A CLUSTER ANALYSIS METHOD FOR MATERIALS SELECTION

by

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(ABSTRACT)

Materials have typically been selected based on the familiarities and past experiences of a limited number of designers with a limited number of materials. Problems arise when the designer is unfamiliar with new or improved materials, or production processes more efficient and economical than past choices. Proper utilization of complete materials and processing information would require acquisition, understanding, and manipulation of huge amounts of data, including dependencies among variables and "what-if" situations. The problem of materials selection has been addressed with a variety of techniques, from simple broad-based heuristics as guidelines for selection, to elaborate expert system technologies for specific selection situations. However, most materials selection methodologies concentrate only on material properties, leaving other decision criteria with secondary importance. Factors such as component service environment, design features, and feasible manufacturing methods directly influence the material choice, but are seldom addressed in systematic materials selection procedures.

This research addresses the problem of developing a systematic materials selection procedure that can be integrated with standard materials data bases. The three-phase methodology developed utilizes a group technology code and cluster analysis method for the selection. The first phase is of go/no go nature, and utilizes the possible service environment requirements of ferromagnetism and chemical corrosion resistance to eliminate materials from candidacy. In the second phase, a cluster analysis is performed on key design and manufacturing attributes captured in a group technology code for remaining materials. The final phase of the methodology is user-driven, in which further analysis of the output of the cluster analysis can be performed for more specific or subjective attributes.

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CHAPTER ONE
INTRODUCTION

Materials selection is a necessary step in the design process for every physical object. Correct material choices lead to enhanced performance and/or life of components. However, materials have typically been selected based on the familiarities and past experiences of a limited number of designers with a limited number of materials. Such choices are often based on traditional materials that are on-hand or can easily be obtained. However, the increasingly competitive global market dictates that successful products be of high quality and low cost. Since a large percentage of product cost is committed very early in the design process [9], organizations that make the best decisions possible early in that process avoid costly changes later. Research seeking to improve the materials selection process has therefore become important to maintaining competitiveness, and takes many forms (see Figure 1.1).

The first improvements to materials selection were attempts at systematization of the design process through broad-based heuristics [3, 11, 37, 38, 42, 43]. Some subsequent researchers realized the advantages of computerizing the process, but did not devise actual systems [6, 17, 34, 36]. Others made computerized systems a reality, developing data bases of property information [13, 16, 20, 21, 22, 30, 41], and working material selection systems [2, 4, 7, 15, 18, 32, 33, 35, 44-47, 49]. Regardless of the methodology used, material selection has ultimately consisted of (1) translating the product's

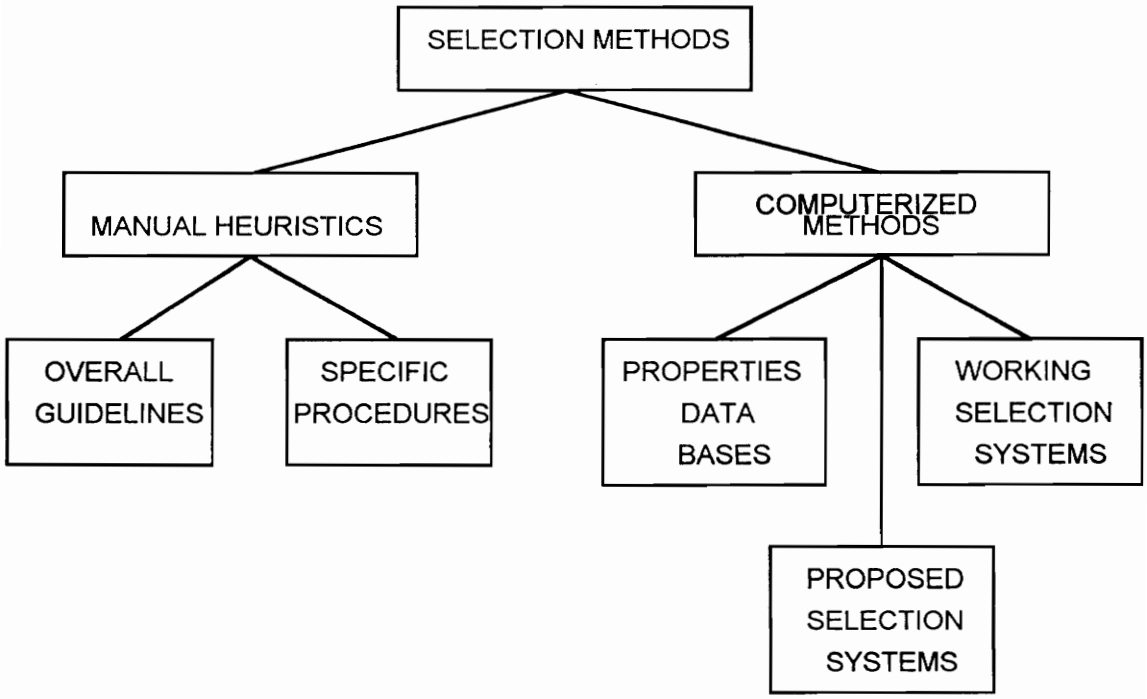

Figure 1.1 Materials Selection Methodologies

required function in a particular service environment (i.e., loading configuration, corrosion, operating temperature range, required component life) into required material properties, and (2) choosing a material possessing those properties. However, most available selection methodologies overlook the interaction between the component design and available manufacturing techniques, and the effect of that interaction on the material choice.

In practice, designers will often simply specify familiar materials that have been successfully used in similar past applications. Such selections already address the combination of design, material, and manufacturing considerations, but problems arise when the designer is unfamiliar with new or improved materials and production processes more efficient and economical than past choices. However, proper utilization of complete materials and processing information would require acquisition, understanding, and manipulation of huge amounts of data, including dependencies among variables and "what-if" situations.

1.1 PROBLEM STATEMENT

Efforts are underway to create publicly available materials data bases of standard form [20, 21, 22, 41]. However, a recent *Materials Selector* [31] estimates over 30,000 available engineering materials. Scrolling through a comprehensive materials data base to flag desired properties would be time consuming, frustrating and expensive. A selection process accounting for

design, materials, and manufacturing concerns that can automatically interface with a standard materials data base is needed.

1.2 RESEARCH OBJECTIVE

The objective of this research is to attempt to establish a realistic, useful approach to materials selection that addresses design, materials, and manufacturing considerations. Operation will be achieved through the use of group technology and cluster analysis.

1.3 SIGNIFICANCE OF THE RESEARCH

No methodology for material selection to date has integrated succinct selection problem representation with selection procedures considering design constraints, manufacturing data, and materials property information. The development of such a system will lead to faster, more rigorous selections that will improve process planning's ability to manufacture reliable components. The proposed methodology will, in addition, provide more economically feasible candidate materials for given applications, and thus provide substantial cost savings to its users.

1.4 DOCUMENT ORGANIZATION

Chapter Two presents a detailed review of the literature in the area of materials selection. The topics covered are Manual Selection Methodologies, including Overall Guidelines and Specific Procedures; and Computerized Selection Methodologies, including Materials Properties Data Bases, Proposed Selection Systems, and Working Selection Systems. An overview of each author's work is presented, followed by critiques. The chapter concludes with a summary of the work related closely to this research, and deficiencies in the literature as a whole.

Chapter Three describes the methodology used to pursue this research. An overview of the selection procedure is first presented. The foundations of the work are next discussed and justified. Finally, each step necessary to formulate this selection methodology is explained and qualified.

Chapter Four details each individual step of the methodology as it is applied to two hypothetical selection situations. The required aspects of the situations are explained textually and numerically, the methodology is applied, and the results are analyzed.

Chapter Five presents future research opportunities stemming from this work. Areas addressed include developing software and a user interface for this selection procedure; altering the GT coding structure; and altering, enhancing and expanding the elimination/ranking criteria.

CHAPTER TWO
LITERATURE REVIEW

This literature review will provide an overview of approaches to improving the materials selection process. Improvement efforts have taken a variety of forms, from overall guidelines [3, 11, 37, 38, 42, 43] to mathematical prioritizing techniques based on property data [2, 3, 5, 11, 15] to complete material specification [7, 33, 44].

2.1 MANUAL METHODS

2.1.1 Overall Guidelines

Gillam [11] specifies five steps common to all systematic materials selections. The first is to define function(s) of the material that will satisfy the customer. Second, the system within which the material is to perform must be defined, especially its boundaries. Third, the material's function(s) is(are) broken down into design and property requirements, including factors such as cost, manufacturing methods, etc. Fourth, a list of candidate materials that may meet the requirements outlined in step three is generated. Finally, the candidates are assessed to determine the rank order of choices by one of several methods: the grid ranking method, Waterman's numerical ranking method, decision-tree analysis, linear programming, or cost-benefit analysis.

Gillam details two of the six methods by which step five of his universal methodology may be executed. The first is the grid ranking method, in which (1) threshold values are determined for all design/property requirements, (2) a grid is formed by listing requirements along the top and materials down the side, (3) materials not meeting one or more of the requirements are eliminated, (4) the final material is selected from those remaining by lowest total cost, (5) a prototype is built and tested, (6) information resulting from the prototype test is placed in the grid, (7) the material selection is modified if necessary.

The second method Gillam details is Waterman's numerical ranking method, that places candidate materials in decreasing order of "suitability." "Suitability" is defined as

$$\Sigma\,(M_i W_i / C_i), \qquad i = 1, N;$$

where *N* is the number of design requirements, *M* is the requirement's degree of merit, *W* is the weighting factor (importance) of the requirement, and *C* is the requirement cost. The author cautions, however, that Waterman's method can yield inappropriate selections in the case of high requirement importance coupled with low degree of merit and cost.

In addition, Gillam presents concerns that should be factored into a material selection, but are not easily adopted into most systematic selection methods. These concerns are: the health and safety of manufacturing workers and consumers, changing customer likes and dislikes, and world business and

political practices that can affect material availability and cost. Gillam does not, however, suggest ways to (1) formulate the above concerns into his methodology, (2) translate required material function(s) into required material properties -- step three of his methodology, (3) generate a candidate list of materials -- step four, or (4) rank candidate materials by the methods of decision-tree analysis, linear programming, or cost-benefit analysis -- step five.

Pye [38] describes the five specification stages of new product development. The first is market specification, which defines the need for the product, its function(s), its target manufacturing cost, estimated total sales and sales rate for the product, and the effects on product sales of added design features. Stage Two is basic product specification, in which a checklist of necessary and desirable product functions is formed. Design specification follows, where product components are described in terms of assembly process, dimensions, and required materials properties of each component. Fourth is the production process specification, which defines how the product will be made. The last stage of product development is quality control specification, where proper functioning is insured by determining what should be tested before, during and after production. Pye notes that design specification is critical to materials selection, and should be prepared by (1) arranging product components in a systematic, hierarchical structure; (2) analyzing each component for functional requirements; and (3) ranking candidate materials by the grid ranking method.

Smith [43] asserts that every materials selection situation is unique and should never be generalized from other choices. He warns engineers to avoid traditional selections based on previous uses or property data, since previous uses may no longer be appropriate in today's market, and available property data may not predict the behavior of the final fabricated material reacting to its specific environment. He proposes a four-step methodology that encourages engineers to concentrate on the general factors in materials selection, which are interrelated with functional, total life cycle, and other major factors in design. The first step in the material selection methodology is to clearly define the selection problem, including constraints and specific functions of the design with corresponding material requirements. Smith's second step is to prioritize the factors defining design performance and the criteria used to evaluate the design. The third step is to translate functional and material requirements into material properties, using current property data compilations (while mindful of the product's final form) and weighted performance indices, if needed. Finally, a material choice is made that best compromises safety and cost.

Plevy [37] likens material selection to value engineering in his recursive seven-stage general framework designed to yield the best overall material choice from a systems perspective. In the first stage, problem situation, the selection is considered from a macroscopic level, and its boundaries are defined. The fixed and variable features of the selection are separated in the second stage, problem analysis. Problem definition, the third stage, specifies the function of the part in question and takes into account the variables defined in the previous stage. The fourth stage, conceptualization, considers alternative

ideas, designs, materials, and manufacturing processes which satisfy the requirements set forth in problem definition. In comparison, the fifth stage, alternatives generated in the fourth stage are examined to identify those that warrant further consideration. The remaining alternatives are tested on technical and economic aspects using a broad treatment of costs in the sixth stage, evaluation. Material selection is the seventh and final stage.

