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A decision support system for material and manufacturing process selection

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The material and manufacturing process selection problem is a multi-attribute decision-making problem. These decisions are made during the preliminary design stages in an environment characterized by imprecise and uncertain requirements, parameters, and relationships. Material and process selection decisions must occur before design for manufacturing can begin. This paper describes a prototype material and manufacturing process selection system called MAMPS that integrates a formal multi-attribute decision model with a relational database. The decision model enables the representation of the designer's preferences over the decision factors. A compatibility rating between the product profile requirements and the alternatives stored in the database for each decision criteria is generated using possibility theory. The vector of compatibility ratings are aggregated into a single rating of that alternative's compatibility. A ranked set of compatible material and manufacturing process alternatives is output by the system. This approach has advantages over existing systems that either do not have a decision module or are not integrated with a database.

Keywords: Multi-attribute decision making, material selection, process selection, design for manufacturing, concurrent engineering, possibility theory, fuzzy sets, manufacturing processes

1. Introduction

The design of a product and its fabrication processes must be simultaneously pursued in the competitive markets of today. Some of the most important decisions, those with the greatest effect on overall cost, are made during engineering design (Whitney, 1988). It is indicated that upwards of 70% of a product's cost is determined during the design stages (Ullman, 1992). This realization has lead to interest in concurrent engineering. Concurrent engineering is the parallelization of the activities involved in the product development process. An important aspect of concurrent engineering is the early consideration of manufacturing in the product development process to achieve a reduction in product development time, production costs, and quality defects. This is called design for manufacturing (DFM), and is typically conducted with a particular manufacturing process in mind. A potentially important decision-making activity proceeds DFM and this is the selection of materials and manufacturing processes.

Designers need systems to aid them in deciding between commonly competing product material alternatives such as plastics versus sheet metal and between competing process technologies such as injection molding versus die casting. The material and manufacturing process selection decisions are difficult due to several reasons. First, the selection must be made during preliminary engineering design which is characterized by qualitative descriptions of requirements, imprecise data, and unknown or complex relationships. Of the multiple factors that influence material and manufacturing process selection, many can only be estimated, such as production volume. Second, the problem is exacerbated since the multiple criteria are of unequal importance. Moreover, many of the requirements can be classified as soft requirements or designer preferences and consequently, they are flexible. Often, designers must trade off one objective to increase another, yet formal trade-off strategies are not commonly practiced. Third, there exist over 100 000 material alternatives to evaluate and new materials are continuously being developed (Waterman and Ashby, 1991). It is impossible for designers to have knowledge of all the possible candidate materials. Manufacturing process selection is no less difficult, since there almost invariably exists more than one method for fabricating a part. Designers are apt to rely on experience and design a new product for the few materials and processes that are

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familiar. Consequently, possibly superior alternatives are not evaluated due to lack of knowledge of these materials and processes. Recognition of these problems has led to the development of systems and methodologies for aiding designers in these important decision-making tasks.

1.1. *Related work*

Material and manufacturing process selection has been addressed by application of design compatibility analysis (Ishii *et al*., 1988), which is a case-based reasoning approach that uses pattern matching of good and bad examples of compatibility. Systems based on this approach have been developed for specific materials, such as plastics (Beiter *et al*., 1991), and for considering certain manufacturing processes (Yu *et al*., 1993). These systems are not integrated with a database, as such; they only consider a small range of processes at any one time.

Commercial database software products exist for the selection of materials when the properties are well defined and the criteria are exact. The material selection system developed by Ashby (1992) concentrates on the data modeling aspect of the problem by presenting the data in a chart format and has been extended to process selection (Esawi and Ashby, 1996). The chart format limits the decision maker to only simultaneously considering two, or at most three, criteria. Moreover, selection for criteria that are difficult to quantify, such as corrosion resistance, is more troublesome and existing techniques are inadequate (Abel *et al*., 1994). Other conventional database systems for storing relevant material and process information do not provide query systems capable of modeling the designer intent or customer preferences. Many of the requirements, as previously noted, are better modeled as preferences and not strict requirements; however, these systems only enable crisp, exact queries. Thus, the conventional query systems do not facilitate the qualitative nature of the preliminary design requirements.

Boothroyd *et al*. (1992) report on developments to address the integrated material and manufacturing process selection problem. Material selection is performed with three predefined queries on crisp data. Process selection is performed using production rules and pattern matching. This approach does not provide support for the weighting of criteria nor support comparisons among the alternatives. Dixon and Poli (1995) use a guided iterative search methodology for performing material and manufacturing evaluations throughout the design process. This is a formalized handbook approach that extensively uses charts and tables to evaluate designs and select materials. The handbook approach gives the designer the burden of locating relevant information, evaluating it, and then comparing the alternatives.

Material and manufacturing process selection should occur as early in the design process as possible to have the greatest overall impact, but most evaluation systems can only work in a domain of well-defined features when the dimensions and tolerances are precisely known. While the work of Ishii *et al*. (1988) recognizes the qualitative nature of the design information content, the examples they provide all require exact design requirements. Yet, it is exactly the lack of exact design specifications that characterizes preliminary design and makes the selection problem difficult. Consequently, the potential for sub-optimization is great since failure to select the process with the most suitable characteristics almost invariably leads to higher unnecessary costs. Furthermore, the absence of database technology makes many of these systems unable to support the large number of alternatives or to handle the frequent updates of newly developed materials and improved fabrication processes.

Resulting from this review, two primary requirements for performing material and manufacturing process selection are identified: (1) decision support; and (2) database support. Current systems either provide decision support or database support but have not successfully integrated the two. Thus, systems that only provide decision support leave the burden of considering the tremendous number of alternatives on the decision maker. Database systems provide a lot of data and information but provide very little decision-making support. The combination of decision theory with database technology has the potential to greatly improve the selection decision and lead to better designs.

1.2. *Organization of paper*

The objective of this paper is to describe an integrated multi-attribute decision and database model to aid in the simultaneous selection of materials and manufacturing processes. Section 2 lists the decision criteria relevant to material and manufacturing process selection. This section also presents the system architecture and the application of possibility theory to assess the compatibility ratings between the product profile requirements and materials and manufacturing processes. The compatibility assessments result in a vector of ratings that must be aggregated into a single rank. A method for aggregating the multiple compatibility values is presented. An illustrative example of selecting the material and manufacturing process for an assembly cover is presented in Section 3. Observations are made concerning the flexible query methodology and selection strategies. This is followed by the conclusions.

