Decision Preferences, Constraints, and Evaluation Objectives in Layout Design: A Review of Modeling Techniques

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The layout design is a ubiquitous problem in engineering and design that is intrinsically knowledge-intensive, complex, vague, ill-comprehended and ill-structured. Inadequate information processing capabilities in tandem with various subjective user preferences, design constraints, and fitness objectives often hamper the acquisition of a superior solution. Consequently, the incorporation of subjective, vague, and conflicting design preferences and objectives into the layout decision process is a difficult, nevertheless, an important task. In this regard, the importance of a sound understanding of existing and promising modeling techniques cannot be overemphasized. This paper provides a review of various modeling techniques employed for explicit representation of experts’ knowledge, subjective preferences, and evaluation objectives. Moreover, it delineates a subjective classification scheme for layout decision preferences for a better appreciation of the significance of uncertain preferences, constraints, and evaluation measures in obtaining superior solutions. In addition, it reports a small-scale study regarding subjective evaluation of such modeling techniques by a group of layout design experts. Finally, we provide some recommendations regarding selection of suitable preference modeling techniques in layout design.

Keywords: Layout Design, Preference Modeling, User Modeling, Decision Modeling, Soft Computing

1. Introduction

The persistent development and pervasiveness of various complex and advanced applications as Facilities, VLSI, and the Web Page Layout Design have created a strong interest in formalizing Layout Design algorithms, preferences, and fitness measures. However, despite being an active research area, layout design is still a vaguely defined field [1], [2], [3], [28]. The existing research literature provides layout design guidelines and algorithms largely without an elaborate methodology for employing those [3], [20]. Moreover, the layout designers are often overwhelmed by the magnitude and vagueness of utility and usability information pertinent to layout design [2], [26]. The combinatorial complexity of existing mathematical formulations for the layout design problem further aggravates the scenario.

Although such subjectivity and complexity also exhibits in other work domains, it should be noted that various peculiar characteristics make layout design distinct from other subjective problems. For instance, it is generally effortlessly easy for a domain expert to look at a certain layout design and proclaim it to be good or not [2], [4]. Here we present a brief overview of modeling techniques for subjective preferences, constraints and fitness functions (PCF) in layout design. Furthermore, we report results of a small-scale study involving subjective evaluation of merits and demerits of various popular modeling techniques by some experts in layout design work domain. In addition, we provide our recommendations regarding the selection of the preference modeling techniques in layout design.

2. The Layout Design Problem

The layout design process is used for obtaining superior outcomes in the spatial arrangement of modules in a specified space based on given PCF [4], [25]. However, the diversity, volatility, and subjectivity of layout design objectives make consideration of entire spectrum of goals beyond the cognitive and functional capabilities of decision makers and information processing capabilities of most automated layout design system. Moreover, such variety and volatility in PCF render the solution space quite noisy. As such, the existing formulations for layout design are known to be strongly NP-Hard [3], [10], [16], [28]. Nevertheless, automating the layout design process through computerized generation, evaluation, and manipulation of superior Layout Alternatives for further consideration by decision-makers is deemed an essential ingredient in layout design [2], [3], [4], [5], [6], [15], [25]. However, the majority of available computerized layout design tools are little more than CAD-style drawing and documentation aids [3], [25]. Conceivably, such complexity, subjectivity, uncertainty, and multiplicity of objectives have deterred the study of the layout design problem in an analytical manner [2], [3].

3. Subjectivity in Layout Design and Classification Scheme

The subjective and imprecise considerations intrinsic to PCF in layout design emanate from multiple sources. Detailed outlines of such subjective PCF in various layout design contexts can be found in the literature [2], [3],
In order to elaborate this point further, we briefly mention a few instances of such subjective, uncertain and inconsistent preferences in various layout design contexts. For instance, in the facility layout design context, the information obtained from experts are linguistic in nature such as flow relationships, control relationships, process relationships, organizational/personnel relationships, political considerations, and environmental relationships [7], [24], [25]. These linguistic notions are often vague and amenable to different interpretations by different people at different times. Similarly, some examples of subjective PCF considerations in the circuit layout design are wire length, wire congestion, power dissipation, circuit delays, crosstalk, layout width/area [21], [28]. These considerations are often conflicting and inadequately defined. Likewise, such instances in the Web page layout design context could include decisions regarding amount of white space, space utilization, symmetry, colour scheme, repetition of modules, chronological value, emphasis, etc. [2], [3]. The potentially diverse scope of the Web and Mobile services mean such considerations cannot be static across demographic and temporal domains. Researchers have resorted to different deterministic as well as approximate reasoning techniques for incorporating such subjective and uncertain PCF in the layout design decisions. Nevertheless, the knowledge-intensive nature of layout design problem implies that even a modest amount of uncertainty in PCF may translate mischievously into the layout fitness [3].