Sandstrom [42] attempts to minimize qualitative decisions in his a two-stage systematic procedure for materials selection. The first stage, discrimination, uses property requirements that do not affect the final size of the part (discriminating properties) to generate candidate materials (those that violate no discriminating property requirement). Discriminating properties are divided into three categories: (1) usage -- material properties that allow the product to withstand its service environment, (2) manufacturing -- material properties that allow the product to be manufactured, and (3) availability -- compatibility of product features and manufacturing requirements with manufacturing technologies available. The designer first formulates a "demand profile" for the part, including component function, component shape, service environment, required life, maximum cost, regulatory requirements, and the object of optimization, e.g., minimum cost. The component demand profile translates into a material demand profile, that will depend on possible materials and manufacturing processes.

The second stage, optimization, ranks candidates using merit parameters which minimize materials cost, including manufacturing costs. Each candidate

material's controlling merit parameter (the inverse of the part of the material cost expression dependent on material properties) is calculated. Material prices are represented by ratios of the actual material cost to that of a simple carbon steel. Candidate materials are then ranked by decreasing values of the controlling merit parameter.

Although Sandstrom acknowledges that manufacturing considerations will affect materials selections, there are numerous disadvantages to his approach. Many aspects of his methodology would be difficult, if not impossible, for an inexperienced designer to accomplish. These aspects include: (1) determining the types of materials and manufacturing processes for which material demand files will be made, (2) formulating selection criterion (i.e., necessary material properties) from component requirements, (3) formulating controlling merit parameters that correctly reflect all material dependencies. In particular, the formulation of selection criteria would require an in depth understanding of the relationships between characteristics needed in the final product and material properties. Also, the ratio treatment of material prices used in the merit parameter expressions may not be appropriate if a simple carbon steel will not satisfactorily perform in the given application. In other words, the material serving as the basis of the price ratio must satisfy the minimum requirements of the job.

In an attempt to quantitatively assess performance-limiting properties of materials, Ashby [3] proposes that critical property equations (i.e., $E^{1/2}/\rho = C$, where E is the Young's modulus and ρ is the density of a material) be converted

to linear form (i.e., ln E = ln ρ + C) and appropriate axes chosen (i.e., x = density, y = Young's modulus), such that the point values of prospective materials can be plotted in the space bounded by the axes. In this way, materials with similar property values will cluster together, and materials that will perform at a given level (i.e., those that fall on a given straight line) can readily be seen. Materials falling above the straight line have a greater value of the critical property, those below have a lesser value. Hence, a user can quickly assess the relative performance of material classes in the critical property and choose the material corresponding to the desired level of performance. However, Ashby's method assumes that the combination of properties that maximizes performance of a component can be reduced to a single equation, and that the equation can be made linear. The method chooses a material based only on properties; there is no consideration of the form, manufacturability, or availability of the raw materials. In addition, generating Ashby's property plots would be labor intensive unless computer generated.

2.1.2 Specific Procedures

Gulyaev [12] provides guidelines for selecting steels to compose machine parts with maximum strength, reliability, and longevity. To follow the author's framework, the part form (including dimensions) and service environment (including operating temperature ranges and loading configurations) must be known. Strength of machine parts under loading is then provided through the specification of an allowance stress, which accounts for both the plastic

deformation occurring before a crack forms, and the microplastic deformation occurring at a crack opening. Next, reliability is insured through the specification of a toughness safety factor to compensate for the range of temperatures in which sharp changes in microplastic deformation at crack openings can occur. Finally, the life of machine parts may be extended through various surface hardening techniques applied to the steels. The author also notes that strength, reliability, and longevity may be enhanced by alloying elements in certain steels. Gulyaev's approach does not, however, guarantee optimal material choices, or even appropriate ones. The only manufacturing considerations Gulyaev mentions are melting properties, which would certainly not represent all those affecting the material.

Kirchner [23] proposes an organized approach for selecting alloys to serve in corrosive environments, in which candidate materials are chosen based on the part's function, design constraints, failure consequences, and service environment; and the final material choice is based on economics. However, Kirchner's steps are very general, and their actual mode of execution is left to the reader. Some of the analyses suggested would be labor intensive unless computer-aided, and no advice is given about where to locate the data necessary to perform such analyses.

Wilhelm and Kane [49] discuss procedures similar to Kirchner's for selecting materials for sour service in the petroleum industry. Conventional analyses of service environment and design information are first performed to determine the material strength needed for the application. The NACE Standard

RP-02-72 is then used as the basis for an economic breakeven comparison between the two candidate materials classes, corrosion-resistant alloys and steel with corrosion inhibitors. Wilhelm and Kane's approach is not novel; it is simply economics.

Chetwynd [5] uses a graphical methodology to choose materials for precision components. A three dimensional space is defined by logarithmic axes representing the three general characteristics found in materials used in precision devices: low distortion under steady thermal load, rapid restabilization in response to thermal load changes, and contribution to low self-weight distortion and high resonant frequencies. Candidate materials are plotted in the space, and the most suitable materials for precision applications are located close to the origin. Chetwynd does not, however, provide any assistance on generating a candidate list of materials to be plotted in the parameter space. His approach is very limited, since narrowing selection criteria to three key material properties in other applications may be difficult. Also, plot generation would be much more efficient if it were computerized. Finally, Chetwynd does not mention manufacturing or cost considerations in his procedure.

Lohne and Saether [26] propose that steels be selected for components of welded offshore installations based on the consideration, in order, of four dependent factors: (1) conditions during service, (2) structural category, (3) desired mechanical properties, and (4) chemical composition. Possible service conditions of elements that should be noted include the type of applied stresses, cyclic loading, and consequences of failure. The authors provide four structural

categories into which all components of a welded offshore installation can be classified, ranging from special (essential to structural stability) to non-structural (i.e., a ladder). The desired mechanical properties of a candidate steel will be dictated by the structural category of the element for which it will be used, and by the service conditions the element may encounter. Mechanical properties of candidate steels that should be specified include ductility, toughness, and strength. The chemical compositions of candidate steels should ensure retention of necessary mechanical properties and corrosion resistance during both material and structure fabrication. Special attention and careful documentation should be given to any alloying or residual elements found in candidate steels. The weldability of candidate steels should subsequently be determined using carbon equivalency equations provided by the authors. The authors conclude that four types of steel corresponding to their four structural categories will be deemed sufficient by their methodology to fabricate every component of a welded offshore installation.

No specific details are provided about how any of the four factors important to steel selection should be addressed. Determining the service conditions and structural category of an element may not be difficult, but defining necessary mechanical properties suitable to withstand fabrication, and a corresponding chemical composition with suitable weldability, are laborious at best. No method is provided by which either of these tasks could be performed. No efficiency improvements are offered in the work, such as standardization and computerization of part or all of the selection process.

2.2 COMPUTERIZED METHODS

Analytical work investigating the area of computerized material selection methodologies was published in 1985 by Martini-Vvedensky [29, 30]. The author describes the benefits of computerized selection procedures as: (1) users need not be materials experts to use extensive materials information intelligently, (2) such procedures could be used to update or verify existing materials selections, and (3) system use could be monitored to assess materials demand. According to Martini-Vvedensky, the requirements of computerized materials selection methodologies should include: (1) the systems focuses on information needed for materials selection, (2) the ability to obtain reliable results, regardless of user knowledge level; (3) the ability to search data bases by a variety of criteria; (4) the range of materials included is large enough to accommodate requests from users versed in materials (50-100 properties for several thousand materials); (5) the material information is kept accurate and current; (6) material cost information is included; and (7) the capabilities of unit conversion, profile matching, graphics, and CAD/CAM interfaces are included. In addition, the author lists needs of computerized methodologies not yet addressed, including: (1) comprehensive data bases of materials and their properties, (2) data bases of manufacturing methods, (3) data bases of lubricants and their effects on the friction and wear of materials, (4) the inclusion of supplier contact information in materials data bases, and (5) linkage of new data bases with materials data bases to provide increased useful information.

2.2.1 Materials Properties Data Bases

Gutteridge [13] explains a computer data base used to generate candidate materials by entering desired values for critical material properties, or by entering particular material codes used in the data base. The computer then outputs all property information for those materials meeting user requirements, and can generate property plots if requested. The program does not, however, employ any ranking or selection methods, and is therefore simply a data base of material properties. Furthermore, the scope of the system is not well defined.

Ho and Li [16] describe the computerized materials properties numerical data system developed at Purdue University. The menu-driven system allows users to search for specific materials, properties, etc., and for candidate materials satisfying a set of user-defined requirements. Separate data bases exist for a large number of properties (often over 100) of each material type, including: dielectric materials, aerospace structural composites and alloys, infrared detector/sensor materials, etc.. The data bases were developed by compiling information from many technical sources (accounting for different testing conditions and research methods), computerizing the information into various data files, and integrating the files into data bases. The properties information is updated and expanded continuously. Although the system provides accurate property data for the materials it covers, it provides no methodology to make material selections, and thus is merely a data base.

Martini-Vvedensky [30] describes MASTUS, an on-line data base system for metals, plastics, ceramics, glasses, and composite materials. The systems contains over 150 properties that may include various types of descriptive information; strengths and moduli; or thermal, electrical, processing, environmental, flammability, or physical properties. Any information not given by a supplier is taken from generic handbook data, and irregular or atypical information for a materials type is flagged in the data base. Materials searches may be performed by combinations of property information, trade name, supplier data, composition, or typical uses. However, MASTUS contains no ranking or selection algorithm, and its treatment of manufacturing considerations is not explained.

Sandstrom and Grahn [41] pose that the three property categories included in the Swedish National Materials Data Base are necessary for materials selection: usage, including factors that allow resistance to service environment; manufacturing, including workability, joining, and hardenability factors; and availability, including cost and accessibility factors. To properly utilize materials data, knowledge of the following is imperative: if data is an extreme or average value, the testing methods used, the accuracy of the data value, and the source of the data. However, the authors suggest that material selection is dependent on innumerate factors and thus is so complex that full description of all associated aspects is impractical, and that simplification techniques must be introduced into the data. The degree of simplification is specific to the criticality of the property in question, the accuracy desired in the materials selection, and the effort and time available in which to make the

selection. The authors only make suggestions to simplify data representation in materials data bases; they do not present a selection methodology in their work.

The American Society for Testing and Materials (ASTM) has undertaken efforts to construct a standardized materials data base format for use in the United States. Kaufman [20, 21, 22] reports on the activities of ASTM Committee E49 on the Computerization of Materials Property Data. The Committee has been active since 1986, and is responsible for providing guidance, eventually from definition of need to data representation and location, in the development of materials data bases able to reliably exchange information with other sources. To promote such activities, several subcommittees have been formed: E49.01 on Identification of Materials, E49.02 on Reporting of Material Property Data, E49.03 on Terminology, and E49.04 on Data Base Interfaces and Functionalities. All committees and subcommittees work with experts in respective material fields, as well as similar international efforts, to develop feasible system construction guidelines. E49 to date has developed preliminary guidelines that identify information critical in public domain materials data bases to promote high quality, reliable, and compatible data (see Table 2.1). However, standard data formats have not yet been developed for any specific group of materials; to date only suggested data layouts are available.

Table 2.1 Categories of Information for Materials Characterization

CATEGORY	EXAMPLE
Material Class	Metal, polymer, composite, ceramic
Material within Class	Stainless steel, SiN
Material Designation	Industry standard or experimental
Material Condition	Industry standard or broad class
Material Specification	ASTM or other
Material Producer or Source	
Producer Lot Number	
Product Form	Casting, forging, laminate, compact
Fabrication History	Major elements of fabrication procedure

2.2.2 Proposed Selection Systems

Chiner [6] provides a plan for constructing a material selection expert system. The knowledge base would contain the following information: types of materials, typical properties with priorities, acceptable ranges of property variation, and traditional applications. The inference engine of Chiner's proposed expert system would follow a five step methodology for material selection. The first step, definition of design, requires analysis of the aesthetic, functional, economic, and use characteristics of the product. Next, these characteristics are translated into necessary material properties with acceptable tolerance ranges and importance weights. Critical properties are identified through construction of a domination matrix or sensitivity analysis. The third step involves the development, preferably by computer, of a list of candidate materials that satisfy the properties determined in the previous step. Next, the optimal material is chosen by uni-criteria methods (for a single decision factor, usually cost), or by multi-criteria methods. Lastly, verification testing yields likely failures and statistically reliable measures of the performance of key material properties in possible service conditions. Chiner's plan, however, is incomplete. He provides no means by which to generate candidate materials in step three, nor does he include manufacturing considerations anywhere in his methodology. His uni- and multi-criteria selection methods account for numerical property considerations only. Also, since an actual expert system was never built from Chiner's plan, there is no proof of the plan's validity.

