Material Substitution in Legacy System Engineering (LSE)

With Fuzzy Logic Principles

by

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ABSTRACT

The focus of this research is to investigate methods for material substitution for the purpose of re-engineering legacy systems that involves incomplete information about form, fit and function of replacement parts. The primary motive is to extract as much useful information about a failed legacy part as possible and use fuzzy logic rules for identifying the unknown parameter values. Machine elements can fail by any number of failure modes but the most probable failure modes based on the service condition are considered critical failure modes. Three main parameters are of key interest in identifying the critical failure mode of the part. Critical failure modes are then directly mapped to material properties. Target material property values are calculated from material property values obtained from the originally used material and from the design goals. The material database is searched for new candidate materials that satisfy the goals and constraints in manufacturing and raw stock availability. Uncertainty in the extracted data is modeled using fuzzy logic. Fuzzy member functions model the imprecise nature of data in each available parameter and rule sets characterize the imprecise dependencies between the parameters and makes decisions in identifying the unknown parameter value based on the incompleteness. A final confidence level for each material in a pool of candidate material is a direct indication of uncertainty. All the candidates satisfy the goals and constraints to varying degrees and the final selection is left to the designer's discretion. The process is automated by software that inputs incomplete data; uses fuzzy logic to

extract more information and queries the material database with a constrained search for finding candidate alternatives.

DEDICATION

This research work is dedicated to my dear parents for their hardship in making my dreams possible and believing in my aspirations. This is also dedicated to my caring sister whose affection I always treasure. I also dedicate this to my friends, Uma Shankar Barathi, Madan Naidu, Kumaraguru Prabakar, Dr. Saravana Prakash Thirumuruganandham and my roommates for their support.

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CHAPTER 1

INTRODUCTION

1.1. Background:

The engineering design process is one of the widely researched areas in the design world. The success or failure of a design ultimately decides the product's reach in the market. Emphasis is on every single stage of the design process from gathering customer requirements, understanding and translating the customer requirements to functional requirements, conceptual design, embodiment design, detailed design and planning for manufacturing. There is no definite timeline for each of these processes and in fact some of these processes are concurrent and some overlap. Particularly for a novel design all the processes are repeated several times over until sufficient number of feasible solutions is obtained. Of all the feasible solutions, those that perform best at a reasonable cost are chosen for production. Hence decisions made in each of these phases and indeed in each cycle are crucial. One such critical decision is that of material selection during the embodiment design stage. It determines the safe life of the product in terms of structural integrity; plays a huge role in downstream manufacturing decisions, affects functionality, recyclability, weight of the component and all other stages of the lifecycle process. Clearly design, manufacturing and material selection are all interdependent and decisions made in one stage affects the other two.

Original Equipment Manufacturers (OEMs) around the world own and operate millions of electro-mechanical components that were designed many years ago. Some components last longer than expected, and those that fail, are repaired to bring them back to full service or for a certain pre-determined life rather than replacing the whole part. This situation is particularly evident in military equipment and commercial aircraft industry. Replacement parts for these systems are not readily available and even if they are available, the cost of change and duration of change is an expensive process. Owing to excessive cost of replacements, such equipment continues to be used for several decades to come, well beyond their intended design life. The problem is even bigger if the OEM manufacturer is no longer around to manufacture the spare components or has stopped providing service for these components. Legacy System Engineering (LSE) stems from such critical issues – A holistic plan that determines optimal strategies for prolonging the life of such products. Legacy system engineering generally involves deduction of design functions/performance, determining product interfacing constraints, extracting part geometry, identifying opportunities for technical upgrade and formulating a best strategy for re-manufacturing.

1.2. Legacy System Engineering:

Some of the tasks involved in Legacy System Engineering (LSE) are similar in some aspects to conventional product design process including novel product design and processes to improve an existing product. Both for instance, involve complete understanding of design intent – functions, performance requirements, constraints etc… but they differ in other aspects. Some of those major factors are addressed here:

1. LSE is heavily constrained: the part being re-designed or re-manufactured must seamlessly fit into a larger existing system whose life it needs to prolong. This may impose geometric constraints (must fit inside a certain envelope, must interface with other components at certain locations, etc.), structural constraints (must carry a certain load, torque), and functional constraints (e.g., must develop a certain pressure, operate in a certain way). This is the predominant difference that separates LSE from new product design in that, all the interfacing components of the system may have not been produced already. This allows for some tradeoff decisions that help in solving the constraints and achieving a better overall design. A general observation is that freedom for innovative product solutions in novel product design is high compared to LSE where it is considerably less.
2. LSE requires small production volumes: Spare parts may be needed in small quantities, sometimes even one part. The part originally designed is best suited for mass production but the same part when re-designed through LSE techniques might not be economical for low production volumes. Thus manufacturing processes and planning for manufacturing plays a pivotal role in justifying the cost benefits of LSE.

3. Short delivery time: As mentioned earlier LSE is critical for OEMs producing spare parts for Military equipment and Aircraft industry where the failure of a critical component could hinder safe functioning of the whole equipment. The replacement parts are needed in a very short time particularly in combat situations that are far from supply centers. Thus delivery times are usually very short compared to novel product designs.
4. Limited manufacturing resources: In order to handle the above mentioned constraints 2 & 3, concepts such as Army Mobile Part Hospitals (AMPH) are proposed to produce the replacement components on site, in limited number, in considerably short time. If it is desired to produce the replacement parts in the field using facilities such as the AMPH, the manufacturing equipment may be limited, both in variety and size. For instance, a field facility may only have a machine shop and some welding/cutting capability; it may not be able to produce a die-casting, forging or injection molding component given a very short delivery time and limited resources.

From all these constraints, we determine that:

- LSE process must be heavily automated in order to minimize the cost in small batch production and maximize the benefits.
- Part geometry may need to be modified to reduce cost and allow production in existing machines

- Material changes/upgrades or design changes may be done to improve the design. Thus consequences of design changes need to be verified with simulation tools such as FEA for structural integrity and knowledge based systems to check if material selection decisions still satisfy the design constraints and performs equally well or better for the specified design objectives.
- Manufacturing resources available in the field, service center or vendor facility must be taken into account. Special tooling such as dies, molds, fixtures should be avoided, because small batch manufacturing cannot sustain the cost and the lead times are substantially large.

In light of these observations a new holistic LSE system is conceived that consists of three major phases:

1. Data Extraction phase - Geometry extraction and material data from physical parts or legacy drawings. Also structural requirements and design functions are extracted that are used in downstream product re-design activities.
2. Rapid Re-engineering phase - Evaluating the legacy design and re-engineering to determine specifications of replacement parts. DfM, Cost analysis, structural analysis and simulation of redesigned part or constraint based system analysis.
3. Rapid Re-Manufacturing phase – Automated manufacturing planning and On-site machining and fabrication.

The focus of this research is to investigate and implement material substitution in a manner that is seamless and useful for the purpose of re-engineering legacy systems that concerns phases 1, 2 and 3.

Material substitution as part of the holistic LSE is particularly done to legacy parts for any one of the following reasons:

- Lack of availability of the existing material – the material is short in supply, material extraction from its natural state is too expensive, existing material is hazardous to work with or the lack of suppliers for the material.
- Availability of new, better and cheaper material – A stronger, lighter, cheaper or easy to manufacture replacement that is abundant
- Improved manufacturing process and tools – Faster machines and tooling that can work well with a different material and that can be used in mass production but is hard to machine the existing material.
- Cost of reproducing a single part that was previously mass produced is too expensive.

For instance, in a design of an appliance motor from General Electric, aluminum alloys were substituted for grey cast iron because the strength and corrosion resistance of aluminum alloys better met the requirements for the usage of the motor [1]. Because of increasing cost and decreasing availability of grey cast iron, designers at General Electric chose to use a better material that still fulfilled the function for which it was designed. For this reason material selection and material substitution is a critical step in the embodiment stage of the design process.

1.3. Material Selection/Substitution in Engineering Design:

Material and manufacturing process that convert materials into useful parts dominate all of the engineering design process as is evident from all of the above discussions. There are over 100,000 engineering materials to choose from and new materials; extraction/production methods are continuously researched all over the world. However a design engineer typically works with only 30 to 60 different materials, depending on the range of application [2]. These groups of materials are typically used for component designs existing for a long time and particularly if the component is an artifact, the materials are sometimes even considered a standard. Emphasis on product quality and cost aspects of manufacturing in the present-day product design, has underlined the fact that

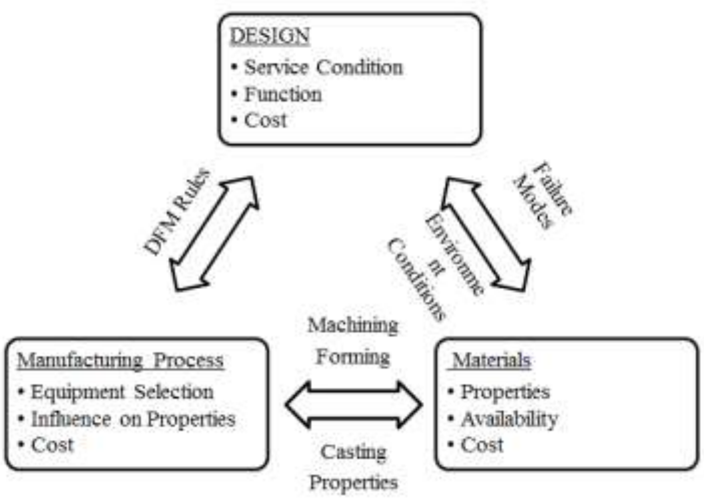

Figure 1: Interrelations of design, materials, and processing to produce a product.

design, materials and manufacturing are closely related in determining the performance of the final product as shown in Fig 1.

Also the increased use of automation in industries means that 60% of the final product cost is attributed to material costs [2]. Essentially all the engineering materials available fall into six broad classes that are commonly recognized: ferrous and non-ferrous metals, thermoplastic and thermosetting polymers, elastomers, ceramics, glasses and composites. Table 1 below shows the classes of different materials with some examples and some common mechanical applications. The range of materials available to the user is much broader than ever before. There is thus an opportunity for innovation in design for new products and legacy products alike for utilizing these materials to provide greater performance at lower cost. A rational material selection is thus inevitable for reaping the above said benefits.

Table 1: Classes of engineering materials, examples and industrial applications (see Ref [2])

Material Classes	Example	Important Applications
Metal & Metal Alloys	cast iron, carbon steels, alloy steels, nickel, titanium, aluminum, magnesium, copper, various alloys of these base metals with other elements	Structures and building materials, reinforcement for concrete, railway, surface transport such as automobiles, materials handling and processing plants, mining, power generation plants, ships and aircrafts etc.
Plastics	Polyethylene, polytetrafluoroether, polystyrene, polypropylene, Nylon, polycarbonate, polyvinyl chloride, epoxy, phenolic, polyester, neoprene, etc.	Beverage bottles, chairs, automobiles interior, dashboard and body panels, bumpers, sport equipment, carpets and flooring, aircraft fuselage and interiors, electronic printed circuit board and housings of electronics, high strength fibres, automobile tires and medical equipment.
Ceramics	Alumina, concrete, diamond, glass, silicon carbide, silicon nitride, zirconia etc.	Reinforcement particles for metal and polymer based composites, human joint prosthetics, cutting tools for metals, knives, building materials, thermal barrier coatings, refractories, magnetic hard disk substrate and automobile brakes.
Composites	Metal-based metal matrix composites, fiber reinforced plastics; ceramic composites	Aircraft fuselage and interior parts, body and vehicle armors, sports equipment, building materials, cutting tools etc.
Natural materials	Wood, leather, silk, wool, cotton, bone, natural rubber	Building materials, house-hold furniture, shoes, tires.

There are four main criteria for material selection:

1. Performance characteristics (mechanical properties) – finding materials that have the mechanical properties matching the requirements and constraints posed by the design problem
2. Processing (manufacturing) characteristics – finding the appropriate material that can be manufactured in the existing setup or finding the process that will form the material into required shape with minimal wastage and reduced cost.
3. Environmental profile – finding a material that has least impact on the environment throughout its lifecycle and meeting government regulations.
4. Business considerations – finding a cheaper alternative. Costs include the purchase cost of the material, manufacturing cost, part replacement cost and the cost of disposing the material at the end of its lifecycle.