A generic classification scheme of subjective and uncertain PCF could serve as a sound basis for choosing the modeling and reasoning mechanism for a specific consideration. As such, we categorize uncertainty in the domain knowledge into incomplete, inconsistent, imprecise, and uncertain classes of information [2], [23]. Incompleteness suggests the unavailability of some of the information necessitating employment of rules of thumb and approximate reasoning. Inconsistency refers to the difference or conflict in the knowledge elicited from experts highlighting the problem in transforming the available information into working rules and guidelines [2], [3]. Imprecision refers to values that are vaguely defined or measured inaccurately. Uncertainty points to the subjectivity in estimate about the value/rule underscoring the impediments in appropriately interpreting the available information [2], [3].

The layout design guidelines, preferences, and constraints are intrinsically incomplete, imprecise, inconsistent, and vague [2], [3]. Consequently, any layout design system requires robust ways of coping with such uncertainties. However, the majority of theories and tools devised to handle subjectivities and uncertainties in information are quantitative in nature. In general, such tools cannot handle the subjectivity and uncertainty in information that falls into more than one of the aforementioned classes.

### 4. Modeling Techniques

The majority of existing approaches are suitable only when deterministic data is reliably available and assignable to specific dynamics of the layout design process. However, such data either do not exist or exist for some designated unrealistic modeling conditions. Thus, effective means of analysis and revision through the incorporation of subjective preferences as well as designers’ cognition, intuition, and vision are virtually nonexistent. In addition, the rigid and myopic character of layout fitness evaluation measures constitutes another source of inflexibility [2], [3], [4], [7] [25]. Recently, various composite multiobjective fitness measurement mechanisms have been proposed to procure more encompassing fitness evaluation regimes [3], [21], [28]. Nevertheless, the majority of existing research literature tackles the layout design problem against some rigidly defined fitness measure from a very narrow perspective [2].

As already mentioned, uncertainties and dynamics of the layout design problem underscore the need for a methodology pertinent to incomplete, imprecise, inconsistent, and uncertain PCFs [2], [23]. It should be noted that the majority of existing subjective PCF modeling techniques fail to deliver in uncertain environments falling in more than one of the aforementioned classes. This shortcoming is more evident and imperative when the available information is incomplete [2]. Here we provide a glimpse on some of the popular of modeling techniques in such a domain with emphasis on their merits and demerits from the layout design perspective.

#### 4.1 Deterministic and User-Controlled Approaches

Deterministic approaches work under the simplifying assumption that all subjective PCFs can effortlessly be quantified and made available when needed. Such approaches usually make use of arbitrary default, user-defined, or some expected values that are possibly refined by the user during the course of experimentations and generation of superior layout alternatives [25]. For instance, extended formulations of the unequal area facilities block layout problem are available that explicitly consider uncertainty in material handling costs by using expected value and standard deviations of product forecasts. However, even under relatively deterministic environment, the cost of procuring exact and complete information could frequently be prohibitive [25], [26]. Furthermore, various layout design applications are so intricate that the validity of such approaches could easily
be challenged. Ironically, the major portion of relevant literature builds on such incredibly simplifying assumptions [1], [2].

Similar to the deterministic approach, many existing models in the layout design rely on procuring weights, preferences, and properties through user inputs [13], [27]. Although such an approach renders higher degree of flexibility and control, users are usually overwhelmed by the flood of data and domain specific knowledge. Consequently, the usefulness of such approaches is severely limited by attentional, informational, and functional capabilities of the user. Users may produce poor layouts if they do not properly follow domain specific task related guidelines [27]. Furthermore, such an approach frequently becomes impractical in view of prevailing cognitive, economic, ergonomic, and temporal constraints. Moreover, at times, it is not possible to get access to a domain expert for procuring the required inputs [3]. Consequently, we deem the user-supplied approach as intrinsically inflexible and counterproductive.