Hopgood [17] describes two methods product designers may use to select materials with expert systems, one based on point data values, and the other based on material relationships. The first method requires the user to enter a list of desired material properties and their relative importance. Materials that do not meet the user's numerical specifications are eliminated from the search. The system then ranks the remaining materials using the alternative inference method (AIM). AIM connects the materials' property performances (values from 0-9) with user-specified weightings indicating property importance (values from 0-10). Entered specifications may be altered to test the sensitivity of the ranked materials. Hopgood's second expert system method employs object-oriented programming techniques, and operates by sending messages between objects. Neither of the methods consider manufacturing in making material choices. In addition, the author provides no details on how to convert either of his selection methodologies into working systems, thus there is no proof of their validity.

Olsson, et. al. [34] interpret materials selection as part of a five stage design process. In the first (exploratory) stage, design alternative to meet some demand are identified. All materials are candidates during this stage, compared by figures of merit for a few properties. A technical study is next performed, in which feasible design objectives are specified, and deeper investigation of materials properties narrows candidate materials to a few identifiable groups. In primary design, all necessary product functions and possible service environments are defined, and materials choices are further limited with the specification of more required properties and with prototyping. One material (with one to two alternatives available) is produced and consumed in production

design. During the final stage, feedback, customer input and analysis of failures and spare parts demands are fed back into design and future efforts.

The authors next present a proposed computerized system structure for materials selection, in which the properties of company-used materials are linked with a CAD/CAM coupling available to the system user. Access would be available to the following information: (1) national standards, (2) information on materials other than what the company currently uses, and (3) other/international materials data bases. The system would flag any data not from the company data base. The material selection system would have the following features: (1) training in use of the system; (2) case studies of system use; (3) interaction with users of many skill levels; (4) documentation of features; (5) labeling of data categories; (6) data ranking by compliance with desired characteristics; (7) generation of candidate materials by desired characteristics; (8) presentation of candidate property information in list, tabular, or graphic form in relation to desired characteristics; (9) warnings during use of data not company-owned.

Problems with the authors' systems are numerous. Material properties only are used as selection criteria; no manufacturing or design considerations are addressed directly. In addition, the method employed to narrow from the population of materials to one material is not specified, thus the suitability of the system's materials choices is not guaranteed. The proposed system may rely too heavily on current company practices; system selections will be useless if current company practices are wrong. Finally, the authors provide no means of

translating their desired system structure into an actual working system, therefore, the system's validity as a whole remains unproved.

Pilgrim, et. al. [36] determine similar materials that may be interchangeable using cluster analysis on a similarity measure that is independent of actual materials data. The method assumes that some preselection has generated a list of candidate materials. The user first chooses selection criteria and corresponding allowable variance for numeric property values. The user next specifies the number of hierarchical levels used and the properties assigned to each. Properties placed in the first level are most important, those in the second level are next, etc. The similarity criterion *A(i,j)* is defined as the number of string (or substring) matches plus the number of numerical property values falling within allowable variances,

$$A(i,j) = \sum [\, C_k(i,j) / (M(i) * M(j)) \,](qn + 1)^{p-k}, \quad k = 1,p;$$

where C_k is the total number of *k*-level matches between cluster subset *i* and *j* of the adjacency matrix, *M(r)* is the number of materials represented in a subset *r*, *n* is the number of candidate materials, *p* is the number of hierarchical levels, and *q* is the maximum number of properties to be matched at each level. The scale factor $(qn + 1)^{p-k}$ ensures that a single match at a given level *p-k* will surpass cumulative matches at lower levels. Using the *A(i,j)* measure, materials that are similar on the criteria most important to the user may be considered interchangeable, and are clustered together.

Although this method reduces user interaction and search time, it has drawbacks. First, the only degree of matching visible with this method is level-related, not data-related. All that is apparent is how many matches were made and for what level. For most applications, a more rigorous analysis that successively eliminates materials using actual data would be more desirable. Second, although it reduces search time, the assumption of preselection to generate candidate materials greatly limits the applicability of the methodology. Third, the only selection criteria used by the authors are materials properties, although design and manufacturing data could easily be incorporated.

2.2.3 Working Selection Systems

Hanley and Hobson [15] assume a particular material class has been chosen for a given application, and present a geometric and an algebraic computerized method for choosing the proper material subclass. In the geometric approach theory, desired subclass property values Y_i are plotted along radii from a polygon center. Candidate subclass polygons X_i are subjectively judged on their deviations in size and shape from the ideal. The geometric concept reduces to two dimensions with the introduction of the "mean weighted characteristic" (*MWC*), indicating closeness of the candidate polygon size to ideal (*MWC*=1); and the "balance factor" (*BF*), indicating closeness of the candidate polygon shape to ideal (*BF*=0). First, weighting coefficients α_i, ranging from zero to one as importance increases, are subjectively assigned to

each required property. Next, the *MWC* and *BF* for each candidate are calculated as:

$$MWC = (\alpha_i X_i / Y_i) / \sum \alpha_i, \quad i = 1, n;$$

and

$$BF = [\sum (X_i/Y_i - MWC)^2]^{1/2}, \qquad i = 1, n.$$

Subclasses with *MWC* < .8 and *BF* > .2 are then eliminated. Remaining subclasses are ranked in order of increasing distance on a plot of *MWC* versus *BF*,

$$d = [(1 - MWC)^2 + BF^2]^{1/2}.$$

The goal of the authors' algebraic approach is to minimize the sum of the per unit deviations of candidate subclass properties X_i from desired subclass properties Y_i. First, as in the geometric approach, weighting coefficients α_i are assigned to each required property. Then, the objective function is calculated for each candidate subclass,

$$\min Z = \sum \alpha_i * | X_i / Y_i - 1 |, \qquad i = 1, n.$$

Subclasses with $Z > 2$ are eliminated, and remaining subclasses are ranked in order of increasing Z. Constraints on deviations may be incorporated into the algebraic approach in the following way: lower limits ($X_i/Y_i > 1$), upper limits ($X_i /$

$Y_i < 1$), equality limits ($X_i / Y_i = 1$); where there is contribution to Z if a constraint is violated. However, the fundamental problem with the authors' approaches is the subjective choice of weighting coefficients. If the weighting factors are incorrectly chosen, results from the selection methodologies will be useless. In addition, the authors begin their selection strategy by assuming a particular material class has been prechosen, which may ignore many feasible solutions in other material classes.

Dargie, et. al. [7] describe MAPS-1, a computer program that generates candidate materials and manufacturing processes for a given application based on a group technology (GT) code. Users are prompted for input, and their responses are used to construct a 12-digit code, although digits nine through 12 have not been fully developed. The first five digits of the code (batch size, bulk, shape, tolerance, and surface roughness) are used to eliminate manufacturing processes from the 47 contained in the program. The next three digits (service temperature, corrosion rate, and corrosive medium) eliminate materials from the 50 considered by the program. A figure of merit calculated from the remaining digits (loading mode, structural geometry, loading schedule, and criterion of excellence) will be used to rank remaining materials.

The first stage of elimination of processes/materials in MAPS-1 is achieved through the use of a data base of nine "suitability matrices," one for each of the first nine GT code parameters. The rows of the suitability matrices correspond to the possible processes/materials in the program, while the columns correspond to each possible digit value of the parameter in question

(usually zero through nine). The matrices' entries are either *0* (indicating unsuitability) or *2* (indicating suitability). An example of a partial suitability matrix appears in Figure 2.1. Processes/materials unsuitable for the application are eliminated. Processes/materials are eliminated in the next stage using a "compatibility matrix," which indicates the compatibility of all remaining processes with all remaining materials. The matrix's rows correspond to processes, columns to materials, entries of *0* to basic incompatibility, entries of *1* to difficult combinations, and entries of *2* to compatible combinations. Property matrices are still under development, but will be used to rank candidate materials and processes remaining after the first two elimination stages.

The authors consider design, material, and manufacturing factors in their selection methodology and succinctly represent large amounts of information about the application through a GT code. However, the greatest limitation to the authors' approach is the use of the suitability and compatibility matrices. Actual property data would provide a much more rigorous analysis of suitable material and process combinations. It is unlikely that relationships among materials and processes are as clear cut as the matrix representation forces them to be. There may be degrees of suitability or compatibility that cannot be adequately represented in the authors' matrix format. In addition, the source of the suitability and compatibility data is unclear, and replication of such data for new materials/processes could be labor intensive. The program to date has no ranking method for outputted candidate materials and processes, so that if many remain after the two stages of elimination, the user could have a difficult time making a final choice.

	BATCH SIZE DATA	REF.	PAGE
1 2222222222	Centrifugal Casting	YANK79	91
1 0000222222	Die Casting	YANK79	136
1 0000222222	Hot Extrusion	GENE60	PSG1
1 0022222222	Closed Die Forging	GENE60	C1
1 2200000000	Open Die Forging	DALL76	14-12
1 2222222222	Full Mold Casting	DALL76	22-7
1 0022222222	Hot Isostatic Pressing	ESTIMATE	
1 2222222222	Investment Casting	YANK79	67
1 0002222222	Permanent Mold Casting	YANK79	76, 136

Figure 2.1 Partial Suitability Matrix [7]

Unterweiser [45] describes a data base used at Deere & Co. for the analysis of linkages. It contains material information in the form of 17 key material properties subdivided into three categories: engineering, true stress-strain, and fatigue. The data base includes manufacturing information on the variables of welding, machining, and casting. Its design information consists of external loading and cost parameters. Deere's system is one of the few which recognizes the importance of addressing design, material, and manufacturing factors when selecting materials.

The factors considered in automated materials selections made by Deere & Company and Ford Motor Company are outlined by Obrzut [33]. Both companies address design, manufacturing, and material characteristics in their selections. Deere's modular system uses material properties suitable for the application in question to choose compatible manufacturing processes, and then predicts the results of the combination. Factors incorporated in the systems include: materials properties (including the manufacturing characteristics of machinability, formability, weldability, and hardenability), service loads, process characteristics, company production time standards, process capabilities of available production equipment, cost data, and parts geometry. Ford Motor Company examines how the environment, processing, and failure modes of a particular requirement affect the materials properties needed, and choose materials accordingly. Both company's procedures are very organization-specific, and therefore may not easily transfer to a different materials selection environment.

Alexander and Appoo [2] present the methodology used to rank candidate materials in their program COMAS. The user provides the following input to the program: the number of materials in the data bank (*N*), the number of required properties (*NC*), the primary property number (*L*), the serial number in the data bank of the material to which all other materials in the data bank will be compared (*M*), weighting factors (*W*), and design constraints. The program first determines a scaling factor for each property *j*,

$$SF_j = 100 \text{ / max value over all materials.}$$

Next, a weighted property factor (*WPF*) is calculated for each material in the data bank,

$$WPF_j = \sum (P_{ji} * W_j * SF_j) / \sum W_j, \qquad j = 1, NC;$$

where P_{ji} is property *j* of material *i*. Candidate materials are then compared property-wise to the basis material by computing each candidate's relative weighted property factor (*RWPF*),

$$RWPF_i = WPF_i / WPF_{BM.}$$

Candidates are next compared by cost to the basis material through relative critical property costs (*RCPC*),

$$RC_i = (P_{jBM}/P_{ji})*(S_i/S_{BM})*(C_i/C_{BM}),$$

where S_i is the density of material i, C_i is the cost per bulk unit of material i, and P_j is the property with the highest weighting factor. Finally, the ratio of the cost of a candidate relative to the cost of the basis material is computed as the cost per unit requirement (*CUR*),

$$CUR_i = RC_i / RWPF_i,$$

where $CUR_i < 1$ indicates a candidate less expensive than the basis material. The program rank data bank materials in order of increasing CUR_i.

There are numerous problems with the authors' approach. The choices of the weighting factors and their numerical representation are subjective, and can therefore render program output useless if improperly chosen. Secondly, the number of steps and some information included in the methodology are extraneous -- the ratio of cost to *WPF* is the same decision criterion as CUR_i, and requires much less calculation. Also, there is no real need for a basis material; ranking materials in order of increasing cost/*WPF* ratio and choosing the material with the lowest value achieves the same end as the methodology presented. Fourth, the use of simple material costs is incomplete. Manufacturing and other factors should be included to make the analysis more robust. Finally, the program's input mode requires the user to know the quantity and serial numbers of materials in the data bank.