2. Material and manufacturing process selection

The material and manufacturing process must satisfy the product's life-cycle requirements imposed by design engineering, marketing, manufacturing, reliability, aesthetics, and quality. Consequently, the selection problem is a multi-attribute decision making (MADM) problem where each attribute corresponds to one of the product profile requirements. The relevant decision criteria are shown in Table 1. Material attributes critical to the material selection problem are categorized as either mechanical properties or physical properties. Some criteria are represented as ratios of two properties. For example, specific stiffness and specific tensile strength are employed since these ratios are commensurate with typical design objectives of maximizing a property for a given weight. An example is the design of structural aircraft elements where the objective is to maximize stiffness and minimize weight. Product profile requirements critical to manufacturing process selection are categorized as geometric, technological, and production properties. Some of these properties may be estimated since exact values are not always available during preliminary design. For example, production volume may be expressed linguistically as, 'about 10 000 parts'.

2.1. *MAMPS architecture*

A decision support system for material and manufacturing process selection called MAMPS has been developed to support designers during the preliminary engineering design stage. The MAMPS system architecture is shown in Fig. 1. Three modules work together to support the decision-making task. The material selection module and the process selection module are order independent, thus both material first and process first selection schemes are supported. These modules evaluate the compatibility between each alternative and the product profile requirements and output a partially ordered set of compatible alternatives. The aggregation module joins the two datasets using a matrix that relates materials with feasible manufacturing processes. The ranked feasible material and manufacturing process alternatives are provided to the designer.

The material property and manufacturing process capability data are stored in a relational database. The data for material properties and manufacturing processes was compiled from handbooks (ASM, 1988; Waterman and Ashby, 1991; Kalpakjian, 1992; Groover, 1996). The use of a database enables the storage of the large number of alternatives and facilitates updates to material and manufacturing process records.

Table 1. Decision criteria for material and manufacturing process selection

Properties	*Criteria*
Materials	
Mechanical	Hardness, stiffness/density, strength/density, yield strength
Physical	Density Cost/kg, thermal conductivity, corrosion resistance
Manufacturing processes	
Geometric	Undercuts Greatest wall thickness, overall dimensions (length, width, height), weight, shape and complexity
Technological	Tolerances, surface finish
Production	Processing cost/part, production volume, time-to-market

2.2. *Manufacturing process capability and material property representation*

A *manufacturing process capability* is the physical ability of a manufacturing process to perform one or more feature-generating operations to some level of accuracy and precision (Algeo, 1994). Manufacturing process capabilities are determined by manufacturing resource factors, work part material factors and geometry factors. The *manufacturing resources* are the machines, tool holders, and tolls used to achieve process capabilities (Jurrens *et al.*, 1995). Work part material and geometry factors include factors such as the machinability of a metal or length of cut. The complex interactions among these factors prevent a precise representation of manufacturing process capabilities during preliminary engineering design when many of the factors are themselves uncertain. Consequently, manufacturing process capability information is commonly presented as characteristic applications and atypical applications. This is illustrated in Chang and Wysk (1985) for the surface roughness of die casting. Most applications range between 0.8 μm and 1.6 μm, but some applications are capable of producing between 0.4 μm and 3.2 μm. Generally, products with features near the boundaries of a process's capability are more difficult to fabricate than features well within the process's capability. These two ranges specify a possibility profile of the process capability that enhances decision making. It is more desirable to stay within the conservative interval since the designed artifact is better guaranteed of meeting specification. Figure 2 shows the weight capability of die casting represented with Expression 1 as

$$x \to \langle a, b, c, d \rangle \tag{1}$$

where b and c enclose the most preferred values, a is a lower possible bound and d is an upper possible bound. Expression 1 is a generalization of a crisp interval with imprecise boundaries. The interval $[b, c]$ is a conservative estimate of parameter x and the interval defined by $[a, d]$ is an optimistic estimate. The intervals $[a, b]$ and $[c, d]$ repre-