4.2 Traditional Uncertainty Handling Approaches

Most existing methodologies for handling uncertainties in the domain knowledge through approximate reasoning are mainly quantitative in nature. In such approaches, uncertainties are quantified in form of some measures that are propagated during reasoning [1]. Examples include the Bayesian, Certainty Factors, Dempster-Shafer, etc.

Bayesian is a probabilistic approach based on Bayes’ theorem. It requires a very large number of probabilities and, hence, large number of experiments. Moreover, such a probabilistic approach is suited for problems where there is uncertainty in the occurrence of the event. However, such uncertain problem domains as layout design involve uncertainties in the event itself. An ad hoc estimation of such conditional probabilities by human experts is often inconsistent and biased. Furthermore, such an approach requires a large number of inputs from experts making knowledge elicitation both tedious and expensive enterprise. Furthermore, the approach is valid only under the simplifying assumption that the presence of evidence also affects the negation of conclusion, which is often an invalid assumption. In addition, Bayesian approach is not quite suited for providing explanation facilities [24]. It should be noted that Explanation Facilities, that could provide a clear and concise understanding of the reasoning behind certain action to the decision maker, are deemed essential in such knowledge-intensive and uncertain problem domains. For instance, at a very basic level, explanation facility could provide the sequence of rules that were fired in reaching at a specific decision.

Certainty Factors (CF) is another quantitative modeling approach that attempts to address such problems as the need for repeated experiments required in estimating probabilities in the Bayesian approach. In CF, the knowledge is expressed in the form of rules and a confidence factor associated with each rule. It does not call for some statistical basis for supplying beliefs in events. Furthermore, it allows simultaneous rule representation and quantification of uncertainty that makes it a simpler and efficient approach in comparison to Bayesian. However, CF approach is also an ad hoc regime, which is not built on a solid theoretical foundation. It often results in many weaknesses in the reasoning mechanism. For instance, CF approach works under the implicit assumption of independence among hypotheses, which is often an invalid postulation. Furthermore, the need for a large number of inputs tends to become a major preoccupation for the user.

The Dempster-Shafer (DS) theory of evidence addresses some of the weaknesses of the probabilistic approaches including the representation of ignorance, the unnecessary requirement that the sum of beliefs in an event and its negation be unity, etc. However, it does not specify how the probabilities are to be computed or how the results are to be interpreted. Furthermore, in certain instances, obviously incorrect conclusions can be reached [1]. In short, DS is also an ad hoc approach and is not suitable for incorporating explanation facilities.

4.3 Constraints-based Approaches

Constraint processing techniques such as knowledge representation and inference mechanism have extensively been used for automated graphical layout design [18]. Recent research suggests that constraints provide a powerful yet simple formalism for specifying preferences in such dynamic layout design domains as the Web page layout design [19]. In the constraint-based approach, constraints like semantic-pragmatic, inter-relational, spatial, temporal, etc. are represented in terms of equalities and inequalities permitting a flexible, intuitive, and declarative representation of complex preferences [17]. The outcome is simplification of perceived informal domain features [19]. For instance, the relationship between two certain categories of modules can be specified using a single set of constraints instead of delineating it for each pair of modules. Consequently, this approach is close to the knowledge-based approach in a broad sense. Inquisitive readers can find extensive surveys of constraint-based approaches in literature [18].

Although the work in this direction is largely theoretical and applications are limited in scope, the knowledge-based approaches have been quite successful in subjective and knowledge intensive areas other than the layout
Consequently, the knowledge-based approaches offer immense potential in this difficult problem domain, too. Recently, some promising research frameworks and their implementations for tackling the layout design problem using intelligent knowledge-based approaches have been proposed [1], [4].

4.4 From-To Charts

From-To Chart (FTC), or Flow Matrix, is one of the earliest tools adopted for assisting layout designers in development process [15]. It normally contains numbers representing some measure of interactions between pairs of modules. For instance, it could contain some material or information flow between two departments in the facility layout design context. These FTC values are ultimately translated into some sort of proximity measure or Closeness Rating. Despite being intended as a tool to represent quantitative values, FTC has often been used for representing qualitative values, as well. Furthermore, it is a widely accepted premise that even the values that are generally considered quantitative in nature are not easily quantifiable due to subjectivity and uncertainty involved in collection and processing of such data [3]. Consequently, FTC provides a very rigid and myopic solution. Nevertheless, FTC was one of the earliest tools used to provide necessary inputs in a simplified form for a computerized layout design system.