Based on this criterion the general material selection process involves:

1. Analyzing the material requirements: Determining the material property values based on service and environmental conditions.
2. Screening for candidate materials: Filtering the appropriate materials from a material database that meet the requirements criterion.
3. Tradespace studies: From a pool of candidate materials finding the appropriate material that best satisfies the cost, manufacturability and availability constraints for the particular application.

4. Experimental verification: Checking for the performance of the selected material tested under specific conditions to be expected during service through the use of simulations or prototypes.

It can be deduced that material selection is a goal driven process as shown in Fig 2. Functions, constraints and objectives of the component are identified before the initial screening for candidate materials. Understanding the functions, constraints and objectives helps us identify certain material properties for the material selection of component. The properties of engineering materials span over a range of values. One of the ways of visualizing this is a bar chart for each of these

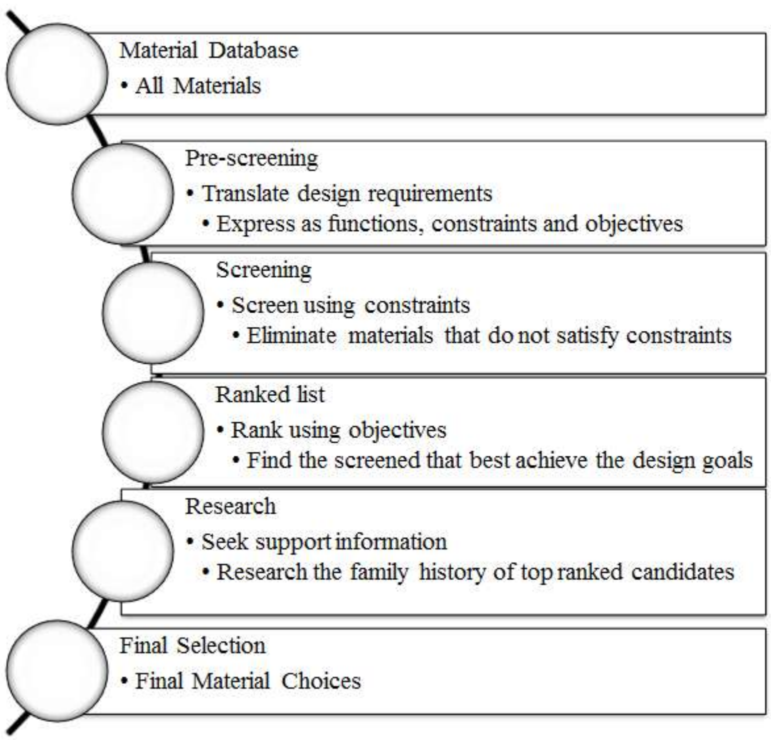

Figure 2: Generic Material Selection Process (Ref [1])

material properties as shown in the Fig 3. This way of representing material properties as bar charts is not very useful for comparison studies. An alternative approach is plotting the properties as Ashby charts [3-4]. Ashby charts are traditionally used in the screening and tradespace study of materials as shown in Fig 4. In this instance, one property is plotted against another on logarithmic scales. Families of materials cluster together on the chart known as property envelopes.

If there is a material selection objective, such as finding lighter materials of higher strength, then constant lines can be drawn across the charts at specific slope values. In this instance if the objective is to increase strength and reduce

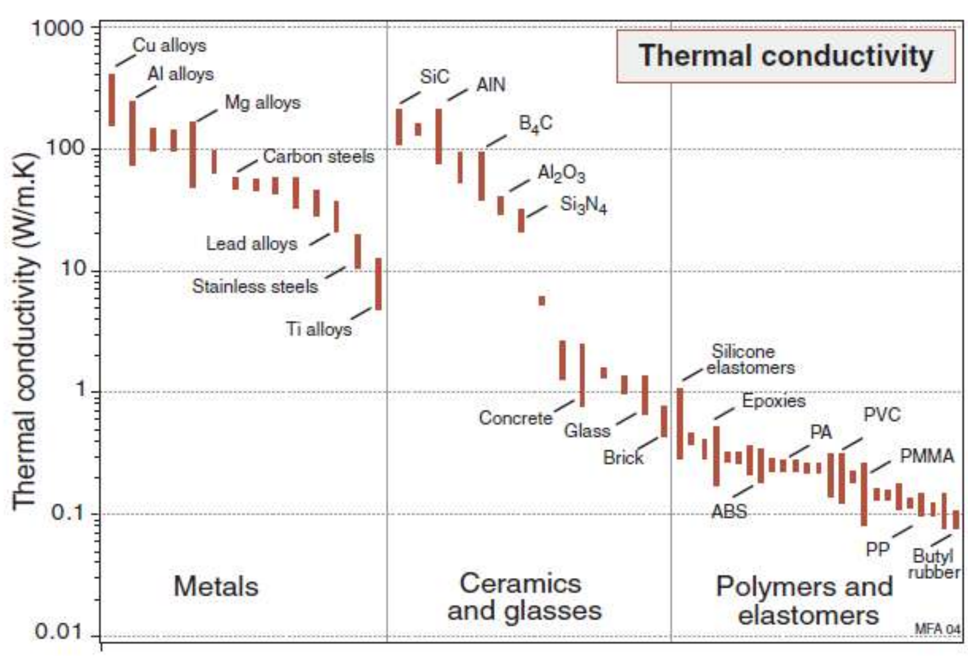

Figure 3: A Bar chart showing thermal conductivity for families of solid. Each bar represents the range of thermal conductivity offered by a material [see ref 3-4]

weight then a material performance index, M* can be defined such that

$$M^* = \frac{\sigma_f}{\rho}$$

Taking log on both sides, the equation reduces to $log\sigma_f = logM^* + log\rho$ which is a straight line in Fig 4. This equation can be further generalized by having relevant material properties, α and β for different n values –

$$M^* = \frac{\beta^n}{\alpha} = C$$

It is clear that the above expression is useful in comparing material selection

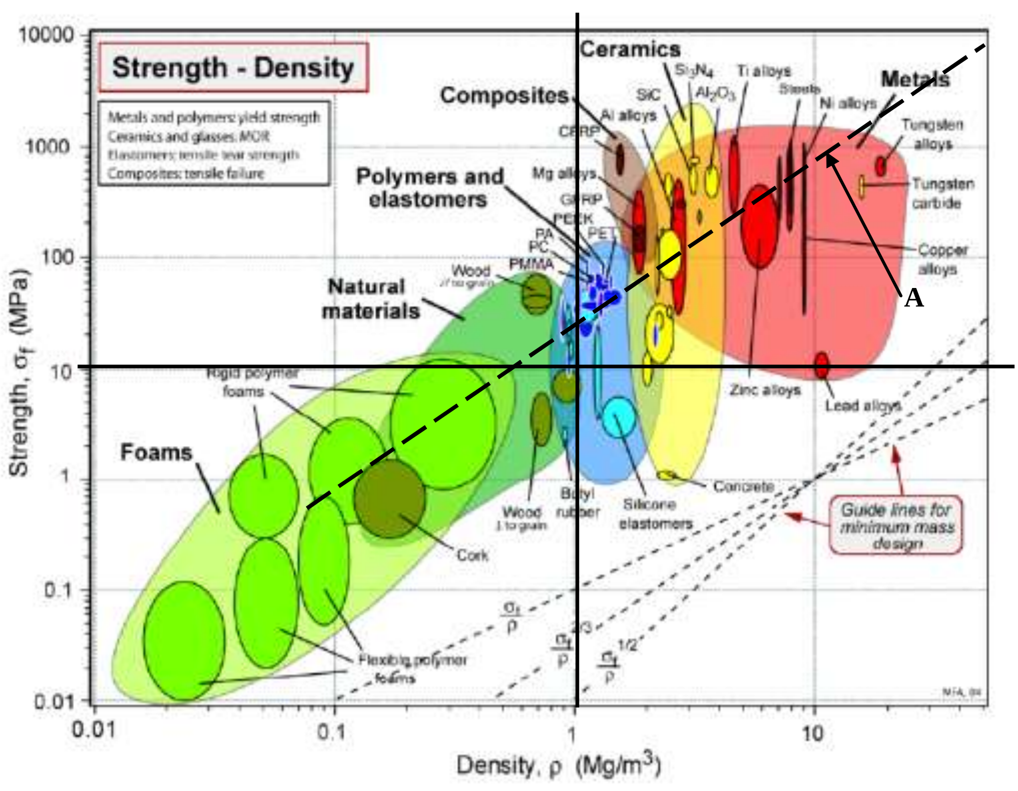

Figure 4: Ashby chart: Strength σ_f, is plotted against Density ρ, on log scales [see ref 3-4]

decisions based on two parameters (α, β) at a time. Material selection indices can be used for,

- Identification of the material properties relevant to performance.
- Determining relative importance of these material properties
- Performance comparison of specific materials

When three or more material properties need to be taken into consideration, as is the case in legacy systems, use of Ashby charts becomes very limited.

Material database resources such as MatWeb [7] are useful in only providing material property values and a library of widely used engineering materials. It should be noted that all the material property values are not made available. Some specific material properties such as creep rate data, or fracture data are not available at all. The cost of conducting cumbersome experiments to obtain these material properties is very high. Also material properties of some of the materials are closely guarded. Hence tests need to be conducted for obtaining some application specific material properties.

DFM based tools such as PSES [8] and MAMPS [9] are developed to perform material and manufacturing selection in preliminary stages of a design characterized by imprecise and uncertain requirements, parameters and relationships. PSES extends the parametric set matching of high level manufacturability analysis to the fuzzy-logic set matching and MAMPS uses intervals rather than fixed values for matching. The material selection module of the MAMPS assesses the degree of compatibility of a material alternative and requirement of a product profile for eventual material filtering.

Meaning Driven Materials Selection (MDMS) is a method which aims to encourage designers to systematically involve meaning considerations in their materials selection process [10]. Meanings of materials refer to what we think about materials, what kind of values we attribute after the initial sensorial input in a particular context of use. There are other domain-specific and application-specific material selections tools used in research but all these tools are loosely based on one of the above said techniques: Ashby charts, Material Database or DFM rule based techniques. These tools are useful particularly for novel designs where functional requirements and constraints are clear, but are not suitable for LSE in for reasons mentioned in the following section.

1.4. Problem Statement:

When only a few parts in a large legacy system are being re-engineered, there are some unique challenges compared to material selection in a new system:

- Form, fit and function requirements with the legacy system – the new part should perform all the basic requirements as the old part if not better (Function), should be roughly the same size as the existing part and occupy the same overall volume (Form) and should have the same number and type of interfaces particularly in an assembly where it interacts with other parts (Fit). All these criterions ensure part replaceability in an assembly.

- Uncertainties about the design intent – Legacy engineered parts are generally designed long time back. Information about the design such as function, loads carried by the part and environmental conditions that can be handled by the part may not be easily extracted. Some information on the part might be available or can be extracted and rest of the information needs to be deduced using engineering principles and knowledge based systems. For example: Tapered round parts can be subjected to bending and torsional loads based on form synthesis principles but the actual load values may not be available. Hence there is uncertainty involved whenever decisions are made on incomplete data.
- Frequency and the mode of failure from actual service in the field – All legacy engineering systems should consider the failure mode and the frequency of failure from actual service. The original part might be designed for a particular failure mode and for a pre-determined life. However the original part could have failed in a different failure mode over a prolonged life or it failed in the expected failure mode but much earlier than expected or combination of both instances. This information is used in re-evaluating the loads, boundary conditions and environmental conditions for redesigning the parts or find new materials that match the new material property values.

The material selections techniques currently used are not multi-attribute as is the need for material substitution for legacy engineered parts. Also the incompleteness of available data from user and uncertainties associated with it are not considered by the existing tools. The objective of this research is to investigate and implement software for material substitution that takes into account the uncertainties inherent in the system and identifies candidate materials that satisfy the functions and constraints of the component design and still performs the same if not better in satisfying the goals for material substitution.

CHAPTER 2

MATERIAL SUBSTITUTION IN LEGACY SYSTEM ENGINEERING

Material substitution for parts in legacy systems 25-50 years old, presents unique challenges that traditional material selections decisions are not plagued by. In the design of new product all the functions, constraints and goals are clearly laid out from the customer requirements. Based on the discussions from previous chapter, this information however might not be clearly defined in legacy parts. Thus one of the tasks involved in redesign of legacy parts is clear understanding of design intent. Function, environmental conditions, loads, failure information, service life designed for, and material properties are some of the information indicative of design intent. Some of this information is available, some can be extracted but majority of information needed to make any significant engineering decision is not available in a readily usable form. For example: Standard machine elements or artifacts have clearly defined functions, but some machine elements have application specific functions that may not be easy to understand without domain expertise. Similarly parts can be analyzed for the type of loads that it can withstand but the actual load value, location and direction information is hard to obtain. The available data may come from several sources including OEMs themselves that originally manufactured the part. Not all these sources of information or extraction methods are same. Some data sources such as OEM provided information are more reliable compared to information from visual inspection. This is a problem inherent of any re-engineering system. Each legacy system is thus analyzed for the following information before material substitution

- Important criteria used in material substitution
- Available data from legacy system
- Data extraction techniques and degree of confidence

Each of this information is discussed in the following sections.