Pecht, et. al. [35] describe Material Selection Program (MSP), developed at the University of Maryland. The program, written in TURBO PASCAL, accesses a data base of material properties to make its decisions. Upon entering the program, the user is presented a main menu with options to create a selection process, manage data in an existing selection process, or enter a specific selection process. If the user creates a selection process, material requirements are entered by accessing the material properties data base and flagging the attributes desired. Next, the user enters desired values for each attribute, which may either be discrete or a range of acceptable values. Weighting factors, which are ratio-valued, may then be assigned to the attributes. From this weighted list of desired properties, a ranked list of materials appropriate to the specifications entered is generated. The user may consult the working data base at any time during the selection to view or output its contents to a printer. The user may also question the decisions about any material. MSP does not consider the effects of manufacturing on the materials chosen, nor is its scope, in terms of what types of materials and properties are included in the data base, well-defined.

Williams [49] describes a computer program, the Ferrous PM Materials Selector, to aid in the selection of the ferrous powder metallurgy materials. The program contains ranges of the minimum properties specified by the International Standards Organization: density, ultimate tensile strength, apparent hardness, relative density, yield strength, and elongation. The program also provides chemical composition and current application information for the materials it includes. Users of the program are first presented with the

main menu. A tolerance range is used to input values for the available properties, which the program matches to those of the materials it contains. Candidate materials, represented by codes used in the program, are then outputted in order of the closeness of their match. The program has limited applications because of the narrow range of materials it covers. In addition, since the program does not employ a data base, the amount of information employed to make decisions, and therefore the program's usefulness, are limited.

Jorgensen and Alting [18] view material selection as one aspect of their Computer Integrated Manufacturing system developed using the GS32 CAD/CAM system and DCLASS as a decision-making information system. A list of candidate materials is generated when a materials taxonomy, or classification system, is searched by a set of user-specified keywords. The materials taxonomy contains various keywords, which represent certain engineering functions or characteristics and point to certain materials classes. General important properties may then be listed for each candidate material using the materials property display module, or detailed data may be obtained from material information files. Materials information files are located on various levels in the CAD/CAM system. The information system contains the CAD/CAM filenames (corresponding to material types) and level numbers (corresponding to the information type, i.e., data for a specific property). The CAD/CAM filenames correspond to material codes found in the material taxonomy and in the candidate materials list. The structure of the proposed CIM system is its most limiting feature. Storage of the material data in levels of CAD/CAM files severely

limits the flexibility normally available when querying data stored in data bases. Materials selection is completely separate from, and has no influence on, process selection in the CIM system.

Swindells and Swindells [44] present a three-stage modular expert system for material selection called PERITUS. The authors envision materials selection as a problem that must consider, for a product's defined function, interactions among material properties (P), manufacturing processes (M), and the shape and failure mode of the component (S). PERITUS was developed as an attempt to effectively deal with the four resulting material selection scenarios: (1) P only is critical, (2) P and M are critical, (3) P and S are critical, or (4) all three variables are critical.

The first stage of PERITUS is the director stage, which influences the broad selection of materials and manufacturing processes. At each step of the director stage, users create lists of requirements to be compared as a whole to the information contained in the knowledge base to generate possible classes of materials and manufacturing processes for further exploration. The director stage may be bypassed by more knowledgeable users.

The user may next enter the second stage of PERITUS, the pre-sort stage. The properties of each class of materials provided by the director stage are first examined. The user is prompted to specify the importance of each property, using values ranging from zero (unimportant) to three (critical). If the user wishes to continue, he prioritizes possible manufacturing methods of each

class of materials as undesirable (given a value of zero) to desirable (given a value of three). A branching algorithm to a data module then identifies which materials in the class satisfy the specified requirements and outputs them in a list. The pre-sort stage may alternately generate candidate materials through an application module, in which the proposed use of the product is matched with previous applications and their corresponding materials and processes contained in the module.

The candidate materials and/or processes outputted by the pre-sort stage are further explored in the evaluation and optimization stage. A ranked list of materials is produced when the properties of each material and/or process on the candidate list are compared to an ideal set of values specified by the user. The ranked list is ordered from top to bottom by closest correspondence with the ideal set (solution to materials selection scenarios one and two mentioned previously). A ranked list of materials may also be produced when desired materials properties and/or manufacturing methods are evaluated in the system's shape and failure mode analysis modules for common engineering problems (i.e., beams in bending or tubes in torsion, etc.), with best performance placed highest on the list. These methods of prioritizing materials represent solutions to the author's selection scenarios three and four. The final selection of a material is left as the user's decision.

The structure of the PERITUS material selection system is modular and could easily be expanded. However, the limited characteristics available in the first stage to designate broad candidate material classes narrow the applications

for which it is suitable. Also, despite the use of three stages to serve even novice users, PERITUS material selections are based solely on degree of conformance to desired material property values. Manufacturing aspects are used only to eliminate candidate materials.

Weiss and Aha [46, 47] describe their MATERIALS expert system for materials selection developed in the LOGLISP programming language at Syracuse University. LOGLISP combines the LISP programming language with logic programming (making assertions from which logical consequences are drawn). The knowledge base consists of assertions, which are composed of facts (i.e., materials properties) and rules (i.e., formulae which use facts and/or other rules to determine additional materials characteristics). MATERIALS' facts were taken from the American Society of Metals 1982/1983 Materials and Processing Databook, and are grouped by material condition. The knowledge base may be queried through the use of various predicates, so that a list of materials having certain characteristics is generated. The results of such a query may be outputted in a user-customized tabular or graphical format. However, knowledge of the available data and of the system structure would be required to effectively use LOGLISP for materials selection. In addition, all requirements of the application would have to be adequately represented by material properties alone for the choices made to be accurate.

Bergamaschi, et. al. [4] explain an expert system for composite material selection, which uses the Nexpert expert system shell in a Window environment and interfaces with a relational DBaseIII data base. The basic shape of the part

is first specified using the EUCLID classification. The user is then prompted for information about the part's interaction with other components or structures, including possible mechanical connections. Five characteristics of the part's service and/or storage environment must be specified: world climatic zone (using military STANAG specifications), operating position (indoor, outdoor, covered, indoor with air conditioning), chemical agent present (acids, hydrocarbons, or solvents), temperature range, and loading configuration. The system uses the above information to infer a list of candidate materials. Possible manufacturing methods are then addressed to eliminate materials too costly to produce. Remaining materials are then ranked according to a user specified priority. The authors do not define the system's operation well, therefore its usefulness and validity are unclear.

Mishchenko, et. al. [32] propose mathematical means of selecting replacement materials for given applications. They first present methods of transforming laboratory test results into tables of representative property data for materials. They then suggest the use of cluster analysis to choose a material having equivalent or more desirable properties than the material presently in use. The authors' selection system includes: a general purpose, standard form data bank that contains property information; an application program that contains the clustering algorithm; and an expert system that serves as a user interface, and transfers information between the data bank and the clustering program.

The population of materials and their properties of importance respectively form an i x j matrix, in which the material to be replaced (the base material, ${}^{j}x_{1}$) occupies the first row. If weighting factors are desired, the authors suggest multiplying individual property values ${}^{j}x_{i}$ by the standard deviation of the values per property ${}^{j}_{D}$. Next, each property value ${}^{j}x_{i}$ is divided by the maximum value found in the matrix of that property to yield standardized, dimensionless data values. The matrix of differences between property values ${}^{j}x_{i}$ and ${}^{j'}x_{i}$ is then constructed using the Euclidean distance measure:

$$jj'd({}^{j}x_{i}, {}^{j'}x_{i}) = [\ \Sigma\ ({}^{j}x_{i} - {}^{j'}x_{i})^{2}\ ]^{1/2}, \quad i = 1, N.$$

The radius of absorption ${}^{j}p$ is determined for each property as the maximum difference between an individual property value and the average property value. A cluster Z_0 is then formed around the base material by pairs of candidates j and j', where:

$$d({}^{j}x_{i}, {}^{j'}x_{i}) <= \max\{\ {}^{j}p, {}^{j'}p\ \}.$$

A third element may join the cluster if the following two conditions simultaneously hold:

$$d({}^{j}x_{i}, {}^{j''}x_{i}) <= \max\{\ {}^{j}p, {}^{j''}p\ \},$$

$$d({}^{j'}x_{i}, {}^{j''}x_{i}) <= \max\{\ {}^{j'}p, {}^{j''}p\ \}.$$

Elements are similarly added to the cluster with base ${}^{j}x_{1}$ until R materials are present:

$$^{*}Z_0(^1x_i) = \{ {}^1x_i, {}^j{}_1x_i, \ldots, {}^j{}_Rx_i \}.$$

The replacement material is that whose "significance" value, θ_k, is largest:

$$\theta_k = \psi_k / \Sigma \psi_k,$$

where

$$\psi_k = 1 / d^*_k,$$

$$d^*_k = [\Sigma ({}^1x_i - {}^j{}_kx_i)^2]^{1/2}, \; i = 1, N;$$

and *k* is the number of the material in the cluster.

The authors use a powerful and accurate tool to choose substitute materials for particular applications. However, the complexity of the selection system is unnecessary and its scope is limited. Fundamentally, the authors assume that appropriate materials substitutions can be made from materials properties information only. No design or manufacturing considerations are addressed in the methodology. In addition, the user chooses only the properties of interest for the application; the population of materials in the data bank are included in the clustering activities. Therefore, the system's search and processing times would be extensive. In a carefully designed system, the interface between the data bank and the clustering program should not be so complicated as to require sophisticated and costly expert system technology. In addition, the authors overly complicate the clustering algorithm itself by including radius of absorption and significance in the methodology.

2.3 CONCLUSIONS

The methodologies presented in this literature review meet varying needs for materials selection. Some are elaborate, complete expert systems that consider a wide range of factors in ranking candidate materials and require sophisticated technology [4, 17, 44, 46, 47]. Others are "quick-hit" solutions that utilize materials properties as decision criteria and require little more than an individual capable of performing the analysis [2, 5, 15]. Still others are simply frameworks for systematic approaches to the selection problem [3, 11, 37, 38, 41, 43]. Each approach has its own costs and benefits.

Expert systems produce solutions in which the user can have confidence, since most systems consider various interrelated factors to produce the solutions. However, these systems usually require sophisticated technologies and tremendous skill, time, and effort to develop. Thus, expert systems may not be feasible answers to the materials selection problem in all cases. "Quick-hit" methodologies are appealing in that they apply in all situations and produce results rapidly. Their solutions, however, may result in much less reliable components than originally anticipated, because important aspects affecting the material selection have been omitted from consideration. Heuristics allow the designer much freedom in customizing the procedure to the situation at hand; however, heuristics can be so general that they are not helpful in selecting materials for specific applications.

A versatile selection methodology considering design, manufacturing, and material property attributes is desired that (1) utilizes "hard" data without "re-inventing the wheel" with system-owned data bases, (2) produces results quickly; (3) does not require great investments of time, effort, or money to develop and utilize; and (4) allows the user to affect system outputs through manipulation of various selection parameters. Four systems presented in this literature review have these qualities in varying degrees: Sandstrom [41]; Swindells and Swindells [44]; Dargie, et. al. [7]; and Mishchenko, et. al. [32]. None of the systems meet requirement (1) above because none utilize standardized materials data base information that has been adjusted to eliminate the effects of different testing methods and environments, and that is constantly updated.

Sandstrom's methodology [41] requires a significant amount of early manual work by the user to employ the process in a given application, and thus meets requirement (4), but fails requirements (2) and (3). Swindells and Swindells [44] meet requirements (2) and (4) through expert system technology. However, the same technology requires large time and money investments, and thus violates requirement (3). Dargie, et. al. [7] meet requirements (2) and (3) by efficiently eliminating candidate materials and manufacturing processes from consideration using a group technology (GT) code generated from user input. The code is a succinct and effective way to represent component requirements in a concise, simplified manner, and has been used successfully in other applications [14, 24]. Mishchenko, et. al. [32] meet requirements (2) and (4)

through the use of cluster analysis to select replacement materials, but violates requirement (3) because selection criteria are generated solely by the user.

Although all of the systems presented have made some unique contribution to the materials selection problem, clearly, no single system "has it all." A combinatorial approach that attempts use criteria in addition to material properties is needed. The details of such a system are presented in the following chapter.