4.5 Relationship Charts

Activity Relationship Chart (REL) is among the earliest and most popular tools for expressing subjective, uncertain, and linguistic considerations in layout design [15], [25]. Typically, activity relationships are translated into the relative proximity requirement between pairs of modules that are used for placement decision. These proximity requirements are expressed in REL through closeness rating such as: A (Absolutely necessary), E (Especially important), I (Important), O (Ordinary closeness is all right), U (Unimportant) and X (Undesirable). In short, REL contains ordinal closeness rating information for evaluating the utility of layouts in the form of a Total Closeness Rating [25].

The REL is designed to facilitate consideration of qualitative factors, political needs, or dynamic situations where precise data cannot be made available due to temporal, financial, and other practical constraints [15], [25]. Yet, the underlying idea remains deterministic and crisp ratings do not provide means for handling conflicting preferences and may result in inconsistent ratings. For instance, one expert assigns an A rating for a certain pair of modules (say X to Y) and a second expert provides a U rating for the same pair of modules (say Y to X) creating a conflict. Moreover, there is no elaborate methodology to work with incomplete and/or dynamic preferences. Furthermore, the multiplicity of inter-module interaction modes requires separate REL for every dimension of interaction [25]. Such factors contribute to the inflexibility and limitations of REL. However, several innate advantages of REL such as ease of use, ease of learning, and the structured nature have positively contributed to the wide acceptance of its various adaptations.

An interesting extension in this direction is the use of Fuzzy REL charts [11]. Fuzzy Logic provides excellent means for tackling such inconsistencies in the information. In f-REL, fuzzy inferencing mechanism is used to generate activity relationship charts. Some small-scale and tightly defined simulation studies have demonstrated the effectiveness of f-REL charts in generating superior layouts against both fuzzy and non-fuzzy fitness metrics [11]. However, REL or f-REL cannot encompass all subjective and uncertain PCFs in layout design. Consequently, we believe that a general fuzzy logic based approach, encompassing both analytical and algorithmic aspects of design process, would deliver most.

4.6 Computer Simulations

The typical absence of some encompassing, closed-form, and analytical fitness functions renders computer simulations a useful alternative [7]. Such an approach would provide detailed analysis, modeling, and evaluation of complex layout design problems. However, simulation models are not easily amenable to optimization and make procurement of a superior layout alternative difficult to achieve. Recently, some efforts have been made to optimize layout design simulation models using Genetic Algorithms in various facility layout design contexts in order to expedite the process and procure a diverse set of superior in layout alternatives [2], [8]. Nevertheless, computer simulations are usually very time consuming and could become prohibitive in the layout design process.

4.7 Automated Preference Discovery

Although we know no published research on automatic preference mining in the layout design area, we believe such automated and intelligent preference discovery mechanisms hold immense promise. As already stated, the layout design rules and preferences are quite dynamic in nature as people learn new concepts and outgrow old ideas thereby pronouncing the need for the designers to re-learn the design rules. This change in preferences
could even occur with decision-makers’ interaction with existing or intermediate solutions. This dynamic nature of rules suggests that some Online Artificial Neural Network based Pattern Discovery and Validation Agent would be of immense value by providing pattern of design rules and preferences in an automated and self-updated manner [1], [2], [3], [27].

4.8 Fuzzy Logic

Fuzzy Logic (FL) is a set of mathematical principles for knowledge representation based on degrees of membership, rather than traditional crisp membership, of a variable to a particular set. It ventures to model the vagueness in humans’ sense of words, opinions, decision-making and common sense tainted with imprecision, incompleteness and uncertainty. The role model for FL is the human mind in which a proposition is neither True nor False, but may be partly true or false to some degree. This degree is usually taken as a real number in the interval [0, 1]. As an example, experts can describe preferences regarding the amount of white space in the layout in fuzzy terms as ‘small’, ‘medium’ or ‘large’. A fuzzy set \( A \) of universe \( X \) defined by a function \( i_A(x) \) is known as the Membership Function (MF); \( i_A(x) : X \rightarrow [0, 1] \). Where \( i_A(x) = 1 \) if \( x \) is totally in \( A \), \( i_A(x) = 0 \) if \( x \) is not in \( A \) and \( 0 < i_A(x) < 1 \) if \( x \) is partly in \( A \).