2.1. Important criteria for material substitution:

Material selection is generally done in the embodiment stage of the design where more information is available on the design intent of the part. Not all information is used in material selection, and some information is critical compared to others [11]. Typically a design engineer bases his decision on the following criteria

1. Predicted failure mode of the part; Hours of operation to failure
2. Part function
3. Material strength values.

All of these parameters are used to determine the safe life of the product for operation. Material substitution decisions are also similar in that all the above mentioned information is required in some form or the other for legacy parts. The criticality of each of this information is analyzed below.

Failure Mode data: Mechanical equipment generally does not enjoy infinite life; they are bound to fail eventually. Material failure is defined as any change in shape, size or material properties of a structure, machine or machine part that renders it incapable of performing its intended function [12]. The failure when it occurs can lead to unpredictable repercussions and sometimes may even be catastrophic. In order to avoid unpredictable failure, it is imperative to understand the mechanics of failure, the service conditions causing the failure and the extent of damage. Hence failure mode plays a significant role in all material selection\substitution decisions.

The design engineer always designs components for a specific life expectancy. The Life expectancy of a part is a characteristic of the strength of the material used. One of the goals of material selection is to maximize this life expectancy of the part based on the service conditions and the modes of material failure that it can undergo. Traditional failure theories are in terms of loads (stresses) and environment conditions exceeding certain material properties. Material properties are quantifiable measures of the strength of the material to withstand a particular failure mode. In fact material properties can also be used to compare different material strengths for different service conditions. Based on the failure theories it is possible therefore to directly relate material properties and failure modes as shown in the Table 2. Some of the generally recognized failure modes are Brittle fracture, Yielding, Elastic deformation, High cycle fatigue, Wear, Corrosion, Creep and 23 other failure modes that are listed in [12-13].

Table 2: Critical failure modes vs. Material properties (see Ref [13])

Failure Mode	Ultimate Tensile Strength	Yield Strength	Compressive Strength	Shear Yield Strength	Fatigue Property	Ductility	Impact Energy	Modulus of Elasticity	K_{IC}	Electrochemical Potential	Hardness	Coefficient of Expansion
Yielding		⊙		⊙								
Buckling			⊙					⊙				
Creep												
Brittle Fracture							⊙		⊙			
Low cycle Fatigue					⊙	⊙			⊙			
High cycle Fatigue	⊙				⊙							
Fretting			⊙							⊙		
Corrosion										⊙		
Wear											⊙	
Thermal Fatigue												⊙
Stress - corrosion cracking	⊙									⊙		
Hydrogen embrittlement	⊙											

Part function or Machine Element: Another important observation from LSE is that machine elements are generally in combined state of loading (i.e. different types of loads acting in the same instance). Very rarely do machine elements fail in only one particular failure mode. Failed parts generally provide evidence of several possible failure modes but critically one failure mode triggers a sequence of other failure modes. Even a single load case in different environments can produce different failure modes. Parts can thus fail by one or more failure modes, but the most probable failure modes based on the service conditions of the part is considered as critical failure modes. Even if the objective for material selection is to increase the strength of the part to withstand a particular mode of failure, care is taken to consider all other failure modes and ensure that its material strength is high enough to withstand other identified failure modes.

Parts that are classified as a particular machine element type share some common part function apart from application specific part functions. Since parts with common functions undergo similar loading conditions, they also share common failure modes. The critical load for failure may however vary from application to application and this is addressed by different materials for different applications. Failure modes are thus typical of the machine element type and its function. For this reason a list of potential failure modes of the part is considered based on the part classification as a machine element type. For the purpose of this research machine element type is treated as an indicator of part function. Hence it is possible to create a table of machine elements with commonly experienced loading conditions, environment conditions, failure modes and the manufacturing processes involved in production of the part as shown in Table 3 (a) & (b).

Table 3: (a) machine element attributes; functional, operational, and behavioral;

MACHINE ELEMENT	LOAD CONDN	STRESS CONDN	ENV CONDN	CONTACT CONDN	FAILURE MODE
Shafts	Fluctuating Torque; Fluctuating Moment; Axial forces when either helical or worm gear is mounted on (or) if the shaft is vertical	Transverse Shear Stress; Cyclic Bending Stress	Corrosive environment (with lubricants involved and in marine applications)	Sliding contact with Journal Bearings	Primary: Fatigue, Wear Secondary: Force induced Elastic Deformation
Plain Bearings	Journal bearings - generally radial loads	Cyclic Hertzian contact Stress	Oxidation of lubricant and acid formation, Friction generated heating, oxidized wear particles, foreign dust particles	Sliding (frictional) contact with Journal Bearings	Primary: Corrosion, Abrasive Wear, Surface-fatigue Wear, Corrosive wear. Secondary: Yielding, Creep, Galling and Seizure, Adhesive Wear, fretting wear, fatigue wear.

(b) Machine element attributes; common material, manufacturing process, and raw stock

MACHINE_ ELEMENT	COMMON_MATERIAL	MFG_PROCESS	RAW_STOCK
Shafts	Steel (ANSI 1020 - 1050);Bronze or Stainless steel (corrosive environment);Case hardened steel (when used as journal or sleeve in bearings)	A steel strip is rolled into a tube, and is drawn over a mandrel (Cold Drawing). Machining and Heat Treatment (if necessary)	Sheet Stock
Plain Bearings	Bronze bearing alloys (leaded, tin and aluminum bronze and beryllium copper), Babbitt metal, sintered porous metals, self-lubricating non-metallic materials (Teflon, nylon, acetal, phenolic or polycarbonate). Silver is occasionally used. Elastomers for water-immersed applications	Machining (boring)	Bar Stocks
Spur Gears	Cast Iron and Steels for non-corrosive environments; Bronze and Nonmetallic (Plastic Gears) for corrosive environments	Casting, Forming, Sintering and Machining Process (Hobbing, Shaping, Milling and Broaching).	Bar Stocks

Material property values: From the discussions above, it can be concluded that material properties are indicative of the strength of the material and that traditional failure theories relate these material property values to the service conditions (loads and environment). Even though material selection and material substitution are similar in that they use the same type of information for decision making, one of the differences is in the source of information. When the material is selected during the embodiment stage of the design, service information (loads and environment conditions) is well understood. However for legacy parts the actual load values (magnitude, location and direction) and service environment is not easy to obtain or may not be available. Thus material and material property values are used instead as proxy for the actual load values. Also if critical failure modes are important to understand the loading conditions of the legacy parts, the material that was originally used in the component is indicative of the intended life expectancy of the part in service. With the original material of the part we can obtain the key material property values for that material from a material database. These properties will be the basis for further computation and choices of new material will be based on the newly computed properties. Even though material with higher strengths for a particular failure mode are of keen interest, the material property values associated with other possible failure modes for that machine element implicitly act as constraints in finding new candidate materials.

However not all of these three parameters are readily available in legacy system for any decision making. Information from existing data needs to be extracted in order to obtain the important parameters. The parameters that are readily available for material substitution and their sources of information are discussed in the following section.

2.2. Available parameters for material substitution:

Lack of usable information is characteristic of legacy engineered systems. Re-engineering legacy components is as challenging as engineering a new system. In order to develop any new automated re-engineering systems it is important to understand available information in legacy systems that can be used. Clearly material substitution is one such re-engineering system that requires understanding of parameters that are available and that can be used in the process based on the parameters that are actually needed.

Failure Mode data: If a legacy part failure cannot be categorized into one of the generally recognized failure modes, then failure descriptors assist in identifying a particular failure mode. Failure modes can be described by three parameters in particular [12]:

1. Manifestation of failure
2. Failure inducing agents
3. Location of failure.

Each specific failure mode is then identified as a combination of one or more manifestations of failure together with one or more failure inducing agents and a failure location. The four manifestations of failure are:

- Elastic deformation
- Plastic deformation
- Rupture or fracture

- Material change (Metallurgical, Chemical etc…)

The failure inducing agents are:

- Force (steady, transient, cyclic or random)
- Temperature (low, room, elevated)
- Temperature change (steady, cyclic, random and transient)
- Time (very short, short and long)
- Reactive environment (chemical and nuclear)

The two failure locations are:

- Body type
- Surface type

Visual inspection of the failed part can identify if the failure occurred on the surface or over a cross-section and also clues to identify the manifestation of failure. It is also easy to identify any ruptures or fractures with the help of laboratory tests such as NDT or microscopic inspection. Information on failure inducing agents is obtained from field service data or from the experiential knowledge of the system by the design engineers. The failure inducing agents are expressed in terms relative to the environment.

Machine element type: When legacy parts cannot be categorized into one of the machine element types then generalized part function data is used in identifying them. Every machine or piece of mechanical equipment has some function to perform. The functions of mechanical equipment can be generalized and categorized by observing that each function consists of some action (e.g. Amplify, Transfer, Transform) and an object (e.g. Mass, Energy, Motion) upon which the action is performed. However the machine element to part function is a (1: n) relationship i.e. one machine element can have several part functions and thus it is not possible to uniquely identify a machine element based on its part function alone. Since most of the machine elements work in an assembly of other machine elements, additional information such as mating machine element and overall shape of the part can be used. Overall shape is the predominant feature of the part. Information about part function and mating machine element is entirely based on experiential and domain knowledge of the designer in the legacy system.

Material property values: Material data for the part may come from visual inspection or from material testing by chemical, spectral or ultrasonic techniques. At this point the material by which the part is made of is either exactly known, for e.g. 1020 cold rolled steel, or class of the material can be identified such as carbon steel. If the exact material is not known, but it can be classified into a family of material, then a range of average values for material properties can be used. If neither the material class nor the exact material is known, then based on the failure mode and the dominant load of the part, load estimates are made to identify the critical material property values of the existing part.

The available data from legacy systems as is seen from above is not readily usable. The data that can actually be used needs to be extracted from the available data using domain expertise and knowledge based systems. The data that can be extracted and techniques that are used in extraction are discussed in the following section.

2.3. Data extraction techniques in material substitution:

Failure Mode data: Crucial information used in identifying the failure modes of the part can be extracted from hours of operation before failure and from failure manifestations. Based on a technical study of an aeronautical parts overhaul company [14], it is understood that not all 23 failure modes listed in [12] are of critical interest with regards to legacy parts. Legacy parts predominantly fail by *Wear* and *Corrosion*. Even though the reliability curve in Fig 5 shown below is used for purposes beyond the scope of this research, the idea can be used in classifying the failure modes. Accordingly the three sections of the curve are the three classifications of the failure modes:

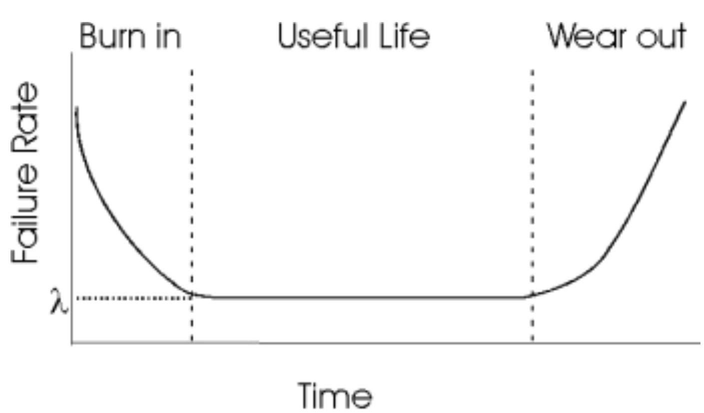

Figure 5: Reliability curve of machine elements [see Ref 15]

- Instant failure during installation or accidental operation of the part
    - Brittle fracture
    - Yielding
    - Elastic deformation
    - Buckling
- Worn out part
    - Wear
    - Corrosion
    - Creep
- Fracture after prolonged service
    - High cycle-fatigue

This classification based on hours of operation before failure can provide a good idea of how the part failed. If the part failed after long service the critical failure modes considered are Wear, Corrosion and Creep and if the service temperature is greater than 0.3 to 0.4 times the materials melting point (for metals) then creep is the dominant failure mode. If however the part is operated within the specified design conditions and if it fails after installation then either the estimated loads are incorrect or the dominant load is different than the one designed for. If the part is operated outside the design conditions then there is no particular reason for failure except the installation methods or operation conditions need to be verified. Fatigue life is predictable and if the part fails within the expected time it mostly is due to dynamic loading. Hence certain failure modes take precedence over others that are critical to legacy parts. Fig 6 shows a flowchart of the failure mode filtering based on hours of operation.