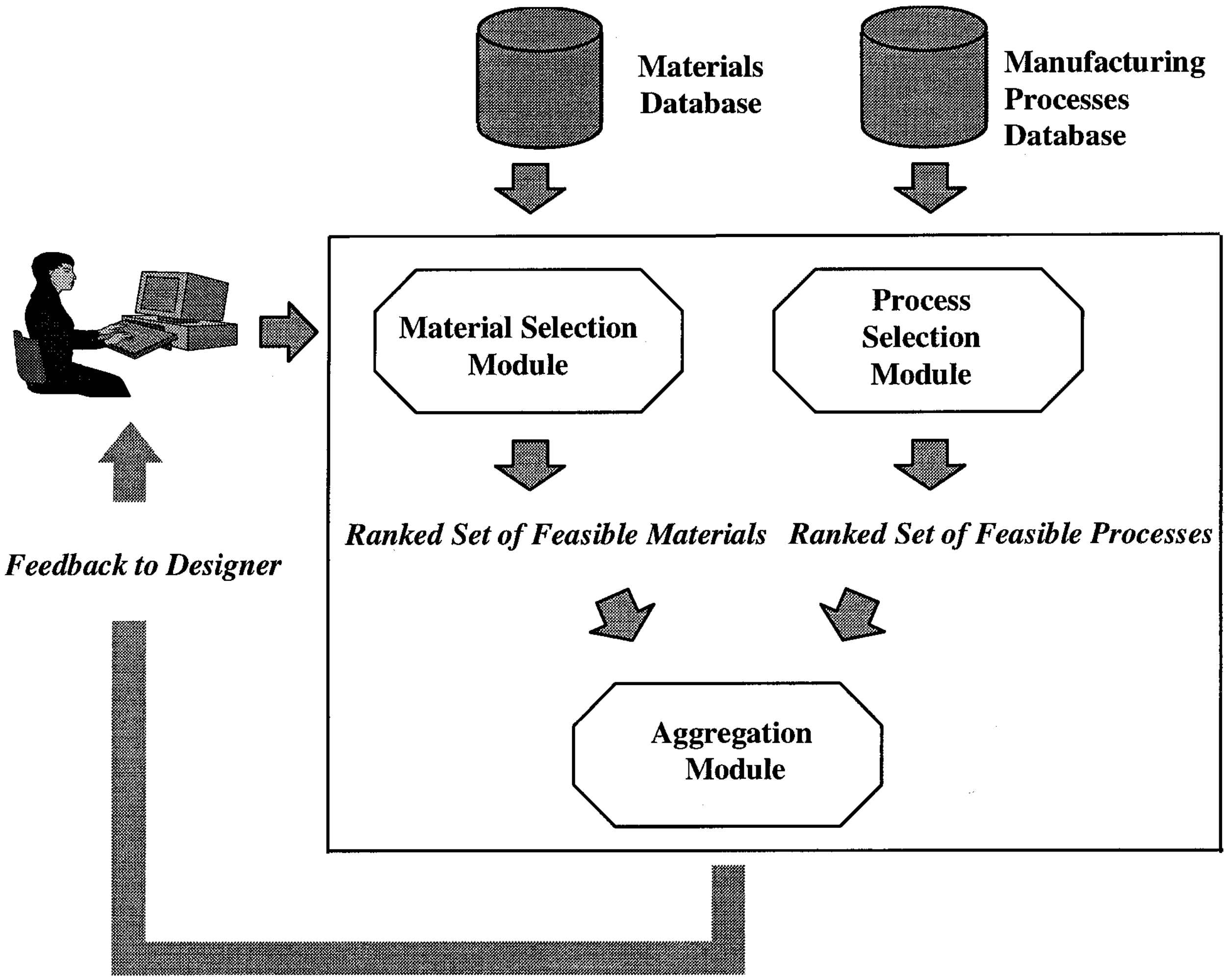


Fig. 1. MAMPS architecture.

sent possible values at a decreasing confidence level (Dubois and Prade, 1988).

The materials are organized into a two-level hierarchy, a group level and a material level. Each group comprises specific materials that have related properties. The properties of a material group represent the possible values from all the individual materials in that group. Example groups are cast aluminum alloys, magnesium alloys, thermoplastics, etc. Group material properties have many influences including alloy composition, heat treatment, and production method and are best represented using a range of possible values. As an example, a range of tensile strengths from 76 MPa to 485 MPa exist in the cast aluminium alloys material group. The material database stores the information using the set representation of Expression 1. The material properties of individual materials are also represented with Expression 1, although it is likely that they will be more precise. When $a = b$ and $c = d$, Expression 1 is degenerate and represents a crisp interval. When $a = b = c = d$, this notation represents a single value.

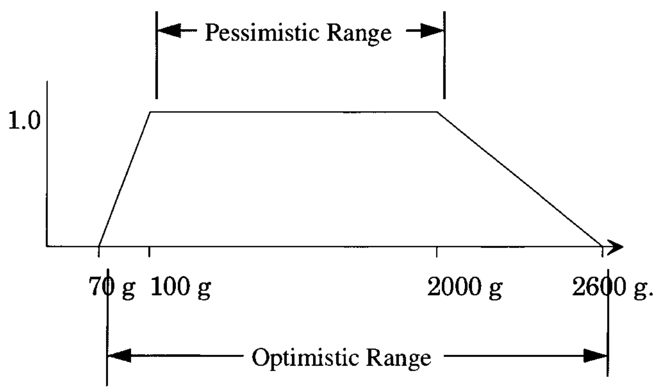


Fig. 2. Weight capability for die casting process (Kalpakjian, 1992).

2.3. *Material selection*

The material selection module assesses the degree of compatibility between a material alternative and the product profile requirements. Material compatibility is performed

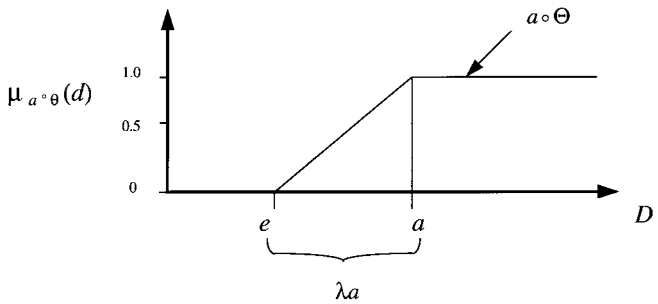


Fig. 3. Example product profile requirement.

via selection queries on the database for each product profile requirement. The queries are based on a relational algebra that supports precise and imprecise queries on crisp, imprecise, and linguistic data. Queries in the domain of material selection are of the form '$A\ \Theta\ a$' where the attribute A is a material property and the requirement a is a preference for a particular value. The comparator, $\Theta \in \{=, <, >\}$ is composed with a to define the product profile requirement that is represented by the membership function

$$\mu_{a \circ \Theta} : D \rightarrow [0, 1] \tag{2}$$

The membership function denotes attribute values in the domain D that are 'strictly compatible' i.e. $\mu = 1$, 'strictly incompatible' i.e. $\mu = 0$, and 'partially compatible' i.e. $\mu \in (0, 1)$ with the product profile requirement. The membership function is shown in Fig. 3.

The Θ-selection query uses possibility theory (Dubois and Prade, 1988) to evaluate the degree to which each material record is compatible with the product profile requirement. The evaluation comprises two measures, possibility and necessity. *Possibility* assesses to what extent the material satisfies the query, or equivalently the extent the material property is consistent with $a \circ \Theta$. This is an optimistic selection strategy. The degree that attribute A of material record k possibly satisfies the product profile requirement defined by $a \circ \Theta$ is calculated using the supremum (sup) of the minimum membership values as

$$\mathrm{Poss}(a \circ \Theta | A_k(d)) = \sup_{d \in D} \min\left(\mu_{a \circ \Theta}(d), \mu_{A_k}(d)\right) \tag{3}$$

where D is the domain of attribute A_k. The vertical bar '|' denotes a separation between the requirement and the database attribute value. Calculation of the possibility measure is shown graphically in Figure 4. *Necessity* assesses to what extent the material certainly satisfies the query. It performs this by measuring the impossibility of the opposite event. This is a pessimistic selection strategy. The opposite event is the complement, $1 - \mu_{A_k(d)}$ of the material attribute. The necessity of material record k certainly satisfying the product profile requirement is defined with the complement of μ_A by calculating the infremum (inf) of the maximum membership values as

$$\mathrm{Nece}(a \circ \Theta | A(d)) = \inf_{d \in D} \max(\mu_{a \circ \Theta}(d), 1 - \mu_A(d)) \tag{4}$$

Calculation of the necessity measure is shown graphically in Fig. 5.