FL can be utilized in layout design in various forms [2]. For instance, it can be used as a Linguistic Tool to model problems comprising fuzzy phenomena/relationships and to acquire/represent the domain-specific knowledge. In addition, FL can be employed as an Analytical Tool to advance insights to the problem through analysis of such models. Furthermore, the use of FL as an Algorithmic Tool could make solution methods faster, robust, and stable. Each of these three application modes of FL is pertinent to the research in the layout optimization. In this section, a brief overview of these modes of FL application in layout design is provided.

It should be noted that FL has been extensively applied in operations management research. Furthermore, a large body of literature exists on fuzzy multicriteria decision-making. As such, FL has wide acceptance in the research community and success of FL in various application areas has motivated its use in the layout design area. Conceivably, a modest but growing body of research employs FL in the layout design.

The most popular application mode of FL in layout design is as a linguistic tool [2]. In such cases, FL is used to model linguistic patterns or preferences mainly in solving the facility layout design problem [2], [3], [12], [15], [23], [25]. For instance, the subjective, uncertain, or fuzzy linguistic preferences corresponding to relationships like ‘importance’ and ‘closeness’ of modules can effectively be modeled using FL. Furthermore, linguistic qualifiers such as ‘high’ and ‘close’ signify the values of the linguistic variables permit robust modeling of vague experts’ opinions using FL. The membership functions themselves can be chosen based on domain experts’ opinions.

In addition, FL has been used as an analytical tool where layout fitness metrics are modeled as a multi-criteria decision making (MCDM) problem [3], [12], [25]. Such approaches essentially form a hybrid layout fitness metric using an amalgamation of both quantitative as well as qualitative criteria. The multiple objectives and constraints of the model can be expressed as linguistic patterns [25]. Powerful and proven techniques like analytic hierarchy process can be used to solicit experts’ opinion regarding parameters influencing module closeness ratings etc. [25]. Moreover, FL has also been used in layout design as an algorithmic tool in which placement decisions and the spatial relationship are determined by fuzzy rules [3], [15]. In such applications, the solution algorithm utilizes various linguistic variables for expressing qualitative and quantitative characteristics affecting the placement decisions.

The efficacy of such procedures is demonstrated in the literature. Nevertheless, an encompassing application of FL covering all aforementioned notions is largely missing. Furthermore, the important issue of efficacy and speed of these procedures for larger problems has not been adequately addressed. In case of some realistically large problems, the speed of the procedure might prove an impediment to the adoption of this methodology. Nevertheless, the fact that various techniques have been employed to counter such problems in other problem domains bodes well for exploiting FL in the layout design. Consequently, there has been growing interest in the use of FL in the layout design.

5. Subjective Comparison of Modeling Techniques

In order to have some kind of comparative evaluation of the aforementioned modeling techniques, we asked some long time researchers and practitioners in layout design field to subjectively rank these techniques on a scale of 1 to 10 against various considerations with higher scores representing a favorable ranking. Among those practitioners, two have expertise in facility layout design, two have expertise in VLSI layout design (macrocell placement), and one has expertise in visual layout design (interface design). The given techniques have varying
familiarity rating among those evaluators. The ranking scores based on averages of experts’ evaluations as well familiarity with techniques are shown in Table 1. For instance, the ease of understanding plays key role in adoption of any methodology. Intuitively, deterministic and user-controlled techniques are considered as simplest to understand and easiest to employ among all techniques. Nevertheless, these techniques receive very low ratings for flexibility, expressive power, robustness and tractability of the approach, which are very important factors in determining the applicability and efficacy of such techniques. Flexibility refers to the ease with which parameters and components of the system can be modified in dynamic scenarios or in performing some sort of scenario analysis. Robustness refers to the capability to perform reliably and effectively in changing situations. Expressive power implies the capability to represent a given scenario as accurately as possible. Tractability is an important dimension in modeling tools for complex domains such as the layout design where combinatorial explosion could severely limit the efficiency and efficacy of the solution methodology.

Conceivably, computer simulation has received lowest ratings reflecting the enormity of task involved in simulation modeling and its inability to swiftly adapt to changing scenarios. Furthermore, as can be seen from Table 1 that FL has received higher ratings for these important determinants of efficiency and efficacy pointing towards its value and promise. However, our selection of experts’ was somewhat biased in the sense that we made sure our experts are familiar with most of the important modeling tools mentioned in the previous section. This bias was introduced deliberately to make sure we could have some insights to the value of these tools with such a small number of experts, which is in itself a limitation of this exploratory study. Nevertheless, this exploratory study does provide some grounds for a well-thought empirical research in this direction.