CHAPTER THREE
METHODOLOGY

The operational structure of the material selection methodology presented in this research is shown graphically in Figure 3.1. First, particular aspects of the component's service environment specified by the user are formulated into a go/no go portion of a group technology (GT) code. These GT code digits are matched to those of the materials in a standard data base, eliminating from consideration the materials not meeting the requirements. User-specified information on desired design and manufacturing characteristics are next used to create desired GT code elements (seed code) based on corresponding material property values. The seed code is compared to the codes of the candidate materials using cluster analysis, a technique which outputs a ranked list of materials able to withstand anticipated service environments and able to be satisfactorily manufactured. This list could then be further analyzed on properties of particular interest in a file customized to the user's organization and available resources.

This research enumerates the desired nature and operation of the materials elimination and ranking procedures and recommends attributes to be included in a user-specific file. The detailed nature and operation of the user-specific file are not discussed in this research. In Chapter Four, the materials elimination and ranking procedures were applied in a case study to classes of

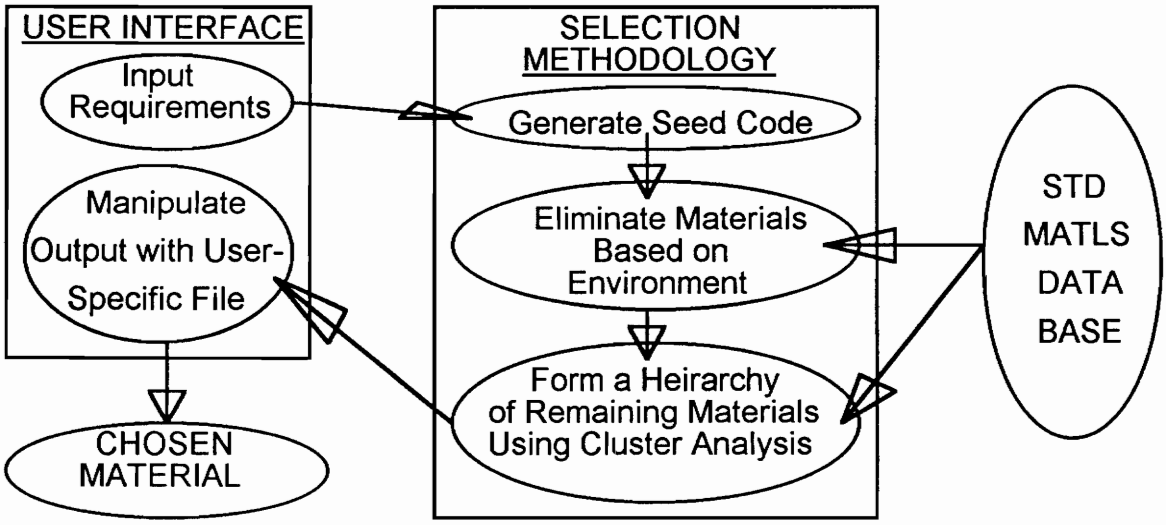

Figure 3.1 Operational Structure of the Materials Selection Methodology

materials containing both new and traditional varieties to determine the effectiveness of the approach.

3.1 BASIS OF THE SELECTION APPROACH

Logical conclusions form the basis of the materials selection methodology of this research. The first is a consequence of determining a means of representing the particular attributes of a material selection problem. Characterizing such a problem can result in lengthy, complicated combinations of textual, numerical, and symbolic information. Selecting a suitable material from the tens of thousands now available based on such a description would be difficult, if not impossible. A GT code is a concise form of representing complex descriptions, and thus is a natural solution to this problem.

GT codes are series of alphanumeric characters, and can be of several types [24, 25]: (1) monocode, in which each successive digit is dependent on its predecessor's value; (2) polycode, in which each successive digit is independent of its predecessor's value; and (3) hybrid, a combination of monocode and polycode. Some of the ranking attributes used in this research are dependent upon one another. Therefore, a hybrid GT code was used in the methodology.

The second idea contributing to the basis of this research stems from conceptualizing the materials selection problem. The hypothetical desired material (seed point) is an entity with n characteristics of specified values. The

material may therefore be represented as a point in *n*-dimensional space, whose location depends on the particular values of the *n* characteristics. Candidate materials can also be represented as points in *n*-dimensional space. Thus, the candidate materials falling within an allowable range from the desired point could be considered interchangeable with that point. A material selection methodology mimicking the above scenario is cluster analysis. A cluster analysis algorithm was therefore used in this material selection methodology.

To perform cluster analysis, a measure of the distance between the seed characteristics and the candidate materials must be chosen. According to Romesburg [39], since the average Euclidean distance,

$$d_{jk} = [\ \Sigma\ (X_{ij} - X_{ik})^2 / n]^{1/2}, \quad i = 1, n;$$

is not sensitive to missing data values and can be used with both qualitative and quantitative data, it is the most widely used in cluster analysis applications. It is used in this research for the same reason.

3.2 FORMULATION OF THE APPROACH

3.2.1 Relevant Decision Criteria

The first step of formulating the material selection methodology of this research was to determine the *n* design, manufacturing, and material property

characteristics necessary to make the best choices possible in as many selection situations as possible. These factors are the method's decision criteria, and are the characteristics on which the GT code elements depend.

Table 3.1 shows an aggregate group of materials selection criteria found in the literature presented in Chapter Two of this document and in various manufacturing processes textbooks [1, 3, 8, 10, 19, 50]. Table 3.2 displays the criteria chosen to make materials selections in this research. The criteria of Table 3.2 capture important and/or limiting factors for general selection problems.

The three service environment parameters listed in column one of Table 3.2 are used to eliminate materials from the candidate population. All that is needed to immediately exclude a large number of materials in problems where a corrosive chemical medium is present and/or ferromagnetism is required is their lack of resistance (or proneness) to that condition. Therefore, *Corrosion Resistance* and *Ferromagnetism* are best used to initially partition the population of candidate materials, and exclude materials failing these simple go/no go tests. The specific information of corrosion rate and/or the materials' susceptibility to magnetism is thus not needed for elimination purposes.

The three *Design/Manufacturing* factors in Table 3.2 are used to determine ranking (clustering) criteria, without the need to manipulate specific information such as dimensions. *Number Axes/Planes Symmetry* indicates the part's complexity. For example, a megaphone has one principal axis of

Table 3.1 Aggregate List of Materials Selection Criteria

DESIGN	MANUFACTURING	MATERIAL PROPERTIES	OTHER/ ENVIRONMENTAL
Shape	Surface/ Heat treatments	Chemical composition	Corrosion resistance
Geometry	Formability	Alloying elements	Corrosive medium
Complexity	Machinability	Density	Corrosion rate
Tolerances	Castability	Specific gravity	Thermal resistance
Surface finish	Weldability	Ductility/stiffness	Wear resistance
Life	Available facilities	Hardness	Oxidation resistance
Reliability	Production quantity	Toughness	Electro-chemical resistance
Safety factor		Elasticity	Magnetism
		Elongation	Radiation sensitivity
		Ultimate tensile strength	Service loading mode/schedule
		Yield strength	
		Fatigue strength	
		Static strength	
		Creep-rupture strength	
		Stress resistance	
		Color	

Table 3.2 Decision Criteria Input into Cluster Analysis Algorithm

ENVIRONMENTAL	DESIGN/ MANUFACTURING	MATERIAL PROPERTIES
Corrosive Acids Present	Number Axes/Planes Symmetry	Corrosion Resistance
Corrosive Alkalines Present	Part Size	Ferromagnetism
Magnetism Required	Suitable Production System	Melting Point
		Hardness
		Percent Elongation

symmetry, while a playing card has several. Both these products are less complex than an abstract sculpture, which has no axes of symmetry. Machining a very complex component may be difficult or cost-prohibitive, whereas machining may be the easiest and most cost-effective method of producing a simple part. The part complexity therefore affects the manufacturing technique used, and thus the material properties important to the success of the method.

Part Size affects what the most appropriate production process for a component is, and will in turn affect relevant material properties. For example, the riding surface of a child's merry-go-round would be best produced by casting or forging; it would be impractical to machine. Therefore, low to medium melting points, low hardness, and moderately high ductility would be desired in such an application.

The quantity needed affects the production process used, and thus the material chosen for the application. Production quantities vary significantly among applications, and the specific identities of quantities for which the method of manufacture should change are not well defined. Therefore, rather than dealing in exact numbers that are questionable, required production quantities are represented by the most *Suitable Production System* for their manufacture: job shop, batch production, or mass production. For example, investing in casting equipment for a component whose demand is only a few products per year would not be recommended in most cases, machining may be the most practical manufacturing option. However, mass production quantities do not necessarily imply that casting is the preferred manufacturing technique.

The material properties included in Table 3.2 are directly dictated by the *Environmental* elimination criteria and by the *Design/Manufacturing* concerns. *Corrosion resistance* and *Ferromagnetism* have yes/no valuation and result directly from the elimination criteria of the methodology. The remaining properties indicate desired characteristics derived from user input about design and manufacturing parameters. *Melting point* is included as an indication of castability. *Hardness* is included as an indication of machinability and formability. *Elongation* is a measure of ductility, which itself is a second indicator of formability.

To facilitate subjective company-specific decisions, the remaining factors found in the literature (see Table 3.1) but not represented in Table 3.2 are better addressed in the customized user file. These factors are not part of this research for a variety reasons, such as interdependence of the criteria, or the inability to quickly simplify and glean the necessary information from a standard data base.

It was desired to limit the number of calculations performed during cluster analysis as much as possible to reduce the methodology's processing times. Environmental constraints are generally the most restrictive, consequently, population of materials is reduced through a stage in which those not meeting environmental constraints are eliminated. In this way, all material classes in the data base are not input into the cluster analysis algorithm, and the system operates faster than if no initial elimination was performed. Using the criteria

and properties listed in Table 3.2, it is insured that materials able to withstand the service environment and able to be manufactured will be ranked by cluster analysis. The user may then subsequently evaluate other functional and subjective aspects of ranked materials, such as strengths and aesthetics, to make a functional and desirable material choice.

3.2.2 GT Code Structure

Both the elimination and ranking properties have numerical GT codes to facilitate system operation. The values of the codes are irrelevant, since they are standardized to allow equal contributions to similarities among the candidates. To simplify the coding as much as possible, the integers from *0 - 9* and combinations thereof are used for all code elements. The attributes of acid and alkaline corrosive resistance and magnetism are coded using *0* and *1*, to indicate whether the attribute is present or absent in the material. Table 3.3 *(a) - (f)* respectively show the digits assigned to the various values of *Number of Axes/Planes Symmetry*, *Part Size, Suitable Production System*, *Melting Point*, *Hardness*, and *Percent Elongation*. Two digits are assigned per attribute, corresponding to the range in which the material's values begin and end. For example, a with percent elongation of 11% would be assigned a GT code value of *22* for *Percent Elongation*.

Number Axes/Planes Symmetry indicates the complexity of the part in question. It is important to determine whether the part is too complex to easily

Table 3.3 GT Code Elements for (a) Number Axes/Planes Symmetry, (b) Part Size, (c) Suitable Production System

Number Axes/Planes Symmetry	Code Element
0	1
1 principal axis	2
> 1 principal axis	3

(a)

Part Size	Code Element
Diameter, Height < 3"	1
3"<= D, H <= 36"	2
D, H > 36"	3
D >> H	4
H >> D	5

(b)

Suitable Production System	Code Element
Job Shop/One-of-a-Kind	1
Batch Production	2
Mass Production	3

(c)

Table 3.3 (cont.) GT Code Elements for (d) Melting Points, (e) Vickers Hardness

Melting Temperature, 'C	Code Element
0 - 500	1
501 - 1000	2
1001 - 1500	3
1501 - 2000	4
> 2001	5

(d)

Hardness, DPN	Code Element
0 - 100	1
101 - 200	2
201 - 300	3
301 - 400	4
401 - 500	5
501 - 600	6
601 - 700	7
701 - 800	8
801 - 900	9
> 900	0

(e)

Table 3.3 (cont.) GT Code Elements for (f) Percent Elongation in 50 mm

Elongation, % in 50 mm	Code Element
1 - 10	1
11 - 20	2
21 - 30	3
31 - 40	4
41 - 50	5
51 - 60	6
61 - 70	7
71 - 80	8
81 -90	9
> 90	0

(f)

and/or economically machine. Therefore, a part whose symmetry code is 0 would most likely be cast or forged, and would require appropriate materials properties. *Part Size* can be estimated without complex tolerancing information by determining the diameter (*D*) and height (*H*) of the smallest cylinder that could enclose the part. A part in which the diameter of the enclosing cylinder could be much smaller than its height may be easily machined from bar stock material, or if the diameter would be much greater than the height, then materials that can be formed may be the most viable selection option. Finally, only the broadest information about production quantity and therefore *Suitable Production System* is needed to sufficiently eliminate materials.