The *Poss* and *Nece* both evaluate to the interval [0, 1] such that the higher the value the more compatible the material alternative is with the product profile requirements. The two values obtained from the possibility measure of Equation 3 and the necessity measure of Equation 4 are combined using a factor β that represents the level of optimism or pessimism of the decision maker (Young *et al.*, 1996).

$$\mu_{ik} = \frac{\beta \mathrm{Poss}(a \circ \Theta | A_k(d)) + (1 - \beta)\mathrm{Nece}(a \circ \Theta | A_k(d))}{2} \tag{5}$$

An optimistic decision maker would use $\beta = 1$, and the other extreme, $\beta = 0$ when the decision maker is pessimistic. A balance between these two extremes is attained for $\beta \in (0, 1)$. The possibility and necessity measures are determined between each material requirement i and

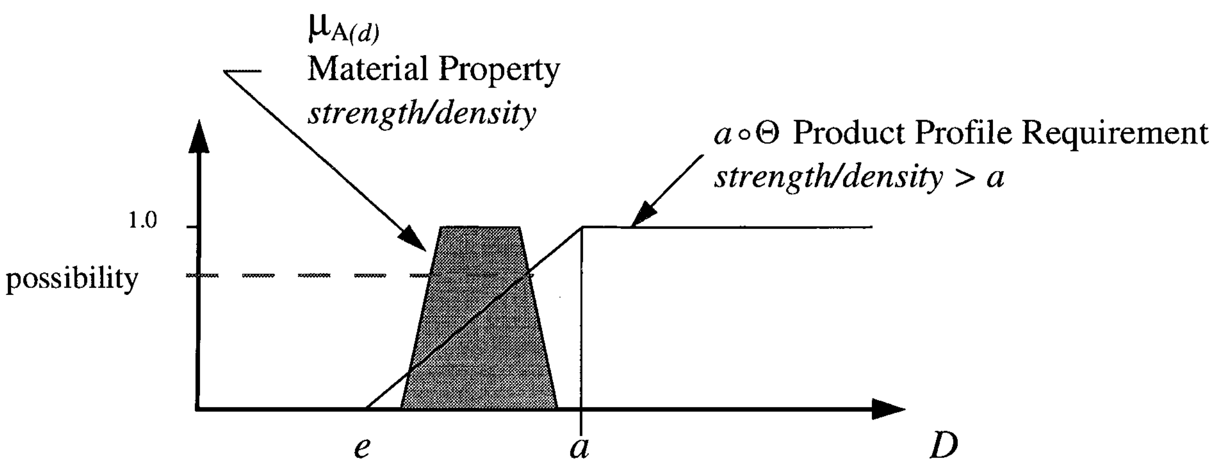


Fig. 4. Possibility measure of material property $A(d)$ under requirement $a \circ \Theta$.

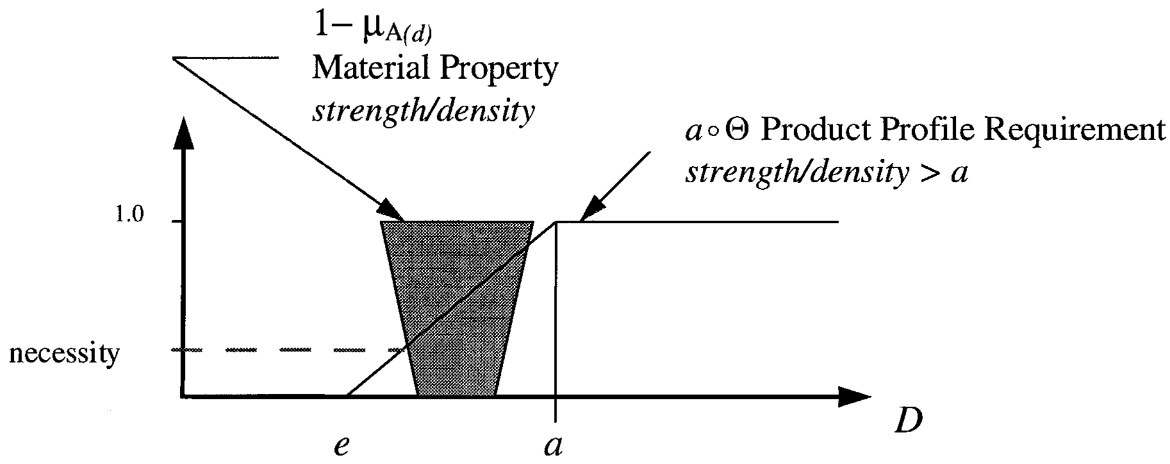


Fig. 5. Necessity measure of material property $A(d)$ under requirement $a \circ \Theta$.

each material alternative k to obtain a compatibility rating μ_{ik}. Each material alternative k will then have a vector of compatibility ratings $\langle \mu_{1k}, \ldots, \mu_{nk} \rangle$ for the n requirements.

2.3.1. *Compatibility assessment using linguistic terms*

Some of the requirements are stated as linguistic terms such as corrosion resistance is 'good'. A normalized range between 0 and 1 is partitioned into five overlapping linguistic sets LS. The sets are 'very poor', 'poor', 'fair', 'good' and 'very good'. Compatibility assessment is performed using the same operators of possibility and necessity as described by Equations 3 and 4 on the normalized range:

$$\text{Poss}(LS \circ \Theta | A_k(x)) = \sup_{x \in [0,1]} \min\left(\mu_{LS \circ \Theta}(x), \mu_{A_k}(x)\right) \quad (6)$$

The necessity is determined by

$$\text{Nece}(LS \circ \Theta | A_k(x)) = \inf_{x \in [0,1]} \max\left(\mu_{LS \circ \Theta}(x), 1 - \mu_{A_k}(x)\right) \quad (7)$$

2.4. ***Manufacturing process selection***

The manufacturing process selection module identifies feasible manufacturing processes and ranks them according to the compatibility of their capabilities with the product profile requirements. Possibility and necessity measures assess the ability of a manufacturing process to produce the part defined by the product profile requirements. Equations 3 and 4 are rewritten in the context of manufacturing process capability evaluation. A manufacturing process capability C_j is possibly compatible with the product profile requirement R_i to a degree defined as

$$\text{Poss}(R_i | C_j) = \sup_{d \in D} \min\left(\mu_{R_i}(d), \mu_{C_j}(d)\right) \quad (8)$$

An example calculation of the possibility measure is shown in Fig. 6.