<table>
<thead>
<tr>
<th>Technique</th>
<th>Familiarity</th>
<th>Ease of Understanding</th>
<th>Ease of Use</th>
<th>Flexibility</th>
<th>Expressive Power</th>
<th>Robustness</th>
<th>Tractability</th>
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<tr>
<td>Deterministic</td>
<td>9.8</td>
<td>9.8</td>
<td>8.2</td>
<td>3.8</td>
<td>3.2</td>
<td>1.2</td>
<td>3.0</td>
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<tr>
<td>User-Controlled</td>
<td>9.8</td>
<td>8.6</td>
<td>6.6</td>
<td>3.8</td>
<td>4.0</td>
<td>3.8</td>
<td>2.0</td>
</tr>
<tr>
<td>REL-Chart</td>
<td>9.2</td>
<td>8.4</td>
<td>6.6</td>
<td>6.0</td>
<td>5.6</td>
<td>5.2</td>
<td>4.6</td>
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<tr>
<td>Bayesian</td>
<td>7.4</td>
<td>3.4</td>
<td>3.8</td>
<td>2.4</td>
<td>4.2</td>
<td>3.0</td>
<td>2.6</td>
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<tr>
<td>Certainty Factors</td>
<td>8.0</td>
<td>6.4</td>
<td>5.8</td>
<td>4.2</td>
<td>5.6</td>
<td>5.0</td>
<td>6.4</td>
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<tr>
<td>Dempster-Shafer</td>
<td>7.0</td>
<td>5.0</td>
<td>3.8</td>
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<tr>
<td>Fuzzy Logic</td>
<td>7.6</td>
<td>7.0</td>
<td>6.8</td>
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<td>7.6</td>
<td>6.2</td>
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<tr>
<td>Simulations</td>
<td>5.4</td>
<td>3.0</td>
<td>1.6</td>
<td>1.40</td>
<td>6.8</td>
<td>2.2</td>
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Table 1: Subjective Ranking of Modeling Techniques in Layout Design

6. Recommendations

It is evident from the brief overview that some approximate reasoning mechanism is most suited for modeling subjective and uncertain PCF in the layout design. Furthermore, the knowledge of human experts is imprecise, linguistic, or fuzzy in conceptualization and articulation. Experts think in vague and imprecise terms, for instance, ‘very high’ and ‘low’ or ‘fast’ and ‘slow’ etc. Furthermore, complex decision-making problems like the layout design are full of uncertainties and ambiguities [2], [3], [26]. Accordingly, the majority of layout design guidelines and rules are essentially vague, differing, and even conflicting in character. Moreover, very little or no a priori knowledge is available in such dynamic domains as layout design. As such, the complexity and dynamics of layout design process make it impossible to gather meaningful statistical data, or even subjective probabilities, that could allow the use of some objective probabilistic approach.

Furthermore, probabilistic approaches are concerned with the imprecision associated with the outcome of a well-defined event. In contrast, FL focuses on the imprecision of the event itself as well [24]. The decision in this intricate area of layout design are based more on human intuition, creativity, common sense, and experience rather than the availability and precision of data. FL provides a very natural representation of human abstraction and partial matching by permitting incorporation of imprecision, incompleteness, and subjectivity in information into the model formulation, solution process, and analysis of alternatives. As a result, FL based modeling of predominantly subjective design guidelines in various layout design applications have been proposed [2], [29].

We see immense potential for the use of ‘degrees of membership’ and ‘partial matching’ techniques provided by the FL.

We envisage fuzzy preferences taking the form of significance parameters and preference parameters. A significance parameter (SP) tells ‘how important’ certain aspect/criteria is for the overall fitness of the layout.
Whereas, a preference parameter (PP) tells ‘how much’ of certain aspect/criteria should be incorporated in the layout generation [3], [15]. Indeed, certain parameters could have significant interaction with one another affecting more than one value of crisp weights used subsequently in layout evaluation phase. As such, the fuzzy decision making system (FDMS) should have some way of handling these interactions and interdependencies. The ability of FL to realize a complex non-linear input-output relation as a synthesis of multiple simple input-output relations can prove invaluable in this regard [27].