Coding for materials that have values other than those listed in Table 3.3 can be easily achieved using combinations of the coding integers. For example, thermoplastics have percent elongation ranging from 5 - 1000. Although this particular range does not appear to be addressed in the coding structure, it can be easily accommodated with a code value of *10*, indicating the percent elongation values begin in the range represented by the digit *1*, and end in the range represented by the digit *0*. Similarly, molybdenum alloys have hardness ranging from 190 - 570 DPN, which is represented by the code value *26*.

The GT code values for *Corrosion Resistance* and *Ferromagnetism* are only used for elimination purposes; they are not input into the clustering algorithm. The user input for *Number Axes/Planes Symmetry*, *Part Size*, and *Suitable Production System* are used to determine the seed code values for *Melting Point*, *Hardness*, and *Percent Elongation*. Each material in the data

base therefore has a six digit GT code, the first three digits of which correspond to elimination criteria, and the last three digits of which are input into the cluster analysis algorithm for ranking (see Table 3.4). In general cases, the following assertions can be made about the *Design/Manufacturing* selection criteria:

(1) *Number Axes/Planes Symmetry*

- having none principal axis inhibits machining,
- having greater than one facilities forming or machining;

(2) *Part Size*

- very small or very large parts inhibit machining,
- flat and thin parts are not easily machined,
- long and narrow parts are not easily cast or formed;

(3) *Suitable Production System*

- casting is not economically viable for small quantities.

Referring to Table 3.3, the above assertions lead to six possible alternatives and related approximations for the seed ranking code values.

(1), (2) None or all of machining, casting, and forming are inhibited:

- use mid-range melting point, hardness, and percent elongation;
- seed code is 33 55 55.

Table 3.4 Format of GT Code Input into Cluster Analysis

Digit	1	2	3	4	5	6
Description	Acid Corrosion Resistance	Alkaline Corrosion Resistance	Ferro-magne-tism	Melting Point	Vickers Hardness	Percent Elongation in 50mm (2")

(3) Machining is inhibited:

- mid-range melting point, high hardness apply;
- seed code is 33 88 55.

(4) Casting is inhibited:

- high melting point applies;
- seed code is 44 55 55.

(5) Casting and forming are inhibited:

- high melting point, high hardness, and low elongation apply;
- seed code is 44 88 22.

(6) Casting and machining are inhibited:

- high melting point and hardness apply;
- seed code is 44 88 55.

These seed code values are input into the clustering algorithm to be matched with the existing candidate materials codes.

3.2.3 GT Code/Data Base Interface

In an ideal material selection system, the GT code would be part of the data base. Under such a system, the information presented in Table 3.5 [27, 28, 40] would also appear in the data base as shown in Table 3.6 (blank cells in the

Table 3.5 Sample Material Data

Material	Acid Corrosion Resistance	Alkaline Corrosion Resistance	Magnetic	Melting Point, 'C	Hardness, DPN	Elongation, %
Al	N	N	N	658	15	45
Al alloys	N	N	N	476-654	25-180	4-45
Cu	N	Y	N	1083	50-100	45
Cu alloys	N	Y	N	885-1260	30-550	3-65
Fe	Y	N	Y	1535	100-670	3-60
Steels	N	Y	N	1371-1532	80-1000	2-65
Pb	N	N	N	327	5	50
Pb alloys	N	N	N	182-326	9-36	9-50
Mg	N	Y	N	650	35	3-15
Mg alloys	N	Y	N	610-621	40-70	1.5-25
Mo alloys	N	Y	N	2500-2600	190-570	7-30
Ni	N	Y	Y	1453	75	30
Ni alloys	N	Y	Y	1110-1454	110-865	5-60
Ta alloys	Y	N	N	2996	100-200	20-40
Titanium	N	Y	N	1680	60	17-30
Ti alloys	N	Y	N	1549-1649	120-1150	7-25
W	N		N	3370	180-2600	.3-3.5
Ceramics			N			0
Glass			N	580-1500	250-1000	0
Graphite	N	N	N		45-65	
Plastics	Y	Y	N	110-330		5-1000

Table 3.6 Sample GT Code Elements

Material	Acid Corrosion Resistance	Alkaline Corrosion Resistance	Magnetic	Melting Point, 'C	Hardness DPN	Elongation, %
Al	0	0	0	22	11	55
Al alloys	0	0	0	12	12	15
Cu	0	1	0	33	11	55
Cu alloys	0	1	0	23	16	17
Fe	1	0	1	44	17	16
Steels	0	1	0	34	10	17
Pb	0	0	0	11	11	55
Pb alloys	0	0	0	11	11	15
Mg	0	1	0	22	11	12
Mg alloys	0	1	0	22	11	13
Mo alloys	0	1	0	55	26	13
Ni	0	1	1	33	11	33
Ni alloys	0	1	1	33	29	16
Ta alloys	1	0	0	55	12	24
Titanium	0	1	0	44	66	23
Ti alloys	0	1	0	44	20	13
W	0		0	55	20	11
Ceramics			0			11
Glass			0	23	30	11
Graphite	0	0	0		11	
Plastics	1	1	0	11		10

tables correspond to unavailable current data). However, if such an ideal data base did not exist, the selection methodology would require a module to generate appropriate code elements based on the data base information, and assign them to the proper data base fields. In either case, the elimination and ranking codes should precede all other information in the data base for each material. In this way, only the materials codes with matching elements in elimination criteria would be placed in the working memory of the system to undergo clustering.

3.2.4 The Clustering Algorithm

Cluster analysis is most successful if a single characterization describes all the decision attributes. In this case, the code values for the decision attribute ranges can be described as the class intervals of histograms. According to Romesburg [39], researchers generally standardize such data using the column-standardizing function

$$Z_{ij} = X_{ij} / \Sigma X_{ij};$$

where

$$i = 1,...,n \text{ attributes; and}$$

$$j = 1,...,t \text{ materials.}$$

Once the data has been standardized, the average Euclidean distance,

$$d_{jk} = [\Sigma (Z_{ij} - Z_{ik})^2 / n]^{1/2}, \quad i = 1, n;$$

is then applied to determine the distance over all attributes of each material *j* from the seed point *k*. Materials are finally ranked by increasing distance from the seed point.

The material selection methodology presented in this chapter is applied in the following chapter. Hypothetical selection situations serve as the test bed for this methodology.

CHAPTER FOUR
METHODOLOGY APPLICATION

The materials listed in Tables 3.5 and 3.6 serve as the candidate population of materials for these case studies.

4.1 CASE STUDY A

A corrosive alkaline substance is present in the service environment of the component in question, to which the material chosen must be resistant.

Step 1: **Elimination.** For *0*, *1* coding values and *x* representing indifference, the resulting elimination GT code is *x1x*, to indicate the need for alkaline corrosion resistance. Using the elimination codes for the population materials given in Table 3.6, the following materials are eliminated from further consideration for their lack of resistance: aluminum, aluminum alloys, iron, lead, lead alloys, tantalum alloys, and graphite. Consequently, the following materials remain as candidates for selection: copper, copper alloys, steels, magnesium, magnesium alloys, molybdenum alloys, nickel, nickel alloys, titanium, titanium alloys, tungsten, ceramics, glass, and plastics.

Step 2: **Design/Manufacturing User Input.** The part in question has the following characteristics (corresponding GT code elements) based on user input:

one principal axis of symmetry (2), the diameter and height of the smallest cylinder able to enclose the part are both larger than three feet (3); and the production system best suited to meet demands for the component is a batch system (2). According to Section 3.2.2, the specified part size inhibits machining, and thus the resulting seed code is *33 88 55*.

Step 3: **Raw Data for Candidate Materials.** Table 4.1 *(a)* displays the GT codes for the candidate materials and for the seed point, in terms of melting point (MP), hardness (H), and percent elongation (PE).

Step 4: **Standardized Data for Candidate Materials.** Table 4.1 *(b)* displays standardized data for the candidate materials (see Appendix A for calculations). Because plastics have a missing data value in *Hardness*, standardization for that material was performed using only two attributes. Similarly, since ceramics has only one available data point, standardization was performed using the single point.

Step 5: **Calculation of Distances from the Seed Point.** Appendix A contains calculations of the average Euclidean distance, using standardized data, of each material from the seed point.

Step 6: **Clustering Heirarchy Output.** Figure 4.1 graphically displays the distance of each material from the seed point as a dendogram, with titanium in closest proximity to the seed point (and thus most similar) and ceramics farthest (and thus least similar).

Table 4.1 Case Study A Candidate Material Data Matrix for (a) Raw Data, and (b) Standardized Data

	Cu	Cu alloy	Steels	Mg	Mg alloy	Mo alloy	Ni	Ni alloy	Ti alloy	W	Cera	Glass	Plas	Seed
MP	33	23	34	22	22	55	33	33	44	55		23	11	33
H	11	16	10	11	11	26	11	29	20	20		30		88
PE	55	17	17	12	13	13	33	16	13	11	11	11	10	55

(a)

	Cu	Cu alloy	Steels	Mg	Mg alloy	Mo alloy	Ni	Ni alloy	Ti	Ti alloy	W	Cer	Glass	Plas	Seed
MP	.33	.41	.56	.49	.48	.59	.43	.42	.33	.57	.64		.36	.53	.19
H	.11	.29	.16	.24	.24	.28	.14	.37	.50	.26	.23		.47		.5
PE	.56	.3	.28	.27	.28	.14	.43	.21	.17	.17	.13	1	.17	.48	.31

(b)

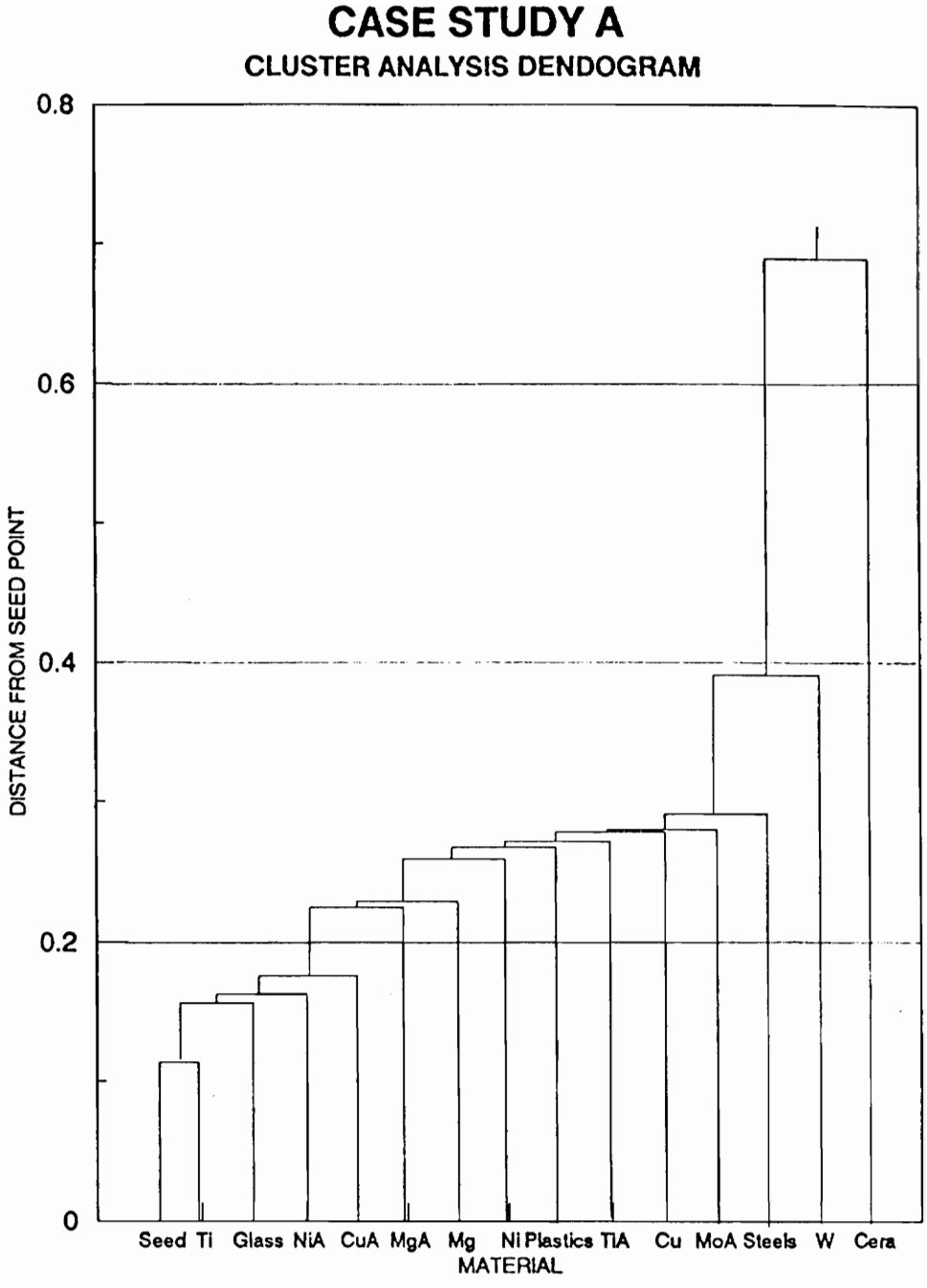

Figure 4.1 Dendogram for Case Study A

4.2 CASE STUDY B

A corrosive acid is present in the service environment of the component in question, to which the material chosen must be resistant.

