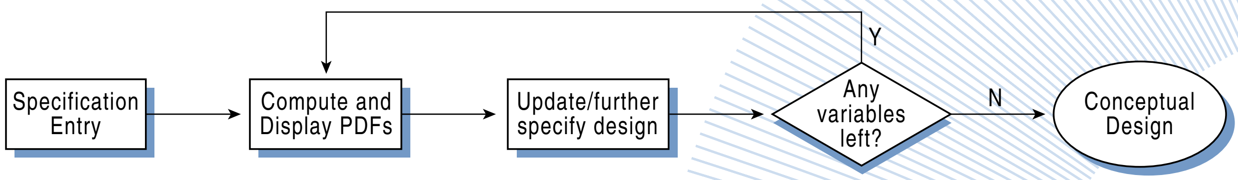

Figure 2: Flowchart representing the overall design search process..

Plotting these functions enables the designer to visualise how the various options are likely to be, given some partial information about the current status of the design. The shape of these functions can be exploited to support the design decision process.

The design process will be initiated with a basic, or partial, specification for a product. Two alternative approaches will be presented: a 'path of least resistance' approach and a 'creative friction' approach.

Path of least resistance

The 'path of least resistance' approach, as the name suggests, directs the designer through the design space in such a manner that minimises the number of challenges that are likely to arise. The search process is given by the following *heuristic* algorithm (see also Figure 2 for a flow diagram):

1. Compute the (conditional) distribution functions for all currently undetermined design variables;
2. Order the variables by 'spikiness' of the distribution function;
3. Starting with the 'spikiest' variable, set the value to the mode given by the distribution function (as this represents the most likely outcome); and
4. Repeat the process, until all variables have been determined.

The rationale for this approach is that the designer aims to produce a design that is aligned with high probability. This high probability represents that the specified aspects of the design are more likely to be able to be successfully manufactured. Effectively, where the probability density functions have been constructed through frequency counting of previous examples, following this route is a form of local case-based reasoning.

The variable ordering heuristic is derived from the basis that as more of the design is specified, the less flexibility remains. Effectively, distributions only become narrower (or spikier) as further information is supplied. Therefore, the design should first set the narrow distributions, before they collapse to zero. The wider distributions will become more constrained as information is supplied, and hence for this reason it is necessary to re-compute the distributions after each step.

Finally, it is important to reinforce that this is a *heuristic* algorithm: the designer is not bound by the suggested decisions. It is assumed that at the point where the designer wishes to use this decision support tool, the important aspects of the design have been determined. What remains is the completion of the design, specifically completing aspects of the design that were not part of the initial design brief or specification. However, should at any point the designer wish to diverge from the suggested design path, they are at liberty to do so, and the Bayesian decision support tool will continue using this information as part of the specification.

Creative friction

Expert designers do not seek the path of least resistance when designing (Cross and Clayburn Cross, 1998; Cross, 2004). The above 'path of least resistance' heuristic algorithm appears to be at odds with the expert designer's search method. However, the expert designer is engaged in seeking meaningful conflict areas within the design space. From a stochastic perspective, this can be expressed as seeking areas that have not been previously explored and are therefore represented by low probabilities. Hence, through a minor change in the heuristic algorithm, it is possible to support the expert approach to engineering design as follows.

1. Compute the distribution functions for all currently undetermined design variables;
2. Order the variables by 'spikiness' of the distribution function;
3. Starting with the 'spikiest' variable, review areas of low probability as follows:
   (a) Consider the neighbouring design variables, as these are the variables that are likely to be creating the conflict;
   (b) See if any of these 'conflicts' create meaningful opportunities for novelty: if not, then select the mode (as in the least resistance approach); then
4. Repeat the process, until all variables have been determined.

Most significantly with this revised heuristic algorithm is that the underlying Bayesian approach remains intact. The spikiness heuristic is unchanged, as otherwise the distribution functions are at risk of collapsing to zero, resulting in the support tool no longer being able to provide any support. The variable value setting heuristic has been modified to direct the designer to consider potential conflicts (through low probability/likelihood regions).

Conclusion

A heuristically driven Bayesian decision support tool has been presented. A basic, 'path of least resistance' design search heuristic was developed that exploited the Bayesian decision support tool. This was shown to be able to guide a designer along a path that would lead to a design with aspects that were similar to previously designed products. The benefits of this approach are that there will be knowledge of how to manufacture such products and that therefore these designs are likely to produce manufacturable products.

However, based on evidence from design literature regarding expert designers' search methods, a modified heuristic search algorithm was presented. This approach is based on the need to identify areas of potential conflict, or friction, within the design, effectively to force the designer to generate creative and novel solutions to overcome the manufactured conflict.

It can be concluded that both these design support tools have their uses. The path of least resistance presents itself as a useful support tool for novice designers who are likely to need to identify designs that are likely to have good success in later phases. This is particularly true if the concept of novice designer is extrapolated to a non-designer, for example a non-technically expert customer designing their own custom-built product through an interactive web-based platform. The manufacturer wishes the customer to be able to design their own product, but at the same time wishes to guide the customer to design a product in which they have previous experience in manufacturing. Where the 'difficulty' of manufacturing is linked to the price of the product, the customer will further benefit by being able to minimise this cost to them.

A final note is worthwhile emphasising with regards to the expert version of the design tool. Although this approach is able to direct the designer towards potential areas of conflict, the system has no means for identifying 'good' conflict and therefore this is left to the expert. It introduces the question of whether it is possible to couple some form of engineering knowledge to this system that would be able to compute some form of utility for conflict quality. Given such a score, this would then enable a significantly more efficient search heuristic to be implemented and provide a means for training novice designers to become expert by guiding them towards meaningful conflicts which they would then need to resolve.

Acknowledgement

This research was undertaken while the author was a visiting Fellow at the Institute of Advanced Studies, University of Durham (UK), working within the Modelling theme.

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