A typical FDMS would accept fuzzy and/or crisp preferences and transform those into crisp weights, using the fuzzy rules present in the knowledge base, for employment in some layout fitness evaluation function [20]. Towards this end, we need some way of measuring the utility/fitness of the layout based on both tangible as well as intangible criterion. One way of accomplishing it is through development of a composite fitness function comprising of some sort of weighted sums of utilities arising from various design issues. The weights in such a fitness function correspond to preferences provided by experts [2], [3]. FL is expected to reduce the computational requirements substantially while making the representation more realistic. The reduction in computational requirements would result from merging of rules in fuzzy knowledge-based systems, by virtue of fuzzy sets, which often renders more than 90 per cent reduction in the number of rules [2], [24]. It is to be noted that FL has demonstrated expressive power to accommodate any number of fitness measures and preferences in numerous applications including layout optimization [3], [29].

In an FDMS, fuzzy inferencing takes place by mapping a given input to an output using the theory of fuzzy sets. The Mamdani-style inferencing method is the most popular technique for capturing experts’ knowledge, sanctioning a more intuitive and human-like description of expertise [24]. It involves four steps: Fuzzification of input variables, Rule Evaluation, Aggregation of rule outputs, and Defuzzification [2], [24]. The first step is to fuzzify all the crisp inputs and determine the degree to which these inputs belong to each of the appropriate fuzzy sets. The Rule Evaluation step requires taking the fuzzified inputs, and applying them to antecedents in the fuzzy rules. The results of antecedent evaluation are then applied to the membership function of the consequent. The consequent membership function is ‘clipped’ or ‘scaled’ to the level of the truth-value of the rule antecedent. The Aggregation step is the process of unification of the outputs of all rules. The input to the aggregation process is the clipped or scaled consequent membership functions and the output is one fuzzy set for each output variable. The fuzziness facilitates in evaluating rules in the layout design using FL; however, the final output of the FDMS has to be a crisp number so that it could be used in some fitness evaluation function. The most prevalent technique for ‘defuzzification’ is the ‘centroid’ technique where a vertical line carves the aggregate fuzzy set into two equal masses. This way vague linguistic rules can be used to realize important and useful crisp values to be employed in evaluation and generation of superior layout alternatives. For instance, these crisp values could be used in some Genetic Algorithm based intelligent layout generator, in conjunction with some efficient placement heuristics, in form of weights used in a composite layout fitness function [2], [3].

Furthermore, we recommend a paradigm shift in tackling the layout design problem. It has long been noted, “… most of the previous computer-assisted layout design techniques have limited or ignored the creativity and the natural ability of [layout designer] to understand complex flow and spatial relationships” [cf.12, pp. 92]. Ironically, such statements are as true today as were two decades ago. It is because most existing solution methodologies usually adopt an Optimization, instead of a Decision-Making, paradigm for the layout design. Thus, the applicability of such techniques is limited in both temporal and operational dimensions. We recommend a radical shift in the modeling paradigm seeking a synergistic bliss of the cognitive and sub-cognitive expertise of decision-makers as well as technologies that have demonstrated efficacy in modeling such subjective and dynamic research areas. For instance, the Expert System paradigm is known to be very effective in uncertain, subjective, and knowledge-intensive application domains like layout design and FL is known to be an effective technology for incorporating preferences in the knowledge-base of expert systems [1], [3], [24], [27]. Consequently, we believe that layout optimization systems based on intelligent expert system paradigm that utilize synergic strengths of various soft computing technologies would prove to be very promising research endeavors. Such an integrated framework for tackling layout design problem is still largely missing. Recently, a promising Expert System based Intelligent Decision-Support paradigm has been proposed and implemented at a small-scale [1], [3]. Continued efforts in this direction are expected to enhance the efficiency of layout designers from economic and ergonomic viewpoints as well as improve the quality of outcome [2], [3].

7. Conclusion and Future Work
This work is primarily motivated by a need to address the apparent lack of an critical, integrative, and comparative analysis of modeling techniques for subjective and vague preferences in the layout design context.
To address these needs, we provide a brief overview of such techniques with some recommendations. Furthermore, we have furnished a broad classification scheme of subjective preferences. In addition, a small-scale exploratory study has been reported towards evaluating strengths and weaknesses of various modeling techniques in the eyes of layout design experts. We believe a carefully designed and extensive study along these lines would be a good research endeavor. Furthermore, a more critical classification and comparative review of effective modeling techniques for subjective and uncertain preferences specific to each category, or combination of categories, defined in this paper would be a valuable extension of this work. Moreover, a review of existing and promising fitness evaluation metrics for various layout design domains would be a worthwhile effort.

8. References