Necessity expresses to what extent a manufacturing process capability is certainly compatible with the product profile requirement. The process capability C_j is necessarily

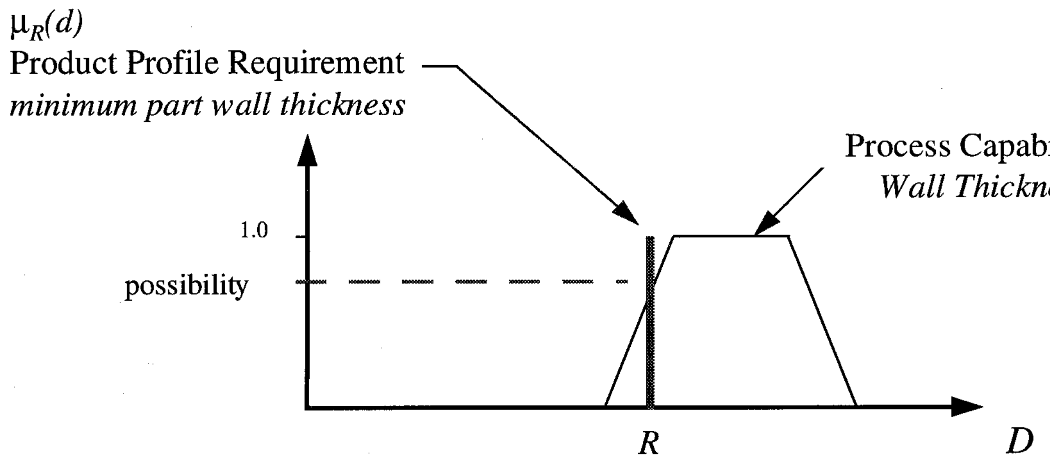


Fig. 6. Possibility of wall thickness under a manufacturing process capability.

compatible with the product profile requirement R_i to a degree defined with the complement of μ_{C_j} as

$$\mathrm{Nece}\left(R_i|C_j\right) = \inf_{d\in D} \max\left(\mu_{R_i}(d), 1 - \mu_{C_j}(d)\right) \tag{9}$$

An example calculation of the necessity is shown in Fig. 7. Values from Equations 8 and 9 are combined using Equation 5 to obtain a degree of compatibility between a manufacturing process and the product profile requirements. The possibility and necessity measures are determined for the m product profile requirements to obtain a vector of compatibility ratings for each manufacturing process j as $\langle \mu_{1j}, \ldots, \mu_{mj} \rangle$.

2.5. *Aggregation of selection objectives*

The previous section described how to calculate a compatibility rating vector for each material alternative and a compatibility rating vector for each manufacturing process alternative. A single compatibility rating is determined for each material alternative as an aggregate of the material compatibility rating vector. Likewise, a single compatibility rating is determined for each manufacturing process alternatives as an aggregate of the manufacturing process compatibility rating vector. Then these two aggregated compatibility ratings are joined based on feasible material and manufacturing process combinations for an overall joint compatibility rating. The result is a final ranking of feasible combinations of materials and their associated manufacturing processes for that set of product profile requirements.

The product profile requirements comprise requirements that must be exactly met and requirements that are flexible. This breakup of requirements has been observed by Dubois *et al.* (1995) in scheduling and by Otto and Antonsson (1994) in design. The hard requirements cannot be relaxed, they must be strictly satisfied. Otto and Antonsson (1994) reviewed different methods of aggregating imprecise attributes for mechanical design and found that design problems require the additional axiom of annihilation to account for hard requirements. The axiom of annihilation states that when one compatibility rating, denoted by Equation 5, evaluates to zero then no trade-off occurs and the entire alternative is not compatible. A geometric mean is used to aggregate the individual ratings. This method obeys the aggregation axioms of monotonicity, continuity, symmetry, idempotent, boundary, and annihilation (Klir and Yuan, 1995). For n criteria the geometric mean aggregate is

$$h(\mu_1, \mu_2, \ldots, \mu_n) = \left(\prod_{i=1}^{n} \mu_i\right)^{\frac{1}{n}} \tag{10}$$

This aggregate was also separately developed by Yu *et al.* (1993) based on empirical studies with engineers in industry who wanted a metric that evaluated to zero when one of the objectives is not satisfied. Equation 10 is termed a *compensatory* operator since higher satisfaction of one objective will partially offset a lower satisfaction of another objective. This aggregate treats all the objectives as if they are of equal importance. Often this is not the case and decision makers desire to assign weights to represent the importance of one objective relative to another. The incorporation of weights into the decision-making analysis using this metric was first examined by Yager (1977). The geometric mean with weights is

$$h(\mu_1, \mu_2, \ldots, \mu_n) \prod_{i=1}^{n} \mu_i^{r_i} \tag{11}$$

The importance or weights of each objective are specified using linguistic terms of importance. The importance of an

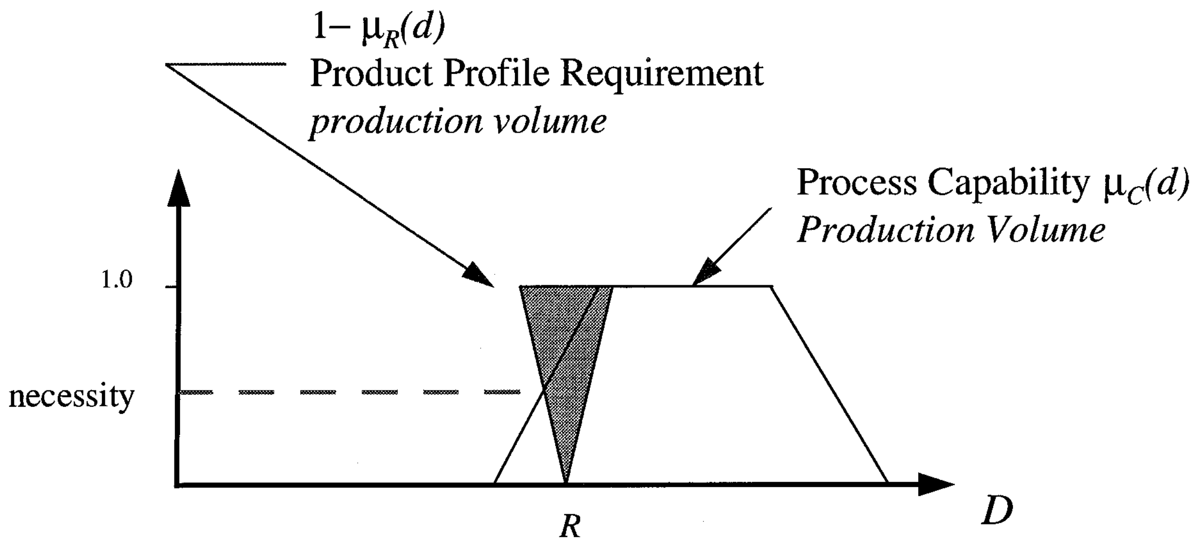


Fig. 7. Necessity of a product profile requirement under a manufacturing process capability.