Part ruptures or fractures occur due to extreme environment conditions (For e.g. ductile parts fail by brittle fracture in very low temperatures, or failure by elastic deformation at very high temperatures) or due to sudden changes in

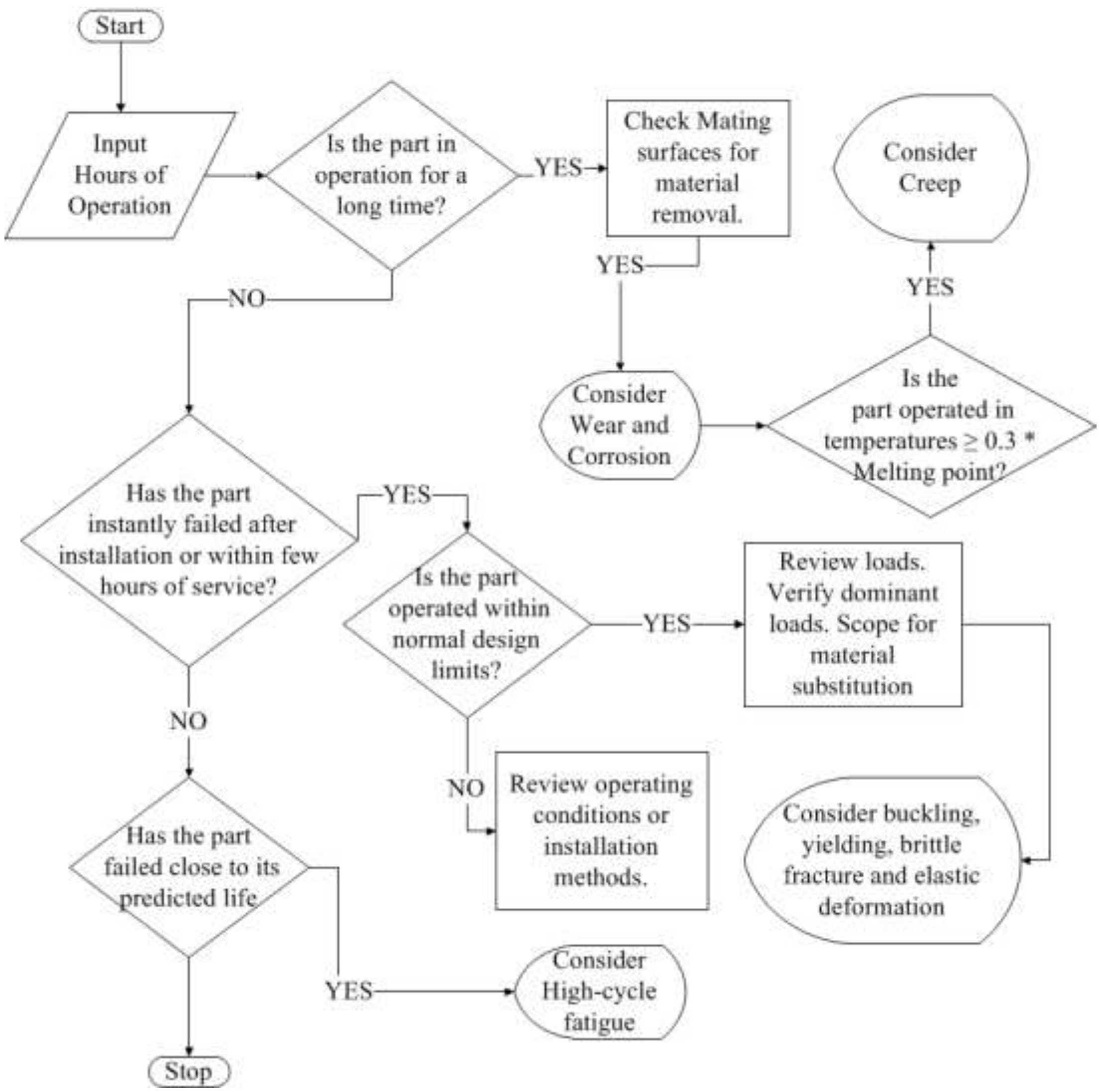

Figure 6: Failure Mode filtering based on Hours of Operation

loading conditions (For e.g. spalling failure of surfaces due to impact forces). A part that does not rupture but has deformed from its original shape has undergone some sort of plastic deformation (For e.g. necking is a sign of plastic deformation in highly ductile materials under high tensile loads). Structural parts that do not undergo any shape change after installation but fail to perform the function indicate elastic deformation due to lack of stiffness in the material. Parts under extreme environmental conditions undergo material and chemical change. Legacy part failure by elastic deformation and material change is particularly rare because the part was in use already for a long service life. These failure manifestations tend to occur in the early stages after the installation and hence their corresponding failure modes must have been taken into account when the part was originally designed. Hence some failure manifestations are more important to legacy parts than the others based on the service condition.

Machine element type: Generalized functions such as Amplify motion, Amplify force, Transfer energy, Constrain motion etc… can be constructed by combining a selected action with a selected object. Based on these functions, the application of the parts can be either structural or in power transmission. Power transmission parts are predominantly revolved parts (round) that are designed to withstand torsional loads. Hence overall shape is indicative of the machine element application. For e.g. if one of the functions of the part is to “Transmit Power” and it is a machine-turned part with gears mounted on it then one possible machine element is a shaft.

Material property value: In the case where material is exactly known material property values can be directly obtained from material database such as MatWeb. If the exact material is not known then average values of material properties can be obtained from the material class it is classified under. If neither the material not the material class is known then the dominant load estimations help in making estimation on the properties of the original material. Some of the techniques used in load estimation are:

- Weak link analysis on overall shape for critical sections. Dominant load can be determined using form-synthesis techniques and from the boundary condition of the part.
- Load locations are obtained from mating surfaces. Also for power transmission components Horse Power (HP) is a useful design variable for estimating torsional loads.
- Application specific rough estimates of loads can be determined for machine element components from different ranges. This is an iterative process.
- Load estimations from strain testing, service data and hours of operation or from OEM data.

From the discussion in this chapter, it can be summarized that three important parameters in material substitution for legacy systems are of prime importance but only some parameters are available and the critical parameter values need to be extracted from available parameters. The available parameters are expressed in relative imprecise terms. Thus there is uncertainty whenever data extraction techniques are used. Conventional systems do not consider data extraction uncertainty but it can play a major role in crucial decisions. For e.g. in identifying the failure modes, failure descriptors such as failure manifestation, failure agents and failure locations are used. The combination of these failure descriptors does not necessarily identify a failure mode every time. However if there is a very high confidence in one of the failure descriptor data based on the inspection method used, it can help in identifying a failure mode, however the confidence in the data obtained should affect the downstream decision making process. So based on the input confidence in failure descriptors the identified failure mode should be handled with care and the final material selection decisions may be optimistic or pessimistic based on the criticality of the part in the assembly. The lower the uncertainty in extracted data, the higher the confidence on material decisions. This data uncertainty can be modeled using several established techniques. One such technique – Fuzzy logic is used in this research. The importance of fuzzy logic and its implementation in this project is discussed in detail in the following chapter.

CHAPTER 3

FUZZY LOGIC IN MATERIAL SUBSTITUTION

3.1. Background

Fuzzy logic is one of the standard techniques used popularly to model expert knowledge and representation of information extracted from inherently imprecise data. Fuzzy member functions are good in modeling linguistic variables such as age, weight and height. Fuzzy rule sets model imprecise dependencies such as “IF age(x) < 25 THEN risk(x) > 60%” which are rules in a car insurance company. Conventional set theory is a collection of crisp sets. A crisp set is a collection of distinctly well-defined objects. Classical set theory deals with deterministic variables which are either part of the set (0) or not part of it (1). A classical set can be expressed by a characteristic function as shown below in Fig 7.

Real world variables however lack this crisp boundary definition. Engineering problems have variables such as part function, failure mode that has

$$m_A(x) := \begin{cases} 1 & x \in A \\ 0 & x \notin A \end{cases} \qquad m_A(x) \in \{0,1\} \quad \text{Example Middle\_Age}=\{x|a \le x \le b\}$$

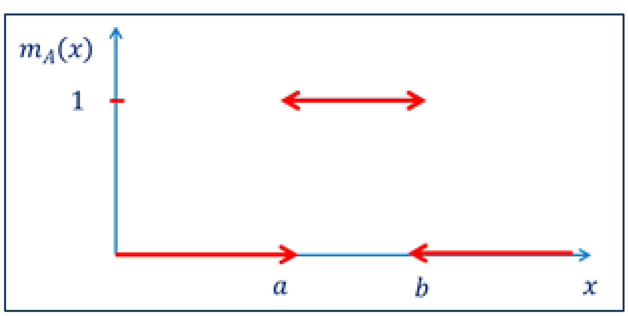

Figure 7: Crisp sets and characteristic function of a crisp set

several contributing values and each of these values has their own degree of contribution to the variable set. For example a part failure could be described as 50 % chance of Fatigue, 30 % chance of Brittle fracture and 20% chance that it is Fretting. So clearly we cannot completely agree on one single failure mode that the part could fail by and any engineering decision based on the failure mode should consider all three failure modes. The influence on the final decision however is dominated by fatigue failure mode more than other failure modes. Legacy engineered parts have design variables commonly expressed in these terms because there is no clear distinction. The fuzziness in this type of data can be easily modeled using fuzzy member sets as shown Fig 8.

Probability is different from fuzzy logic in that it describes the likelihood of occurrence of a crisp event. Probability assumes that the data obtained is precise and works best when there is a large volume of data. Legacy systems lack enough information to be modeled using probability and make any conclusive decisions based on the data [16]. Several other approaches to handle information

$\mu_A(x) \in [0,1]$ Example A=Middle_age is roughly in [a,b]

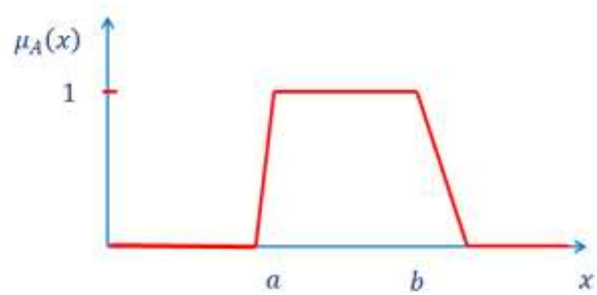

Figure 8: Fuzzy set and fuzzy member functions

about uncertainty have been proposed. Interval arithmetic allows us to deal and compute with tolerances rather than deterministic variables [17]. Numerical analysis offers ways to propagate errors along with the normal computation [18]. However in this research, Fuzzy logic is chosen over all other methods owing to ease of use, ability to model linguistic variables, uncertainty modeling and the low computational expense required for implementing in software systems. Fuzzy logic is used extensively in industrial automation, power plants, thermostat controllers, motor controllers, vehicle controllers, electrical appliances, automotive applications (ex: surface adjustable brakes), traffic control and aircraft flight path planning.

3.2. Steps involved in Fuzzy Logic Implementation

Fuzzy logic generally involves fuzzification of available information, combining different fuzzy inputs using fuzzy operations, generating rule sets, rules processing and defuzzification. Each of these steps is analyzed and the implementation for the legacy framework is also discussed in the following sections.

3.2.1. Fuzzy member functions

In example shown above in fig 3.1 the function for *middle_age* can be defined as being in the interval [*a, b*]. So in order for a person to be qualified as a middle age person he needs to be within the limits [*a, b*] and outside this limit he is not qualified as a middle age person. The actual values [*a, b*] may be [30, 50] for a person and [40, 60] for another person. Thus there is no clear definition for middle age limits. To avoid the problem of redefining the function for each person, fuzzy member functions as shown in fig 3.2 can be defined. The fuzzy member function *middle_age* is defined as being roughly within the limit [*a, b*]. Now the set contains people with ages '*a' and 'b'* with a linearly decreasing degree of membership, i.e. the closer someone's age approaches '*a'*, the closer his degree of membership to the set of middle age people approaches one. In contrast to classical sets where an element can either belong to a set or lies completely outside of this set, fuzzy sets allow also partial memberships.