Step 1: **Elimination.** For *0*, *1* coding values and *x* representing indifference, the resulting elimination GT code is *1xx*, to indicate the need for alkaline corrosion resistance. Using the elimination codes for the population materials given in Table 3.6, the following materials are eliminated from further consideration for their lack of resistance: aluminum, aluminum alloys, copper, copper alloys, steels, lead, lead alloys, magnesium, magnesium alloys, molybdenum alloys, nickel, nickel alloys, titanium, titanium alloys, tungsten, and graphite. Consequently, the following materials remain as candidates for selection: iron, tantalum alloys, ceramics, glass, and plastics.

Step 2: **Design/Manufacturing User Input.** The part in question has the following characteristics (corresponding GT code elements) based on user input: greater than one principal axis of symmetry (3), the diameter and height of the smallest cylinder able to enclose the part are between three and 36 inches (2); and the production system best suited to meet demands for the component is mass production (3). According to Section 3.2.2, the specified part size inhibits machining, and thus the resulting seed code is *44 55 55*.

Step 3: **Raw Data for Candidate Materials.** Table 4.2 *(a)* displays the GT codes for the candidate materials and for the seed point, in terms of melting point (MP), hardness (H), and percent elongation (PE).

Step 4: **Standardized Data for Candidate Materials.** Table 4.2 *(b)* displays standardized data for the candidate materials (see Appendix B for calculations). Because plastics have a missing data value in *Hardness*, standardization for that material was performed using only two attributes. Similarly, since ceramics have only one available data point, standardization was performed using the point.

Step 5: **Calculation of Distances from the Seed Point.** Appendix B contains calculations of the average Euclidean distance, using standardized data, of each material from the seed point.

Step 6: **Clustering Heirarchy Output.** Figure 4.2 graphically displays the distance of each material from the seed point as a dendogram, with glass in closest proximity to the seed point (and thus most similar) and ceramics farthest (and thus least similar).

Table 4.2 Case Study B Candidate Material Data Matrix for (a) Raw Data, and (b) Standardized Data

	Fe	Ta Alloys	Ceramics	Glass	Plastics	Seed
MP	34	55		23	11	44
H	10	12		30		55
PE	17	24	11	11	10	55

(a)

	Fe	Ta Alloys	Ceramics	Glass	Plastics	Seed
MP	.5574	.122		.36	.09	.2858
H	.1639	.2927		.47		.3571
PE	.2787	.5853	1	.17	.91	.3571

(b)

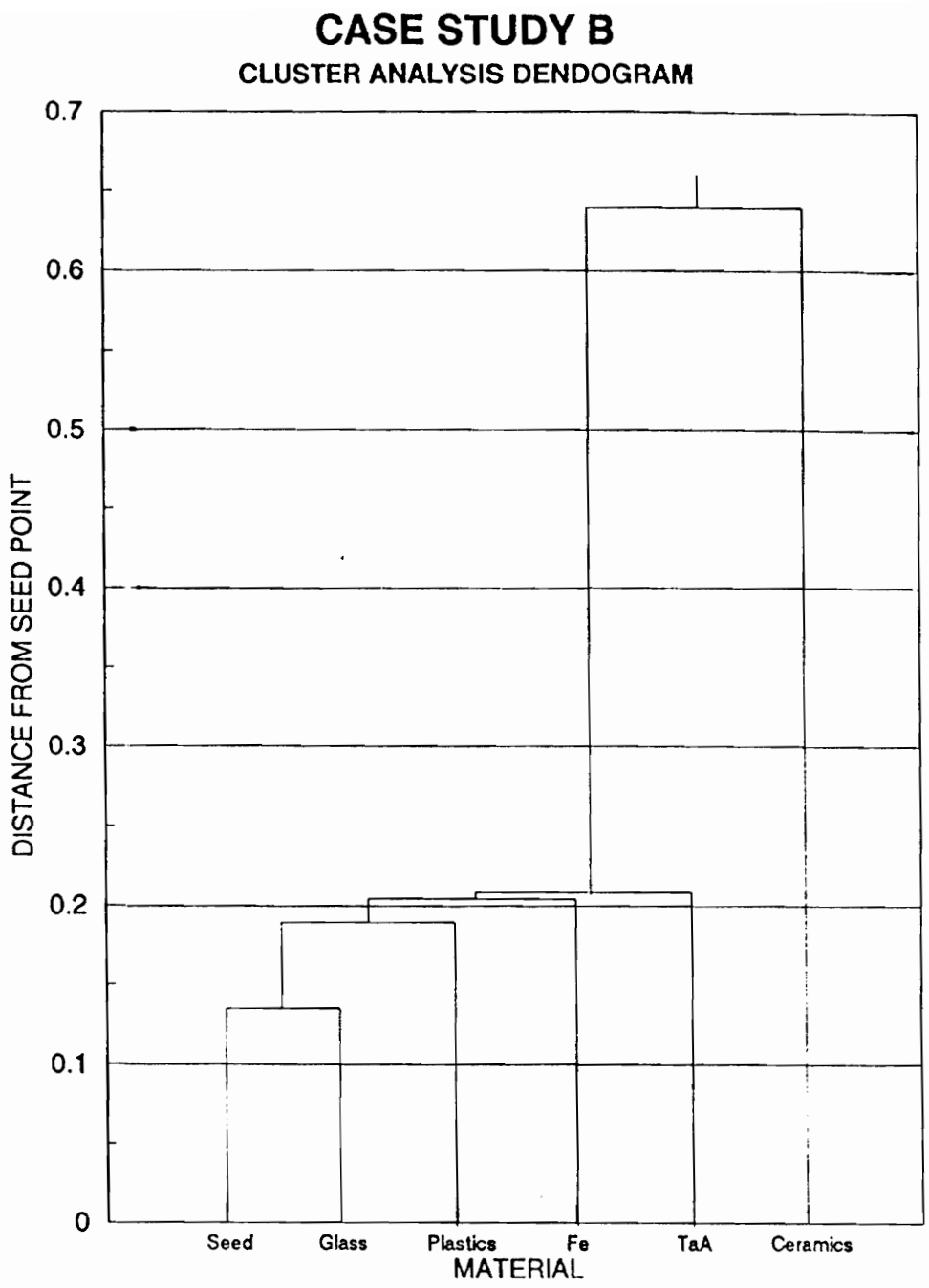

Figure 4.2 Dendogram for Case Study B

4.3 IMPLICATIONS OF THE METHODOLOGY

The benefits of this materials selection methodology lie in its partitioning ability. Standard material data bases can include over 150 properties for multiple material classes. Performing mathematical operations or simply scrolling through such a data base to glean useful information would be time consuming and frustrating. This research presents a realistic alternative to such actions.

The simple case studies presented in this chapter demonstrates the value of manipulating information on a reduced number of candidates. In Case Study A, instead of 18 material classes to assess, only 14 were applicable to the problem because of the alkaline corrosion resistance requirement. In Case Study B, only 5 material classes were feasible. If many more material classes and properties were present, the advantages would increase.

Environmental and manufacturing data are more restrictive than many criteria used to select materials in the past, such as strengths and moduli. Insuring that materials can survive the environment in question and that they can be manufactured into the shape required before assessing other material properties saves tremendous effort. The use of group technology provides succinct representation of selection problems, and has other possible uses outside of material selection. Cluster analysis allows the user to actually see the relative performance of various materials on the desired attributes, and to

determine for him/herself what is "good enough." The methodology presented is a viable, useful selection aide that can be applied without significant investments in expensive technology.

CHAPTER FIVE
FUTURE RESEARCH

The first and most obvious opportunity for future research is in computerization of the materials selection methodology presented in this research. This broad and complex process would require a variety of tasks. Data base designers could determine the most appropriate way to represent the material property data and GT code information to maximize system performance. Automated procedures by which to generate GT codes from non-ideal data bases must be developed. Methods by which to link the selection system to various data bases would be needed due to the nonhomogenous structures of data bases to date. In addition, the feasibility of applying object-oriented programming to the materials selection problem should be extensively investigated.

The development of the system's user interface presents tremendous opportunities. The system could be menu-driven and could include help and explanation text. Prototypes of user-specific files could also be created. Many varied capabilities could be included in user-specific systems, such as the ability to analyze the effects of changes in user input on the system outcome, weighting decision criteria, data base searching by material or characteristic, graphing and tabularizing of selection criteria, etc.

Another area of research opportunity is the change/expansion of the selection system's elimination and ranking criteria. The ranking results achieved with various combinations of criteria could be analyzed to determine those yielding the most desirable results. Alternatively, the effects of adding additional elimination or ranking criteria, for example, on the system's processing times could be assessed to determine where diminishing returns are achieved. In addition, the order in which elimination criteria are applied to the problem may be examined. Also, research could be concentrated, for example, on particular manufacturing processes to more exactly determine their relevant material properties and desired values. Each of the *Design/Manufacturing* characteristics that contribute to the seed ranking code could be studied with hopes of precisely determining significantly different class intervals for each attribute. For example, the manufacturing techniques best suited to precise production quantities of particular component types could be determined. Various GT coding schemes for the ranking criteria could be investigated to assess their affects both on the ranking results of the methodology, and on the usability of the coding scheme for other applications, such as material control or procurement.

The research opportunities stemming from this thesis are numerous and challenging. Approaching the materials selection problem by first achieving environmental and design/manufacturing feasibility before addressing additional materials properties is novel. Much unnecessary effort can be avoided with this approach, which uses group technology and cluster analysis to simplify a complex problem.