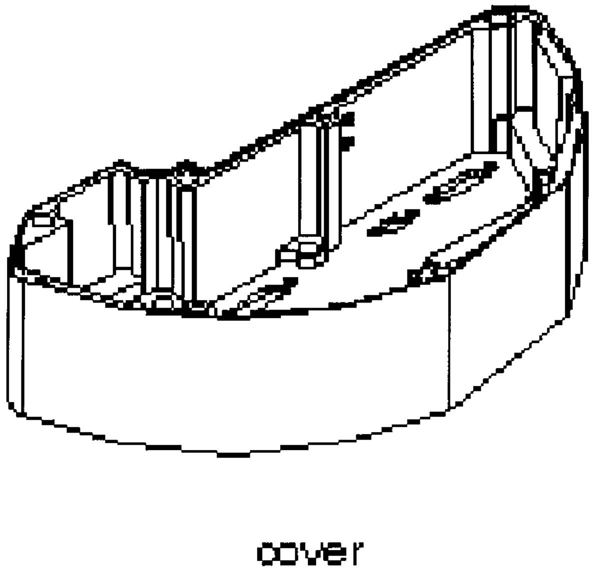


Fig. 8. Example designed artifact (obtained from NIST, 1997).

objective is relative to the other objectives being considered and for this reason the weights must be normalized.

The user assigns weights through one of five linguistic terms ('very important', etc.) which map to a numeric rank w_i for objective i. After all the n criteria are assigned linguistic importance weights w the normalized rank r_i is determined using the expression

$$r = \frac{w_i}{\sum_{i=1}^{n} w_i} \tag{12}$$

Equation 11 is used to determine a material compatibility rating as $\mu_{mtl} = h(\mu_1, \ldots, \mu_n)$ and a manufacturing compatibility rating as $\mu_{mfg} = h(\mu_1, \ldots, \mu_m)$. The material dataset and manufacturing dataset are joined via the manufacturing process and material matrix that identifies what materials can be associated with each manufacturing process. The two compatibility values for feasible combinations are combined into a single compatibility rating using

$$\mu_{final} = \sqrt{\mu_{mtl}\mu_{mfg}} \tag{13}$$

to provide a partially ordered set of compatible material and manufacturing process alternatives.

3. Illustrative example

A proposed cover assembly design is shown in Fig. 8. The product profile requirements are that the cover be strong and stiff enough to protect the internal assembly. It should be corrosion resistant, not significantly add to the product weight, and it should have visually aesthetic characteristics. Note that the compatibility approach described herein could evaluate the cover design even if substantially less geometric detail than shown in Figure 8 was available. The form for entering the product profile requirements and importance weights relevant to material selection is shown in Fig. 9. An information button is available to provide typical ranges of values for material groups in the database. This provides the decision maker with some knowledge of the scale that is used to measure the attribute and can guide novice designers towards good solutions.

MAMPS uses three parameters a, Θ, and λ to build the membership function shown in Fig. 3 for expressing the designer's preferences as a query. To specify the first product profile requirement for hardness the design engineer would choose $\Theta =$ ' $>$ ' using a pull-down menu. The requirement value is typed in as $a = 15$. The query precision level is one of five linguistic terms in the set {exact, precise, imprecise, medium imprecision, very imprecise} that correspond to $\lambda \in \{0.0, 0.1, 0.15, 0.2, 0.25\}$. In this case 'medium' is selected via the pull-down menu. The offset value e is calculated by the equation

$$e = a^{*} \lambda a \tag{14}$$

where for $\Theta =$ '$<$' then $* \rightarrow -$ and for $\Theta =$ '$>$' then $* \rightarrow +$. The hardness requirement is represented by Equation 1 as $\mu_{a \circ \Theta}(d) \rightarrow \langle 10.5, 15, 15, \infty \rangle$.

The same three values, Θ, a, and λ are input for the other material selection criteria. The factor β is input to indicate the decision maker's level of optimism or pessimism. For each product profile requirement Equations 3, 4, and 5 are used to determine compatibility ratings. Importance weights for each product profile requirement are input via pull-down menus. Equation 11 is used to obtain an aggregate for each material alternative. The aggregate values for the material alternatives are shown in Fig. 10. Five of the materials fully satisfy all the requirements and two materials partially satisfy the requirements.

Similar queries are formulated based on the product profile requirements to select a manufacturing process. The form for performing manufacturing process selection is shown in Fig. 11. The results from the selection query are shown in Fig. 12.

The results from material selection and manufacturing process selection are joined together via the material/manufacturing process matrix that links them. The final ranking is determined from Equation 13 and the final results are shown in Fig. 13.

MAMPS provides feedback by showing the design engineer how a certain manufacturing process or material is ranked. In this example the designer may want to better explore the injection molding option even though it ranks the lowest. Forms are available to analyze the system feedback and in this case MAMPS indicates that thermoplastic is ranked low primarily due to a low specific stiffness. The designer could compensate for thermoplastic's low specific stiffness by modifying the geometry to provide stiffness. This could be accomplished by adding ribs for stiffness, and is a common design strategy practiced in plastic part design.