In legacy engineered systems we have both deterministic and non-deterministic variables. Those parameters for which values can be directly obtained are deterministic and for those that are obtained from relative imprecise definitions of other related parameters are non-deterministic. The deterministic variables have values either 0 or 1 such as the critical variables used directly in material substitution that are discussed in section 2.1. Non-deterministic variables such as the available variables that are used in finding the three critical parameters mentioned in section 2.2 have membership functions with values ranging from 0 to 1. The membership function for each value of the non-deterministic variable is based on the user's perception of degree of contribution of the value in the set. The user's perception is expressed in four categories ("Very High", "High", "Low", and "Very Low"). One of the example membership functions is shown below in fig 9. The X axis corresponds to the input confidence % and the Y axis corresponds to the equivalent fuzzy membership value for the input confidence %.

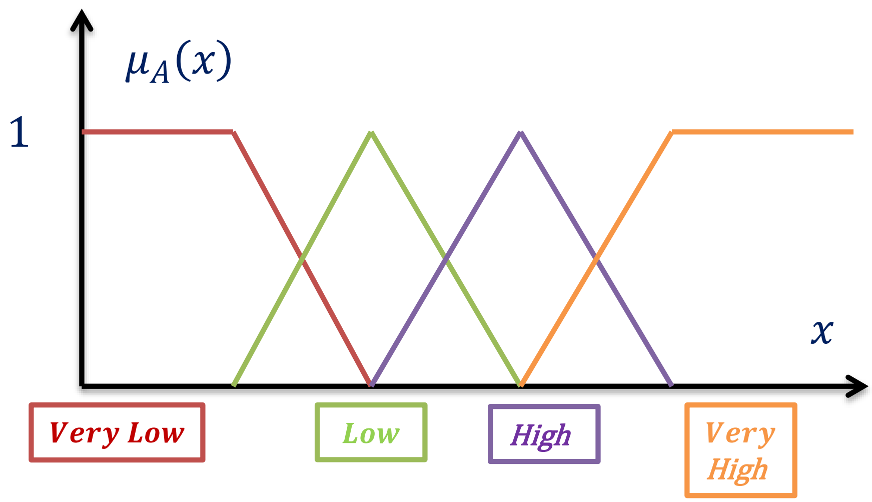

Figure 9: Generic Fuzzy Member Function for Fuzzy Sets in LSE

The fuzzy membership value for a given confidence input % may be in one or two confidence categories. This way of defining fuzzy sets over the domain of a variable is often referred to as granulation, in contrast to division of crisp sets (quantization) which is used by classical sets. Granulation results in a grouping of objects into imprecise clusters or fuzzy granules, with the objects forming a granule drawn together by similarity. Thus fuzzy quantization or granulation could also be seen as a form of fuzzy data compression.

3.2.2. Fuzzy operations

Fuzzy member functions help fuzzify uncertain information of real world variables. In engineering problems the real values of these variables are used in calculating other variable values with arithmetic or logical operators indicative of the physics of the problem. After fuzzification of the real world variables, the output of the member function is just a fuzzy number with values ranging from 0 to 1. Thus there is a need to extend the arithmetic and logical operations such as *Boolean operations* like *conjunction, disjunction and complement* to fuzzy numbers and sets. In effect we are retrieving a new degree of membership resulting from an operation of one or more existing degree of membership. Thus an entire family of operators can be defined to derive the resulting member function. Lofti Zadeh [19] introduced prominent examples of these operations.

- conjunction: $\mu_{A \wedge B}(x) := \min\{\mu_A(x), \mu_B(x)\}$

- disjunction: $\mu_{A \vee B}(x) := \max\{\mu_A(x), \mu_B(x)\}$

- complement: $\mu_{-A}(x) := 1 - \{\mu_A(x)\}$

The above sets of operations are called as the *min/max norm* and it represents the most optimistic approach. The most pessimistic of operations for the Boolean conjunction and disjunction is called the *product sum norm* as shown below.

- conjunction: $\mu_{A \wedge B}(x) := \mu_A(x) \times \mu_B(x)$
- disjunction: $\mu_{A \vee B}(x) := \min\{\mu_A(x) + \mu_B(x), 1\}$

The Hurwicz criterion [20] is a compromise between the two approaches and is defined using the coefficient of realism, α that $0 \leq \alpha \leq 1$. The Weighted outcome is defined as

$$WO = (\text{Optimistic-outcome}) \times \alpha + (\text{pessimistic-outcome}) \times (1 - \alpha)$$

However the co-efficient α is problem dependent and is the philosophy of the decision maker. In this research, since we are concerned with failure mode of parts and owing to uncertainty of available information we are inclined to use the most pessimistic of approach for fuzzy set operations – product sum norm.

In legacy engineering systems, a matrix is setup with parameters paired against each other and each of their possible values are listed. The user also inputs the fuzzy member function score for each of the value input based on the confidence level of his data extraction techniques mentioned in section 2.3. For example: if the data is obtained directly from the OEM manufacturer then variable values have high degree of membership and for data obtained through visual inspection have very low degree of membership for the variable values. The combined score of two parameters for the combination of values selected is the product of their fuzzy degree of membership. This is illustrated in table 4 below.

Table 4: Fuzzy score computation in Rule Matrix

<table>
<tr><td colspan="2" rowspan="2">Parameter-1/ Parameter -2</td><td colspan="2">Value -1</td></tr>
<tr><td>Value</td><td>Member function score</td></tr>
<tr><td rowspan="2">Value-1</td><td>Value</td><td>Consequent</td><td>X1</td></tr>
<tr><td>Member function Score</td><td>X2</td><td>Fuzzy score = X1*X2</td></tr>
</table>

3.2.3. Fuzzy rule selection and processing

Fuzzy rules are used to characterize imprecise dependencies between different variables. Real world engineering problems are plagued by imprecise dependencies between variables such as the one in ECU, where CAN BUS messages controls the engine based on several vehicle parameters that do not have clearly defined equations. Consider for example a rule:

IF $vehicle_{speed}$<30 mph AND $throttle_{position}$>70% THEN $Engine_{BHP}$>200 HP

It would be easier if the same rule can be expressed in terms of relative linguistic values for variables. Most of the controller messages in engineering applications are expressed this way.

IF $vehicle_{speed}$ is low AND $throttle_{position}$ is high THEN increase $Engine_{BHP}$

Thus fuzzy rules are of interest whenever problem's physics cannot be defined in clear numerical terms and a high level of precision is not desired in order to maintain a high level of interpretability. The generic form for this rule is then:

IF x_1 is A_1 AND x_2 is A_2…AND x_n is A_n THEN y is B

Here the A_i is the antecedent and B is the consequent for the linguistic values of input vector x and the output variable y, respectively. These types of rules are called *Mamdani rules* [21] where the consequent is also a fuzzy number. Engineering controllers make their decision based on crisp real values and so there is a need to defuzzify the output of a mamdani rule which is discussed in the next section. However there are rule types where the consequent is a crisp value and they are called *Takagi-Sugeno* rules [22]. In this research, we are interested in the *mamdani rules* due to its simplicity of setup, use and low computational expense required to implement the rules in a database setup.

3.2.4. Defuzzification

Once all the consequents are identified from mamdani rules the final step is the defuzzification. As mentioned before engineering decisions are based on crisp real values of variables but the output of a Mamdani rules are fuzzy number which are degree of membership of output variables. Several methods exist to determine a crisp output value, but the two most popularly used methods are *Center of gravity method* and *Maximum value method*. Center of gravity tries to identify the center of each of the membership function of the output variable and finds the weighted product sum. Maximum value finds the corresponding crisp output for the highest degree of membership of the output variable. Irrespective of the method used the crisp output is the confidence % on the selection of the consequents of the critical parameter identified. In this research, a pessimistic approach is followed and hence the maximum value method is used, since the maximum value corresponds to maximum % confidence on the output parameter.

3.3. Application of Fuzzy logic in Material Substitution

A Rule matrix can be setup for determining each of the three critical parameters discussed in section 2.1. When the values for these parameters are known then the variables are considered deterministic and a pool of candidates is chosen based on the goals and constraints discussed in section 4.2. However when the critical parameters are not known then available parameters described in section 2.2 and 2.3 are used to identify these critical parameters. In the rule matrix, for each pair of value of the available parameters a consequent critical parameter is identified. For e.g. if the failure of the component is not known then for each combination of antecedents - failure manifestation, failure agents and failure location, a consequent – failure mode is identified to setup the failure mode rule matrix. Note that these kinds of rules for legacy engineering systems, instead of a single consequent could have multiple consequents. There can be several combination of rules based on the granularity of the member functions and the accuracy of problem (or controller) required. Multiple rules can be selected at a time and so there also needs to be a way to combine several fuzzy member functions. Fuzzy set operations help in combining two or more fuzzy membership values. Product/Sum operations are a pessimistic approach for combining fuzzy membership values, since material substitution decisions deal with failure mode of the part. The fuzzy rules are setup in the mamdani rule format and thus the output is also a fuzzy membership value. Defuzzification method such as Maximum value method – a pessimistic approach – is used in combining two or more rules. The result of a defuzzification process is an output confidence % that corresponds to the output fuzzy membership value and also the value for the parameters identified. The higher the rule scores, higher the likelihood of the particular the parameter value identified being the actual parameter value.

CHAPTER 4

MATERIAL SUBSTITUTION: LOGIC FOR CANDIDATE SELECTION

To summarize we have discussed the parameters that are important for material substitution in section 2.1, the parameters that are available in section 2.2, extraction techniques in 2.3 and modeling the uncertainty in data extraction using fuzzy logic in chapter 3. The final step in the material substitution process is the candidate material filtering from database using the critical parameters. Each of these candidate materials should satisfy all the design and manufacturing constraints explicitly mentioned by the designer, implicit constraints of the design, and should reach the goals specified by the design engineer. The list of goals and constraints considered and the sequence of steps involved in the final candidate selection logic are discussed in the following sections.

4.1. Goals and Constraints in selection logic

Material selection and material substitution is always a goal driven process. Without the need for a new goal, the existing material will perform equally well in the existing service conditions. There are several motives for material selection discussed in detail in section 1.2 & 1.3 and each of these motives can be translated to user specified goals. Some of the common objectives are:

- *Improve Strength* of the failed component.
- *Reduce Weight* of the existing component.

- *Reduce Cost* of the existing component.

Usually a desired % improvement is also input along with the goal specified. Based on the target percentage, new material property values are calculated. The objective of *improving strength* is to find new materials that have high strengths in resisting the critical failure mode the part originally failed with the existing material. This implies that the designer is not satisfied with the performance of the existing material to withstand failure owing to the frequency of failure or due to the criticality of failure. *Reduce weight* objective is to find new materials that are lighter than existing material. It also implies that, the new materials that are lighter than the existing materials should have the same or better material strength values. Here in addition to the existing material properties, the density property is considered as function of weight. The assumption here is that the re-engineered part also occupies the same volume as the original part and thus is lighter than original part eventually after material substitution. Reduce cost is similar to Reduce weight in that it tries to find cheaper alternatives that are abundant, easily available and also critically have the same or better material strength values as the original part.

Manufacturing processes available for producing the material are explicitly specified constraints. Even if the candidate substitute materials satisfy the strength requirements if they cannot be manufactured with the available processes then the candidate is deemed useless. *Raw Stock* availability of the material is another constraint. For instance if the new material is generally available as a bar stock and as sheet stock, if the supplier provides only a bar stock and the user desires a sheet stock for manufacturing, the material is still deemed useless. New materials that match target property values and satisfy the constraints are all considered as candidate materials. It is possible that no candidate substitutes be found for one of the following reasons:

- The user specified targets are too ambitious for any new candidates to satisfy.
- None of the candidate materials satisfy the constraints
- Either one of the three key parameters 1) Critical failure mode, 2) machine element or 3) originally used material identified is incorrect.

A pool of candidate materials after identification is presented to the user with the final confidence percentage calculated using fuzzy logic. The confidence percentage is important in that the uncertainty in the user input is directly indicative of the confidence level of output.