APPENDIX A

STANDARDIZATION OF DATA

General Equation: $X_{ij} / \Sigma X_{ij}$, $i = 1,n$

(1) Copper

$$Z_{1j} = 33 / (33 + 11 + 55) = 33 / 99 = \mathbf{.33}$$

$$Z_{2j} = 11 / (33 + 11 + 55) = 11 / 99 = \mathbf{.11}$$

$$Z_{3j} = 55 / (33 + 11 + 55) = 55 / 99 = \mathbf{.56}$$

(2) Copper Alloys

$$Z_{1j} = 23 / (23 + 16 + 17) = 23 / 56 = \mathbf{.41}$$

$$Z_{2j} = 16 / (23 + 16 + 17) = 16 / 56 = \mathbf{.29}$$

$$Z_{3j} = 17 / (23 + 16 + 17) = 17 / 56 = \mathbf{.3}$$

(3) Steels

$$Z_{1j} = 34 / (34 + 10 + 17) = 34 / 61 = \mathbf{.56}$$

$$Z_{2j} = 10 / (34 + 10 + 17) = 10 / 61 = \mathbf{.16}$$

$$Z_{3j} = 17 / (34 + 10 + 17) = 17 / 61 = \mathbf{.28}$$

(4) Magnesium

$$Z_{1j} = 22 / (22 + 11 + 12) = 22 / 45 = \mathbf{.49}$$

$$Z_{2j} = 11 / (22 + 11 + 12) = 11 / 45 = \mathbf{.24}$$

$$Z_{3j} = 12 / (22 + 11 + 12) = 12 / 45 = \mathbf{.27}$$

(5) Magnesium alloys

$$Z_{1j} = 22 / (22 + 11 + 13) = 22 / 46 = \mathbf{.48}$$

$$Z_{2j} = 11 / (22 + 11 + 13) = 11 / 46 = \mathbf{.24}$$

$$Z_{3j} = 13 / (22 + 11 + 13) = 13 / 46 = \mathbf{.28}$$

(6) Molybdenum alloys

$$Z_{1j} = 55 / (55 + 26 + 13) = 55 / 94 = \mathbf{.59}$$

$$Z_{2j} = 26 / (55 + 26 + 13) = 26 / 94 = \mathbf{.28}$$

$$Z_{3j} = 13 / (55 + 26 + 13) = 13 / 94 = \mathbf{.14}$$

(7) Nickel

$$Z_{1j} = 33 / (33 + 11 + 33) = 33 / 77 = \mathbf{.43}$$

$$Z_{2j} = 11 / (33 + 11 + 33) = 11 / 77 = \mathbf{.14}$$

$$Z_{3j} = 33 / (33 + 11 + 33) = 33 / 77 = \mathbf{.43}$$

(8) Nickel alloys

$$Z_{1j} = 33 / (33 + 29 + 16) = 33 / 77 = \mathbf{.42}$$

$$Z_{2j} = 11 / (33 + 29 + 16) = 29 / 77 = \mathbf{.37}$$

$$Z_{3j} = 33 / (33 + 29 + 16) = 16 / 77 = \mathbf{.21}$$

(9) Titanium

$$Z_{1j} = 44 / (44 + 66 + 23) = 44 / 133 = \mathbf{.33}$$

$$Z_{2j} = 66 / (44 + 66 + 23) = 66 / 133 = \mathbf{.50}$$

$$Z_{3j} = 23 / (44 + 66 + 23) = 23 / 133 = \mathbf{.17}$$

(10) Titanium alloys

$$Z_{1j} = 44 / (44 + 20 + 23) = 44 / 77 = \mathbf{.57}$$

$$Z_{2j} = 20 / (44 + 20 + 23) = 20 / 77 = \mathbf{.26}$$

$$Z_{3j} = 23 / (44 + 20 + 23) = 23 / 77 = \mathbf{.17}$$

(11) Tungsten

$$Z_{1j} = 55 / (55 + 20 + 11) = 55 / 86 = \mathbf{.64}$$

$$Z_{2j} = 20 / (55 + 20 + 11) = 20 / 86 = \mathbf{.23}$$

$$Z_{3j} = 11 / (55 + 20 + 11) = 11 / 86 = \mathbf{.13}$$

(12) Ceramics

$$Z_{3j} = 11 / (11) = 11 / 11 = \mathbf{1}$$

(13) Glass

$$Z_{1j} = 23 / (23 + 30 + 11) = 23 / 64 = \mathbf{.36}$$

$$Z_{2j} = 30 / (23 + 30 + 11) = 30 / 64 = \mathbf{.47}$$

$$Z_{3j} = 11 / (23 + 30 + 11) = 11 / 64 = \mathbf{.17}$$

(14) Plastics

$$Z_{1j} = 11 / (11 + 10) = 11 / 21 = \mathbf{.53}$$

$$Z_{3j} = 10 / (11 + 10) = 10 / 21 = \mathbf{.48}$$

(15) Seed

$$Z_{1j} = 33 / (33 + 88 + 55) = 33 / 176 = \mathbf{.19}$$

$$Z_{2j} = 88 / (33 + 88 + 55) = 88 / 176 = \mathbf{.5}$$

$$Z_{3j} = 55 / (33 + 88 + 55) = 55 / 176 = \mathbf{.31}$$

EUCLIDEAN DISTANCE CALCULATIONS

General Equation: $d_{j,k} = [\Sigma (X_{ij} - X_{ik})^2 / n]^{1/2}$

(1) Copper

$$d_{Cu,k} = [((.33 - .19)^2 + (.11 - .5)^2 + (.56 - .31)^2) / 3]^{1/2}$$

$$= ((.0196 + .1521 + .0625) / 3)^{1/2}$$

$$= (.0926 / 3)^{1/2}$$

$$= (.07807)^{1/2}$$

$$= \mathbf{.2794}$$

(2) Copper alloys

$$d_{CuA,k} = [((.41 - .19)^2 + (.29 - .5)^2 + (.3 - .31)^2) / 3]^{1/2}$$

$$= ((.0484 + .0441 + .0001) / 3)^{1/2}$$

$$= (.0926 / 3)^{1/2}$$

$$= (.03087)^{1/2}$$

$$= \mathbf{.1757}$$

(3) Steels

$$d_{Steels,k} = [((.56 - .19)^2 + (.16 - .5)^2 + (.28 - .31)^2) / 3]^{1/2}$$

$$= ((.1369 + .1156 + .0009) / 3)^{1/2}$$

$$= (.2534 / 3)^{1/2}$$

$$= (.08447)^{1/2}$$

$$= \mathbf{.2906}$$

(4) Magnesium

$$d_{Mg,k} = [((.49 - .19)^2 + (.24 - .5)^2 + (.27 - .31)^2) / 3]^{1/2}$$

$$= ((.09 + .0676 + .0016) / 3)^{1/2}$$

$$= (.1592 / 3)^{1/2}$$

$$= (.05307)^{1/2}$$

$$= \mathbf{.2304}$$

(5) Magnesium alloys

$$d_{MgA,k} = [((.48 - .19)^2 + (.24 - .5)^2 + (.28 - .31)^2) / 3]^{1/2}$$

$$= ((.0841 + .0676 + .0009) / 3)^{1/2}$$

$$= (.1526 / 3)^{1/2}$$

$$= (.05087)^{1/2}$$

$$= \mathbf{.2255}$$

(6) Molybdenum alloys

$$d_{MoA,k} = [((.59 - .19)^2 + (.28 - .5)^2 + (.14 - .31)^2) / 3]^{1/2}$$

$$= ((.16 + .0484 + .0289) / 3)^{1/2}$$

$$= (.2373 / 3)^{1/2}$$

$$= (.0791)^{1/2}$$

$$= \mathbf{.2812}$$

(7) Nickel

$$d_{Ni,k} = [((.43 - .19)^2 + (.14 - .5)^2 + (.43 - .31)^2) / 3)^{1/2}$$

$$= ((.0576 + .1296 + .0144) / 3)^{1/2}$$

$$= (.2016 / 3)^{1/2}$$

$$= (.0672)^{1/2}$$

$$= \mathbf{.2592}$$

(8) Nickel alloys

$$d_{Ni,k} = [((.42 - .19)^2 + (.37 - .5)^2 + (.21 - .31)^2) / 3)^{1/2}$$

$$= ((.1444 + .0576 + .0196) / 3)^{1/2}$$

$$= (.2216 / 3)^{1/2}$$

$$= (.07387)^{1/2}$$

$$= \mathbf{.2718}$$

(9) Titanium

$$d_{Ti,k} = [((.33 - .19)^2 + (.5 - .5)^2 + (.17 - .31)^2 / 3)^{1/2}$$

$$= ((.0196 + 0 + .0196) / 3)^{1/2}$$

$$= (.0392 / 3)^{1/2}$$

$$= (.01307)^{1/2}$$

$$= \mathbf{.1143}$$

(10) Titanium alloys

$$d_{TiA,k} = [((.57 - .19)^2 + (.26 - .5)^2 + (.17 - .31)^2 / 3)^{1/2}$$

$$= ((.1444 + .0576 + .0196) / 3)^{1/2}$$

$$= (.2216 / 3)^{1/2}$$

$$= (.07387)^{1/2}$$

$$= \mathbf{.2718}$$

(11) Tungsten

$$d_{Tungsten,k} = [((.64 - .19)^2 + (.23 - .5)^2 + (.13 - .31)^2 / 3)^{1/2}$$

$$= ((.2025 + .0729 + .0324) / 3)^{1/2}$$

$$= (.3078 / 3)^{1/2}$$

$$= (.1539)^{1/2}$$

$$= \mathbf{.3923}$$

(12) Ceramics

$$d_{Ceramics,k} = [((1 - .31)^2 / 1)^{1/2}$$

$$= ((.4761) / 1)^{1/2}$$

$$= (.4761)^{1/2}$$

$$= \mathbf{.69}$$

(13) Glass

$$d_{Glass,k} = [((.36 - .19)^2 + (.47 - .5)^2 + (.17 - .31)^2 / 3)^{1/2}$$

$$= ((.0289 + .0009 + .0196) / 3)^{1/2}$$

$$= (.0494 / 3)^{1/2}$$

$$= (.0247)^{1/2}$$

$$= \mathbf{.1572}$$

(14) Plastics

$$d_{Plastics,k} = [((.53 - .19)^2 + (.48 - .31)^2) / 2]^{1/2}$$

$$= ((.1156 + .0289) / 2)^{1/2}$$

$$= (.1445 / 2)^{1/2}$$

$$= (.07225)^{1/2}$$

$$= \mathbf{.2688}$$

APPENDIX B

STANDARDIZATION OF DATA

General Equation: $X_{ij} / \Sigma X_{ij}$, i=1,n

(1) Iron

$Z_{1j} = 34 / (34 + 10 + 17) = 34 / 61 = \mathbf{.56}$

$Z_{2j} = 10 / (34 + 10 + 17) = 10 / 61 = \mathbf{.16}$

$Z_{3j} = 17 / (34 + 10 + 17) = 17 / 61 = \mathbf{.28}$

(2) Tantalum Alloys

$Z_{1j} = 55 / (55 + 12 + 24) = 55 / 41 = \mathbf{.61}$

$Z_{2j} = 12 / (55 + 12 + 24) = 12 / 41 = \mathbf{.13}$

$Z_{3j} = 24 / (55 + 12 + 24) = 24 / 41 = \mathbf{.26}$

(3) Ceramics

$Z_{3j} = 11 / (11) = 11 / 11 = \mathbf{1}$

(4) Glass

$Z_{1j} = 23 / (23 + 30 + 11) = 23 / 64 = \mathbf{.36}$

$Z_{2j} = 30 / (23 + 30 + 11) = 30 / 64 = \mathbf{.47}$

$Z_{3j} = 11 / (23 + 30 + 11) = 11 / 64 = \mathbf{.17}$

(5) Plastics

$Z_{1j} = 11 / (11 + 10) = 11 / 21 = \mathbf{.52}$

$Z_{3j} = 10 / (11 + 10) = 10 / 21 = \mathbf{.48}$

(6) Seed

Z_{1j} = 44 / (44 + 55 + 55) = 44 / 154 = **.28**

Z_{2j} = 55/ (44 + 55 + 55) = 55 /154 = **.36**

Z_{3j} = 55 / (44 + 55 + 55) = 55 / 154 = **.36**

EUCLIDEAN DISTANCE CALCULATIONS

General Equation: $d_{j,k} = [\Sigma (Z_{ij} - Z_{ik})^2 / n]^{1/2}$

(1) Iron

$$d_{Fe,k} = [((.56 - .28)^2 + (.16 - .36)^2 + (.28 - .36)^2) / 3]^{1/2}$$

$$= ((.0787 + .04 + .0064) / 3)^{1/2}$$

$$= (.1248 / 3)^{1/2}$$

$$= (.0416)^{1/2}$$

$$= \mathbf{.204}$$

(2) Tantalum alloys

$$d_{TaA,k} = [((.61 - .36)^2 + (.13 - .36)^2 + (.26 - .36)^2) / 3]^{1/2}$$

$$= ((.0625 + .0529 + .01) / 3)^{1/2}$$

$$= (.1254 / 3)^{1/2}$$

$$= (.0418)^{1/2}$$

$$= \mathbf{.2045}$$

(3) Ceramics

$$d_{Ceramics,k} = [((1 - .36)^2) / 1]^{1/2}$$

$$= ((.4096) / 1)^{1/2}$$

$$= (.4096)^{1/2}$$

$$= \mathbf{.64}$$

(4) Glass

$$d_{Glass,k} = [((.36 - .28)^2 + (.47 - .36)^2 + (.17 - .36)^2) / 3]^{1/2}$$

$$= ((.0064 + .0121 + .0361) / 3)^{1/2}$$

$$= (.0546 / 3)^{1/2}$$

$$= (.0182)^{1/2}$$

$$= \mathbf{.1349}$$

(5) Plastics

$$d_{Plastics,k} = [((.52 - .28)^2 + (.48 - .36)^2) / 2]^{1/2}$$

$$= ((.0576 + .0144) / 2)^{1/2}$$

$$= (.072 / 2)^{1/2}$$

$$= (.036)^{1/2}$$

$$= \mathbf{.1897}$$

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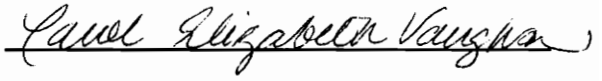

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