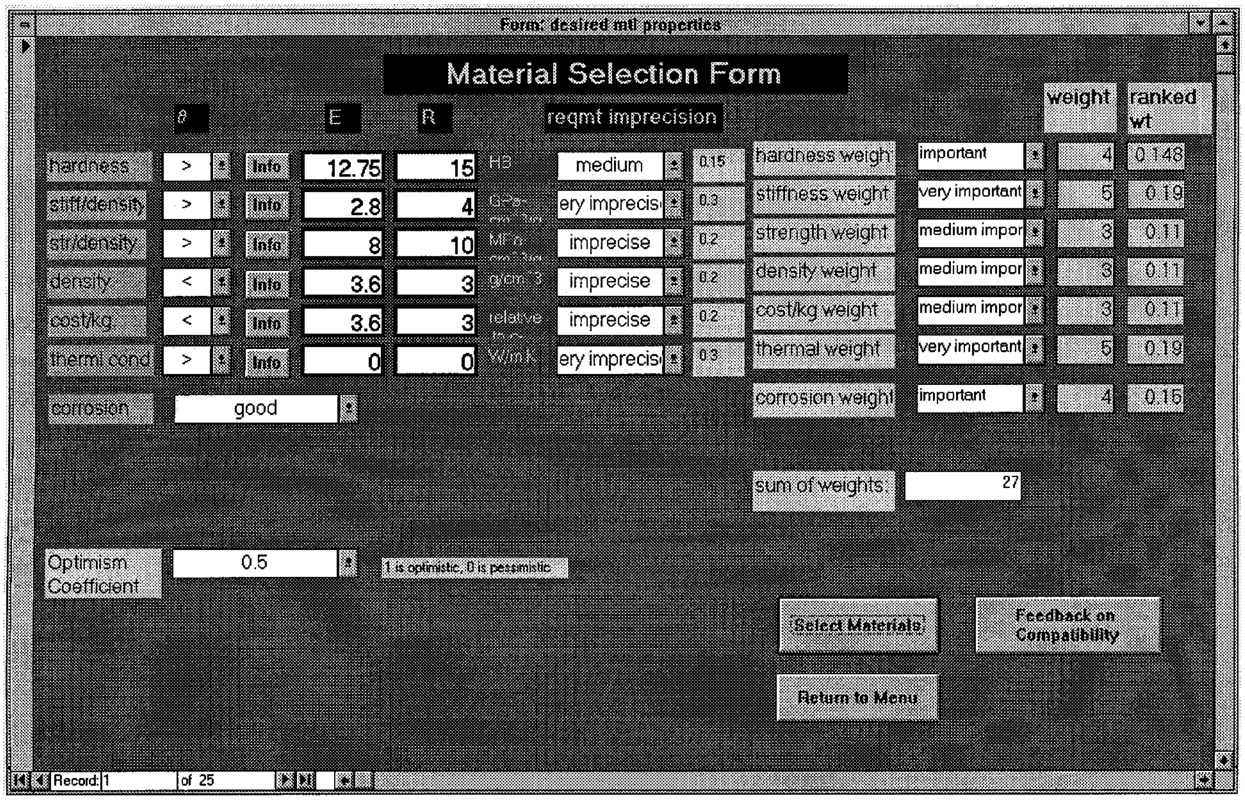
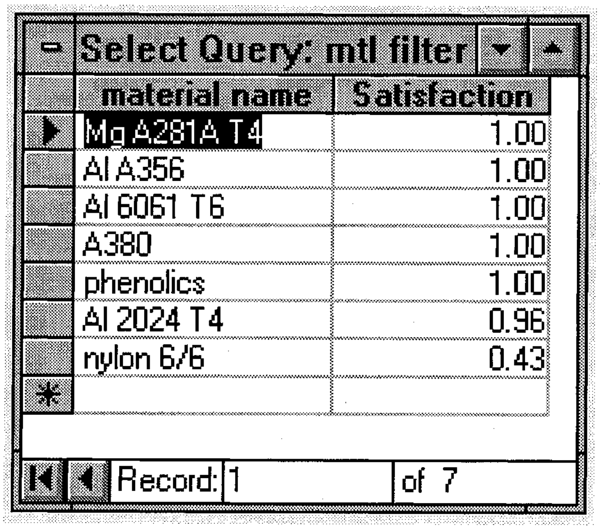


Fig. 9. Material selection form showing product profile requirements.

3.1. *Characteristics of flexible query system and selection problem*

The query precision level λ is inversely related to the number of compatible alternatives in the output set. This is clearly seen in Equation 14 since λ determines the offset value e and the further the offset value from the requirement a then the greater probability of including more alternatives in the output set. Consequently, for a given set of requirements a as the query becomes more flexible or imprecise (λ increases) then the number of alternatives in the resulting dataset will as a minimum remain the same but possibly increase. Two opposing selection strategies are motivated by this observation. The designer may begin with exact queries ($\lambda = 0$) as performed in conventional database systems and if no alternatives are compatible then less important requirements can be relaxed by using more flexible or imprecise queries (increasing λ) for those requirements until an alternative appears in the output set. Alternatively, a selection strategy may be to use a very imprecise query ($\lambda = 0.3$) to obtain many alternatives and then iteratively refine the alternative solution set by increasing the query precision level (decreasing λ). Both selection strategies are demonstrated in Fig. 14. The figure shows five crisp alternatives $A, \ldots, E$ and three queries at different precision levels. The most flexible query ($\lambda = 0.3$) includes all the alternatives in the resultant set, the query at $\lambda = 0$ includes C, D, and E, and the crisp query ($\lambda = 0$) only includes alternatives D and E. Consequently, the relationship is demonstrated between the query precision level and number of alternatives in the resultant set. A second observation is that regardless of the query precision level λ the partial order remains unaffected. Consequently,



Select Query: mtl filter

material name	Satisfaction
Mg A281A T4	1.00
Al A356	1.00
Al 6061 T6	1.00
A380	1.00
phenolics	1.00
Al 2024 T4	0.96
nylon 6/6	0.43

Record: 1 of 7

Fig. 10. Material selection results.