4.2. Candidate selection logic

Figure 10 represents a declarative model of the overall material substitution process logic. There is several input information the user can provide. Thus there are several routes the user can traverse in the model leading to the final material selection. Predominantly there are five major possible cases identified based on the available input information and all other cases are a combination of the five identified cases. The cases are:

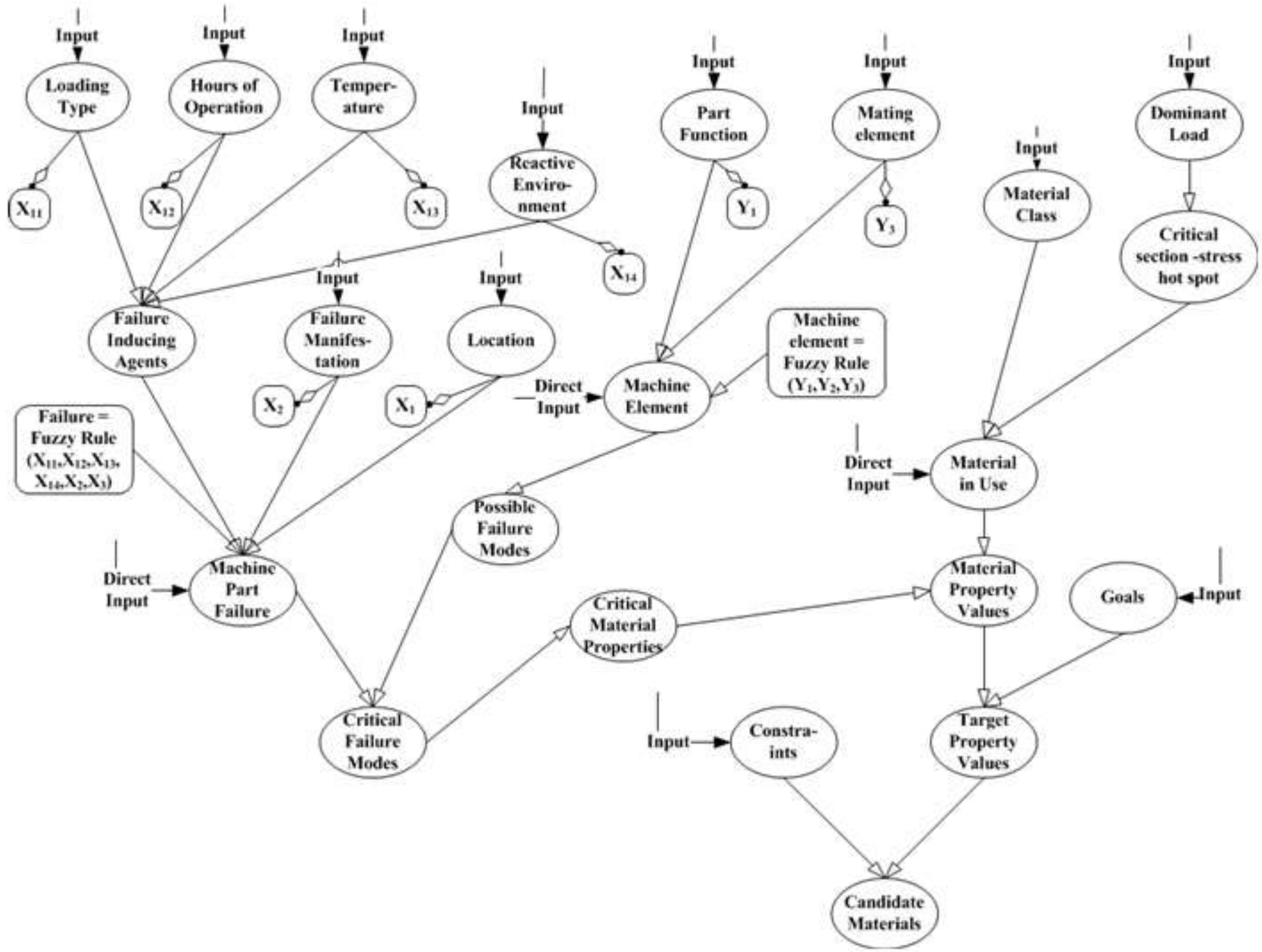

Figure 10: Declarative model of material substitution process

1. The parameters – failure mode, machine element and the originally used material are all known.
2. Failure mode is not known, but machine element and the originally used material is known.
3. Machine element is not known, but the failure mode and originally used material is known
4. Originally used material is not known, but the failure mode and the machine element is known.
5. None of the parameters – failure mode, machine element and the originally used material are known.

The following sections discuss the logic in each of these cases with the sequence of steps leading to identifying the final candidate materials. Some of these cases use fuzzy logic and some don't. The use of fuzzy logic based on discussions in chapter 2 and 3 are subject to the available input information.

4.2.1. Case 1 – All Parameters are known

- Machine element – known
- failure mode – known
- Originally used material – known

From discussions in section 2.1 we know material substitution requires three essential parameters – Part Failure mode, Machine element and the originally used material. In this case considering that all the three necessary parameters are readily available the declarative model shown in Fig 10 reduces to the simplest of scenarios as shown graphically in Fig 11. Again since all of the parameters are available, fuzzy logic will not be used in this scenario. Following are the steps involved in identifying the candidate materials:

1. From the three important parameters the first step in the process is to identify only the critical failure modes. Table 3(a) shows a map of all the potential failure modes associated with a particular machine element. For the given machine element a list of all possible failure modes can be obtained (table 3).

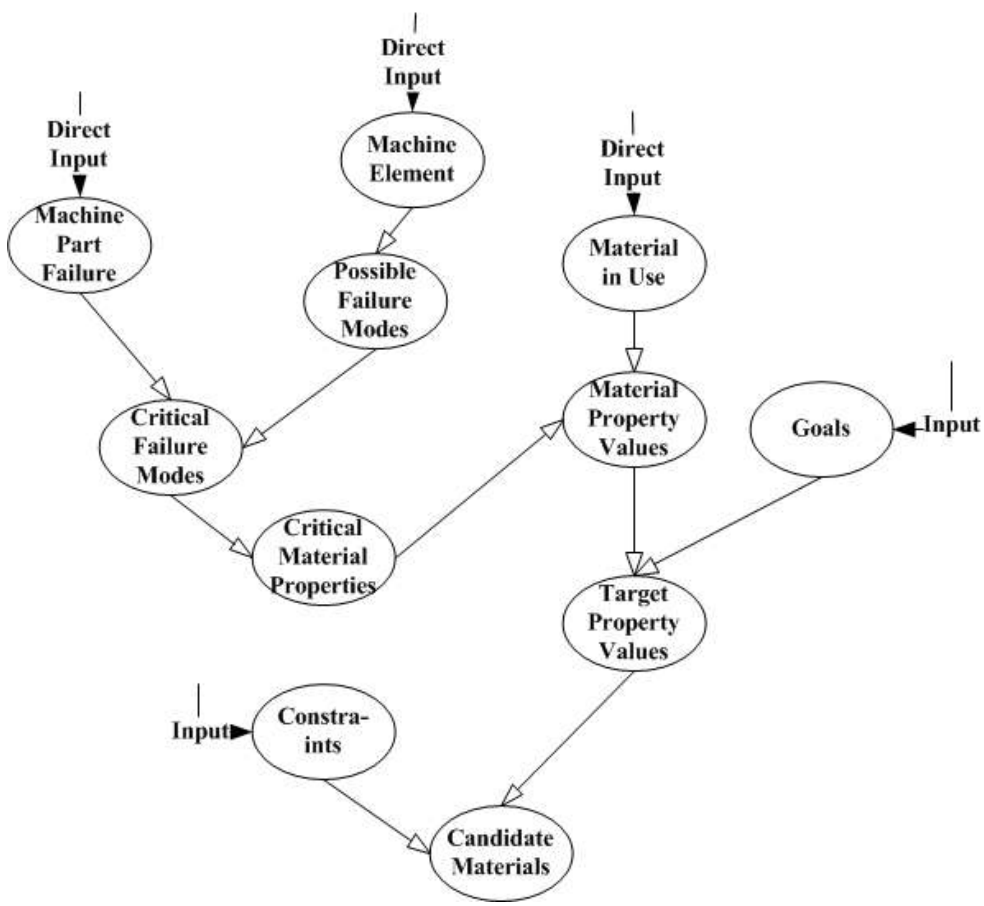

Figure 11: Material substitution logic for scenario 1 - all parameters are known

2. The existing legacy part could have failed by more than one failure mode. To obtain the critical failure modes, the list of failure modes of the existing part and the list of all potential failure modes obtained from the machine element are intersected. The implication of the intersection operation is to check if the user specified machine element can undergo the specified failure mode. If the result of the intersection is null, then either the input machine element is incorrect or the failure modes is incorrect. The user is then prompted to change either the machine element or the failure mode.
3. Table 3(a) also shows the potential failure modes of machine elements classified as primary and secondary. If the intersection of list of potential failure modes of the specified machine element and the failure modes specified by the user is not null, the resulting list of failure modes that are classified primary in table 3(a) are considered to be critical. If none of the resulting failure modes are primary failure modes then the secondary failure modes are considered to be critical.
4. The next step in the process is to obtain the critical material properties for the failure modes identified. Table 2 shows a map of critical material properties and the failure modes. Referring the table, we can obtain a list of material properties associated with the critical failure modes identified.
5. From discussions in section 2.1 the material property values from the originally used material is used in computing the target material property

values. Referring a material database the material property values for the originally used material can be obtained.

6. From discussions in section 4.1, we know that material substitution is always a goal driven process. One such goal is improving the strength of the existing part. The user also specifies a target % increase in the strength desired for the new part. Based on this target % increase the new material property values are calculated for use in searching the material database.
7. The material database is then queried with the target material property values to find the candidate materials that have property values higher than the target property values.
8. The user may also like to specify constraints on cost of the material and manufacturing processes. If such constraints are specified then the resulting candidate list is filtered for those materials that are within the cost limits and are capable of being produced with the manufacturing processes specified.
9. The final candidate materials are then rank ordered based on the target property values. The final selection from the pool of candidate materials is left to the user's discretion.

4.2.2. Case 2 – Part Failure mode not known

- Failure modes - not known
- Machine element - known
- Originally used material – known

In this scenario of the three important parameters the part failure mode information is not available. In order to identify the part failure modes other parameters that describe the part failure such as failure manifestation, failure agents (loads, temperature, reactive environments and hours of operation before failure) and the failure location on the part is used to identify the actual failure modes as discussed in section 2.2. Clearly the information available is incomplete and there is uncertainty with each of these input data. Thus fuzzy logic is used in quantifying the uncertainty and making decisions based on that. A portion of the declarative model shown in Fig 10 that will be applicable to this case is shown graphically in Fig 12. It can also be seen that after the failure mode is identified, the logic follows the sequence of steps in case 1 leading to identifying the final candidate materials. Following are the sequence of steps in identifying the failure mode and the eventual candidate material selection

1. First the three failure descriptors failure manifestation, failure agents and failure location information is prompted for input from the user. Table 5 shows a list of possible values the user can choose from for each of the failure descriptors. The user is also prompted to input a confidence % in the value chosen for each of the failure descriptors. This confidence % is indicative of the user's data extraction techniques and his understanding of the part failure.