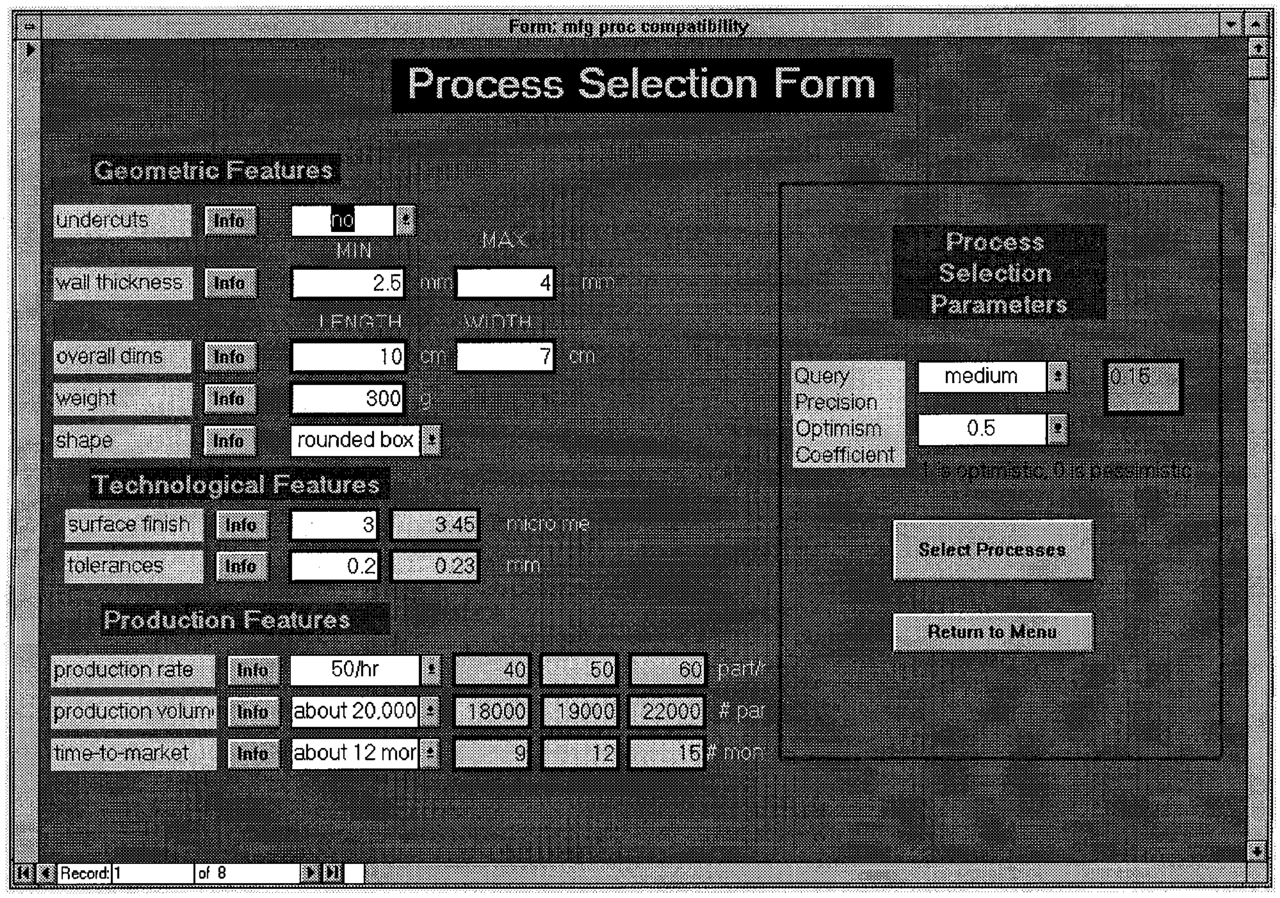


Fig. 11. Manufacturing process selection form and product profile requirements.

only by changing the requirement a or the importance weight can the order of the feasible alternatives be changed. This can also be verified by examining Fig. 14.

4. Conclusion

A decision support system combining a multi-attribute decision making model with a relational database for material and manufacturing process selection was described. The decision criteria concerning material requirements and manufacturing process requirements were identified. The theoretical foundation of MAMPS is based on the assessment of compatibility ratings between the product profile requirements and each alternative using possibility and necessity measures. MAMPS allows the decision maker to specify product profile requirement

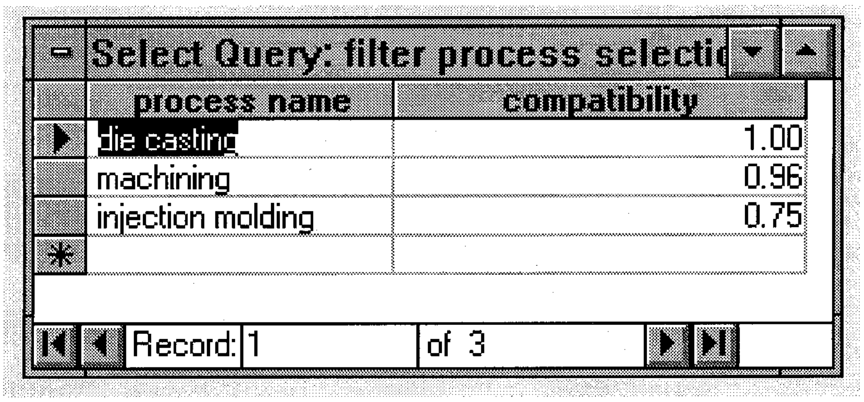


Fig. 12. Manufacturing process selection results.

Select Query: material and process join

material group name	material name	process name	Mfg Compatibility	Mtl Compatibility	Final Rank
cast magnesium alloy	Mg A281A T4	die casting	1.00	1.00	1.00
cast aluminum alloy	Al A356	die casting	1.00	1.00	1.00
cast aluminum alloy	A380	die casting	1.00	1.00	1.00
cast aluminum alloy	Al A356	machining	0.96	1.00	0.98
wrought aluminum alloy	Al 6061 T6	machining	0.96	1.00	0.98
cast aluminum alloy	A380	machining	0.96	1.00	0.98
wrought aluminum alloy	Al 2024 T4	machining	0.96	0.96	0.96
thermoset	phenolics	machining	0.96	1.00	0.98
thermoplastic	nylon 6/6	machining	0.96	0.43	0.64
thermoplastic	nylon 6/6	injection molding	0.75	0.43	0.56

Record: 1 of 10

Fig. 13. Combined material and manufacturing process ranking.

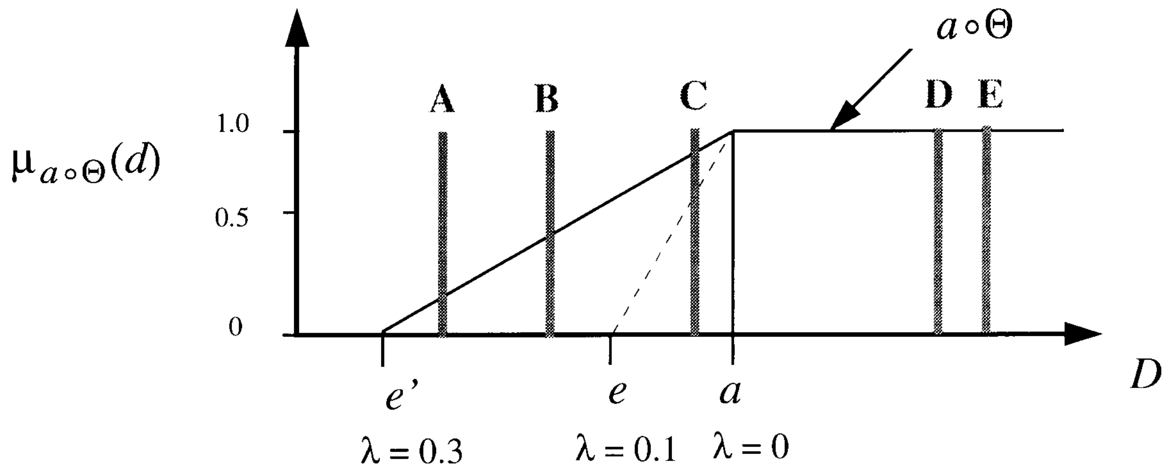


Fig. 14. Three queries and the resultant set of alternatives.

values, their level of precision, and an importance weight. An important contribution of MAMPS is the representation of imprecision in the MADM problem. The imprecise queries better model the qualitative requirements and designer preferences that occur in preliminary design. Consequently, the flexible querying approach better models and supports the selection task. Additionally, the representation of imprecision with respect to the material properties and manufacturing process capabilities better models the uncertainty of this information during preliminary engineering design. This representation approach may instigate the designer to change the design to better use a given material or to reduce the cost of the selected manufacturing process and thus improve the design. The DFM problem must address both feasibility and process economics. The compatibility rating approach concentrates on evaluating the compatibility of using a certain material and manufacturing process. The next step in the design process would be to perform an economic comparison of all the feasible alternatives and is the subject of future research.

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