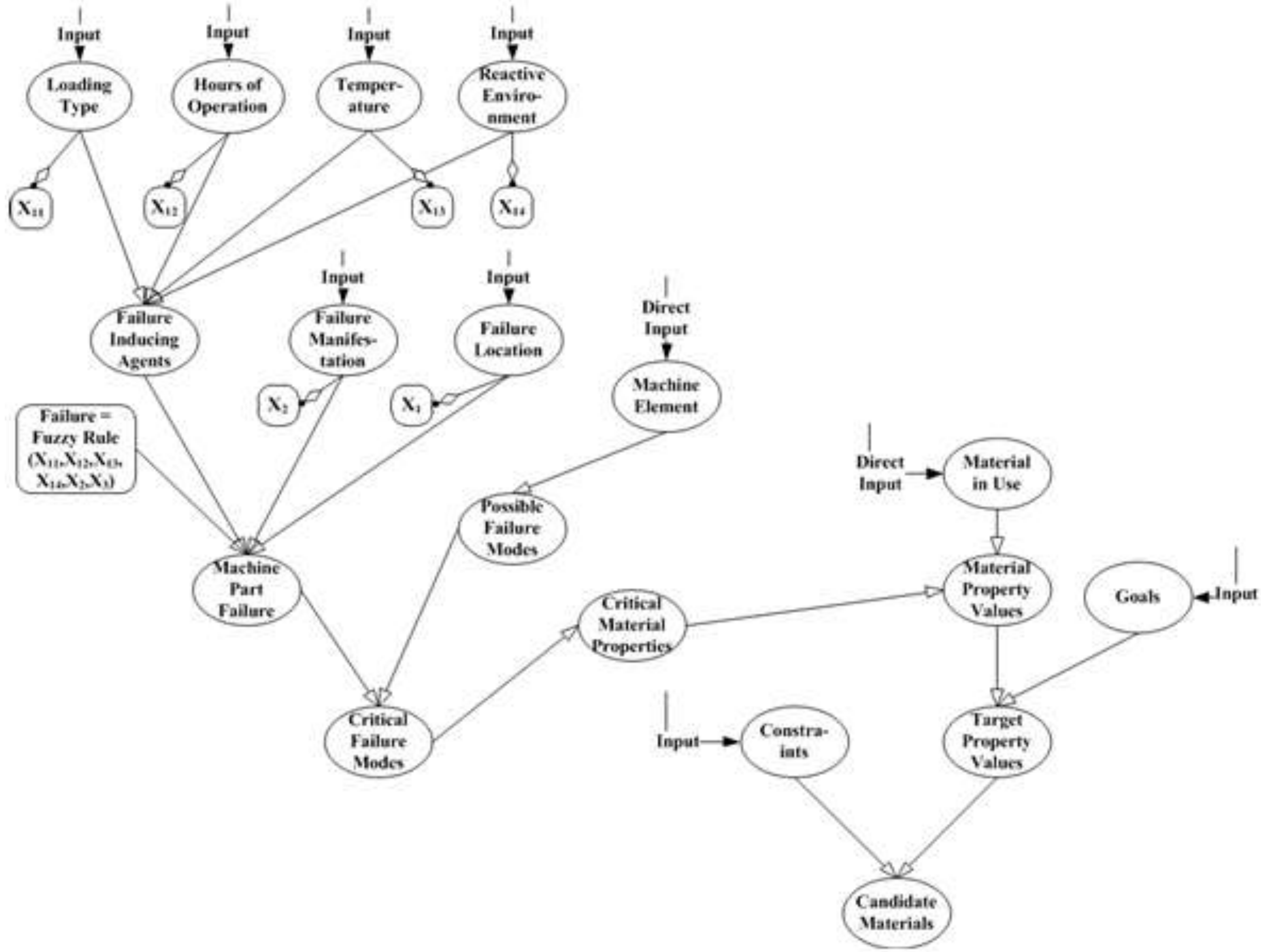

Figure 12: Material substitution logic for scenario 2 - Failure mode is not known

Table 5: Failure Manifestation, Failure Agents and Failure Location

Failure Manifestation
Elastic Deformation
Plastic Deformation
Fracture or Rupture
Material Change

Failure Agent Load
Steady
Cyclic
Transient
Random

Failure Agent Temperature
Low
Room
Elevated
Steady
Cyclic
Transient
Random

Failure Agent: Reactive Environment
Chemical
Nuclear

Failure Agent Hours of Operation
Very Short
Short
Long

Failure Location
Body
Surface

2. Each of these failure descriptors has fuzzy member functions that convert the input confidence % into a fuzzy member ship value. Each fuzzy membership functions have two categories: LOW and HIGH confidence. The input confidence % falls into one or more categories and from the actual confidence %, the membership value for each category is computed. Fig 13 shows an example fuzzy membership function for failure manifestation with the two categories and the fuzzy value computed for 40% input confidence %. The equations for computation are:

$$\mu_n = \left| \begin{array}{l} \left\{ \text{LOW:} \begin{array}{l} 1 \text{ if } X_n \leq 30\% \\ \dfrac{70-X_n}{70-30} \text{ if } X_n > 30\% \end{array} \right. \\ \left\{ \text{HIGH:} \begin{array}{l} \dfrac{X_n-30}{70-30} \text{ if } Xn < 70\% \\ 1 \text{ if } X_n \geq 70\% \end{array} \right. \end{array} \right.$$

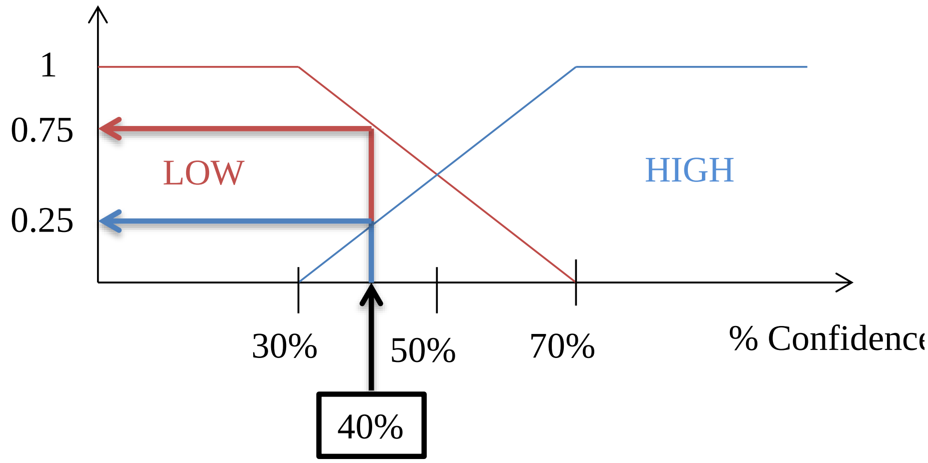

Figure 13: Fuzzy Membership function with values computed for 40% input confidence

Where X_n is the input confidence % and μ_n is the equivalent membership Fuzzy Membership value.

3. The next step in the process is to setup the fuzzy rules. For each value of the failure descriptors there is an associated failure mode. One value of failure descriptors can be mapped to several failure modes. Thus maps can be setup for each of the failure descriptors and their associated failure modes. Table 6 (a), (b) & (c) shows failure manifestation, failure location and failure agents mapped to failure modes. For the highest input confidence % in the three failure descriptors, failure modes mapped to corresponding failure descriptor value are identified as the potential failure modes. Then each identified failure mode is checked with the other two input failure descriptors referring table 6.

Table 6: (a) Failure Manifestation mapped to failure mode; (b) Failure location mapped to failure modes; (c) Failure agents mapped to failure modes

(a)

Failure Mode	Failure Manifestation
Brittle Fracture	Fracture
Elastic deformation	Elastic Deformation
Fatigue High Cycle	Fracture
Gross Yielding	Plastic Deformation
Wear	Dimensional reduction

(b)

Failure Mode	Failure Location
Brittle Fracture	Surface and Body
Elastic deformation	Body
Fatigue High Cycle	Cracks initiated in Surface leading to Body failure
Gross Yielding	Body
Wear	Surface

(c)

Failure Mode	Failure Load	Failure Temperature	Hours of Operation
Brittle Fracture	Steady, Cyclic, Random, Transient	Low, Room	Very Short, Short
Elastic deformation	Steady	Room, Elevated	Short
Fatigue High Cycle	Cyclic, Random	Low, Room, Elevated	Long, Short
Gross Yielding	Steady	Room	Short
Wear	Steady, Cyclic, Random, Transient	Low, Room, Elevated	Short, Long

A resulting fuzzy membership function similar to the one shown in Fig 13 is setup for failure modes with two categories: HIGH and LOW. Those failure modes identified from the highest confidence failure descriptor matching the other two input failure descriptors are grouped in HIGH category and those that don't match any one of the other failure descriptors are grouped in LOW category. For e.g. if the input failure manifestation is fracture, the input failure location is surface and the input failure agents (Load: - cyclic, Temperature: - Room & Hours of Operation: - Long) and failure manifestation has highest confidence %. Thus the failure modes corresponding to Fracture failure manifestation are (Brittle fracture, Fatigue & Wear) of which (Fatigue & Wear) match the other two input failure descriptors and (Brittle Fracture) matches only the failure location. Thus (Fatigue & Wear) are grouped in HIGH category and (Brittle Fracture) under LOW category in the resulting failure mode fuzzy membership function.

4. The next step in the process is to setup the rule table. From above for each input of the failure descriptors a confidence % is input and the fuzzy membership function converts it into a fuzzy membership value based on the category. Rules are setup such that for each input failure descriptor category, a resulting failure mode category is selected. This is similar to a logic table. Table 7 shows the rule table for failure mode identification. For e.g. if the input failure manifestation confidence % is HIGH, the input

Table 7: Fuzzy rule table for failure mode identification

Failure Manifestation	Failure Agent	Failure Location	Failure Mode
LOW	LOW	LOW	LOW
HIGH	LOW	LOW	LOW
LOW	HIGH	LOW	LOW
HIGH	HIGH	LOW	HIGH
LOW	LOW	HIGH	LOW
HIGH	LOW	HIGH	HIGH
LOW	HIGH	HIGH	HIGH
HIGH	HIGH	HIGH	HIGH

failure agent confidence % is also HIGH but if the input failure location confidence % is LOW, the resulting failure mode should be chosen from HIGH category. This is also shown graphically in figure 14. The resulting failure mode membership value is the product of membership values of three descriptors based on the product-sum norm discussed in chapter 3.

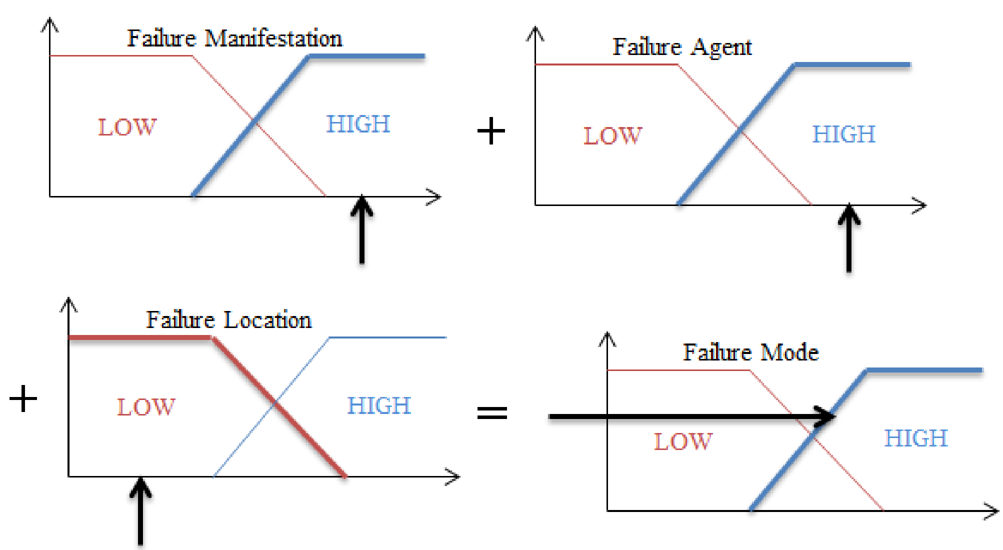

Figure 14: Rule selection and fuzzy operation for failure mode identification

For one input value of failure manifestation, failure agent and failure location one or more rules in the rule table can be applicable.

5. Final step in the process is combining the selected rules and defuzzifying the output to identify the failure modes. For each of the selected the failure mode member function value is computed using the product-sum norm. From the computed values the rule corresponding to the maximum value is selected based on the maximum value defuzzification method discussed in chapter 3. Based on the resulting rule category on the failure mode member function, the corresponding failure modes are deemed to be candidate failure modes. The final confidence in the identified failure mode is the equivalent % value for the fuzzy membership score computed for the rule. If there are more than one failure modes, the final failure mode selection for downstream processing is left to the user discretion. After the user chooses a failure mode, machine element and originally used material input are obtained.
6. After the three critical parameters are obtained the material substitution follows the sequence of steps 1-9 in case 1 in identifying the candidate materials. Also the confidence on the final candidate material selection may not be 100%. It depends on the final confidence on the identified failure mode.

4.2.3. Case 3 – Machine element not known

- Machine element – not known
- Failure mode – known
- Originally used material – known

In this scenario of the three important parameters the machine element information is not available. In order to identify the machine element other parameters such as Part Functions and Mating components are used as discussed in section 2.2. Part functions are ontological descriptions of the functions a machine element perform such as “Amplify motion”, “Transfer motion” and “Store Energy”. Mating components are the machine elements that possibly mate with other machine elements in an assembly. For e.g. gears are mounted on shafts with keys or splines. A machine element can have several part functions. Also a machine element will mate one or more machine elements in an assembly. Clearly the information available is not adequate to uniquely identify the machine element in all circumstances and there is uncertainty with each of these input data. Thus fuzzy logic is used in quantifying the uncertainty and making decisions based on that. A portion of the declarative model shown in Fig 10 that will be applicable to this case is shown graphically in Fig 15. Similar to case 2, it can be seen that after the machine element is identified, the logic follows the sequence of steps in case 1 leading to identifying the final candidate materials. Following are the sequence of steps in identifying the machine element and the eventual candidate material selection:

1. First the Part Function input and the Mating element information is prompted for input from the user. Table 8 shows a list of possible part functions and mating machine element the user can choose from. The user

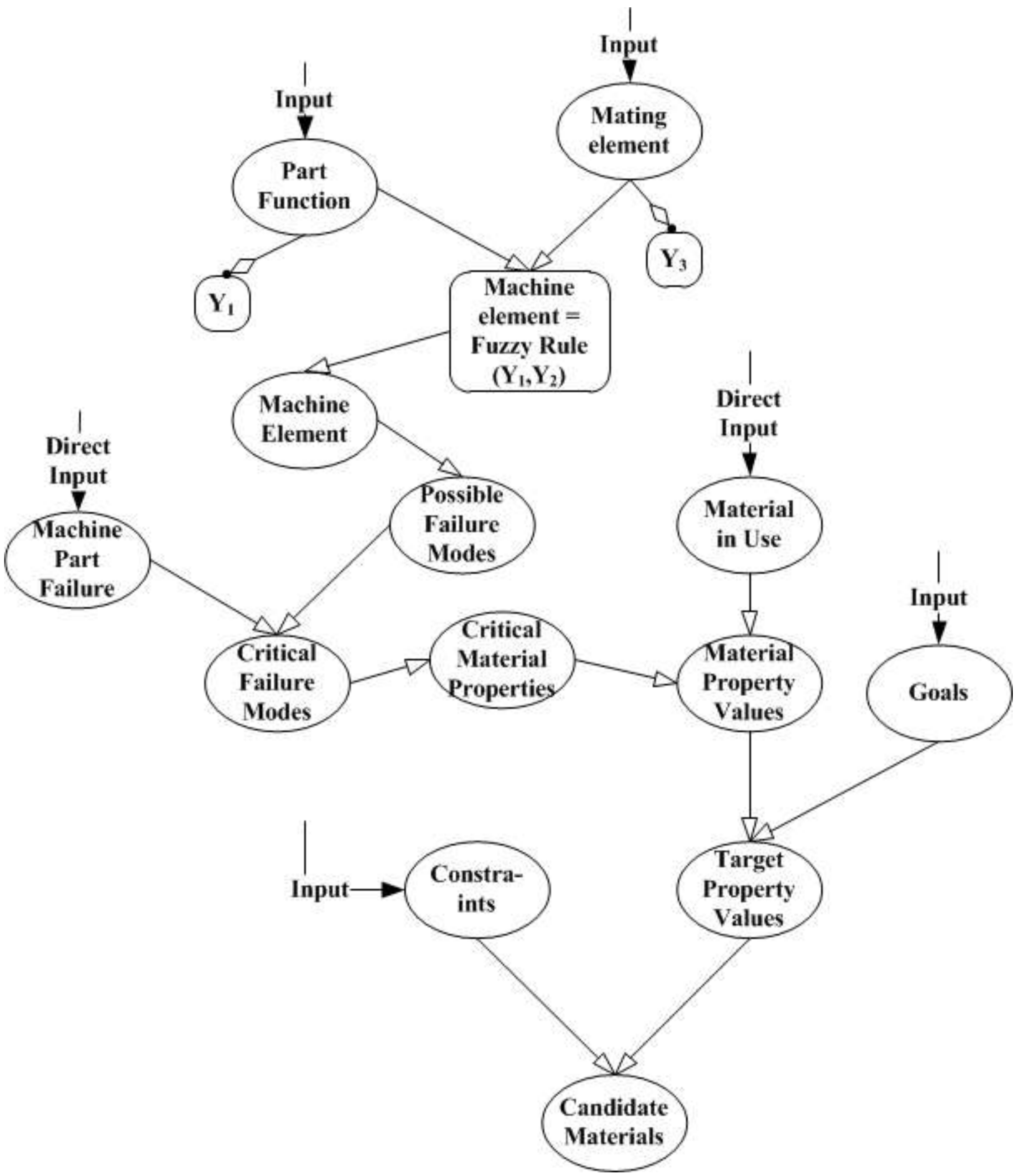

Figure 15: Material Substitution logic for scenario 3 - Machine element is not known

is also prompted to input a confidence % in the value chosen for Part function and mating machine elements. This confidence % is indicative of the user's understanding of the function of the part.

2. Fuzzy member functions are setup for both Part functions and Mating machine elements. The fuzzy member functions convert the input

Table 8: (a) List of Part Functions (b) List of Mating machine elements

(a)

Part Functions
Amplify Force
Amplify Motion
Constrain Motion
Contain Mass
Control Force
Store Energy
Transfer Force
Transfer Motion
Transform Motion
Transmit Power

(b)

Mating Elements		
Ball Joints	Engine Block	Rigid Couplings
Belleville Spring Washers	Fasteners	Shafts
Bevel Gears	Flexible Couplings	Splines
Brackets	Flywheels	Sprockets
Brake Spring	Helical Gears	Spur Gears
Chassis	Keys	Worm Gears
Clutch	Mechanical Seals	Pressurized Cylinder
Crank Shafts	Plain Bearings	Pulleys

confidence % for a particular variable into a fuzzy member ship value. Each fuzzy membership functions have three categories: LOW, MEDIUM and HIGH confidence. The input confidence % falls into one or more categories and from the actual confidence %, the membership value for each category is computed. Fig 16 shows an example fuzzy membership function for Part Function with the three categories and the fuzzy value computed for a particular input confidence. The equations for computation are:

$$\mu_n = \left| \begin{array}{l} \text{LOW:} \begin{cases} 1 \text{ if } X_n \leq 25\% \\ \frac{50-X_n}{50-25} \text{ if } X_n > 25\% \text{ and } X_n < 50\% \end{cases} \\ \text{MEDIUM:} \begin{cases} \frac{X_n-25}{50-25} \text{ if } Xn > 25\% \text{ and } X_n > 50\% \\ 1 \text{ if } X_n = 50\% \\ \frac{75-X_n}{75-50} \text{ if } X_n > 50\% \text{ and } X_n < 75\% \end{cases} \\ \text{HIGH:} \begin{cases} \frac{X_n-50}{75-50} \text{ if } Xn > 50\% \text{ and } X_n < 75\% \\ 1 \text{ if } X_n \geq 75\% \end{cases} \end{array} \right.$$

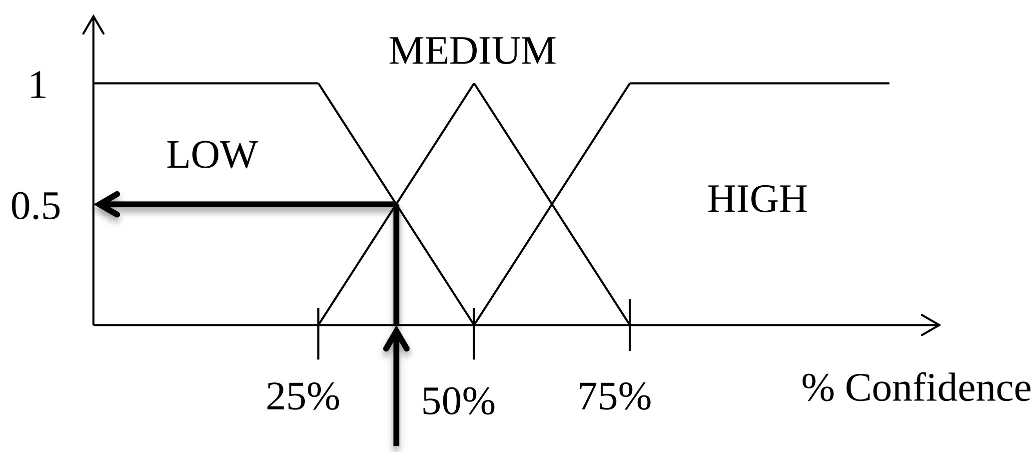

Figure 16: Fuzzy member function for Part Function input

Where X_n is the input confidence % of the variable and μ_n is the equivalent membership Fuzzy Membership value.

3. The next step in the process is setting up the fuzzy rules. Part functions can be associated with machine elements as shown in Table 9 and Machine elements that possibly mate with other machine elements can also be mapped in an adjacency matrix as shown in Table 10. Candidate machine elements are then extracted from table 9 or 10 based on the input variable that has the highest confidence %. If the Part Function has higher confidence than mating machine element input then machine elements are extracted from table 9 otherwise machine elements are

Table 9: Part function and Machine element Map

Function	Machine Element	Function	Machine Element
Amplify Force	Pressurized Cylinder	Store Energy	Brake Spring
	Pulleys		Belleville Spring Washers
	Lever		Flywheels
Amplify Motion	Bevel Gears	Transfer Force	Engine Block
	Worm Gears		Housing
	Spur Gears		Chassis
	Helical Gears		Pulleys
	Sprockets	Transfer Motion	Clutch
Constrain Motion	Disk Brakes		Helical Gears
	Mechanical Seals		Bevel Gears
	Plain Bearings		Rigid Couplings
	Keys		Sprockets
	Gudgeon Pins		Flexible Couplings
	Fasteners		Ball Joints
	Drum Brakes		Worm Gears
	Bushes		Spur Gears

Table 10: Machine Element compatibility adjacency matrix

MACHINE ELEMENT	Ball Joints	Belleville Spring Washers	Bevel Gears	Brackets	Brake Spring	Chassis	Clutch	Crank Shafts	Drum Brakes	Engine Block	Fasteners	Flywheels
Ball Joints	x					1						
Belleville Spring Washers		x									1	
Bevel Gears			x									
Brackets				x		1				1	1	
Brake Spring					x				1			
Chassis	1			1		x				1	1	
Clutch							x				1	1
Crank Shafts								x		1		
Drum Brakes					1				x			
Engine Block				1		1		1		x	1	1
Fasteners		1		1		1	1			1	x	
Flywheels							1			1		x

extracted from table 10. The extracted machine elements are checked for their compatibility with the other input. So if machine elements are extracted from part functions, each of the candidate machine elements is checked to see if it is compatible with the mating machine element. Similarly if the machine elements are extracted from mating machine elements, each of the candidate elements is checked to see if it performs the part functions specified. The resulting candidate machine elements are grouped into three categories of confidence %: LOW, MEDIUM and HIGH similar to the fuzzy member function shown in Fig 16. All the machine elements extracted from a specified parameter, that are compatible with all other specified parameter values are grouped in HIGH confidence category, and the ones that are compatible with at least one value of the other specified parameter are grouped in MEDIUM confidence category and those machine elements that are compatible with none of the values of the other specified parameter are grouped in LOW confidence category. For e.g. if (Store Energy) is the part function with higher confidence over the chosen mating machine elements (Keys, Shafts) then machine elements are extracted from part functions referring table 9 are (Brake spring, Belleville spring washers and Flywheels). Referring table 10, (Flywheels) are compatible with (Keys, Shafts) and so it is in HIGH confidence category and (Brake spring and Belleville spring washers) are not compatible at all and hence are grouped under LOW confidence category.

4. The next step in the process is to setup the rule logic table for machine element identification. From above for each input confidence % the fuzzy member functions compute the membership value based on the input confidence category. Rules are setup such that for each input part function and mating machine element category a resulting machine element category is specified. Table 11 shows the rule logic table used in identifying the machine elements. For e.g. if the input Part Function confidence is categorized as HIGH and Mating part confidence is

categorized as HIGH then the resulting mating machine element is selected from the HIGH confidence category. The resulting machine element member function score is the product of the membership score of part function and the mating machine element. This is also shown graphically in Fig 17.

5. Final step in the process is combining the selected rules and defuzzifying the output to identify the failure modes. For each of the selected machine elements, member function value is computed using the product-sum norm discussed in chapter 3. From the computed values the rule corresponding to the maximum value is selected based on the maximum value defuzzification method. Based on the resulting rule category on the machine element member function, the corresponding machine elements are deemed to be candidate machine elements. The final confidence in the identified machine element is the equivalent % value for the fuzzy

Table 11: Rule logic table for machine element identification

Part Function	Mating Part	Machine Element
LOW	LOW	LOW
MEDIUM	LOW	MEDIUM
HIGH	LOW	HIGH
LOW	MEDIUM	MEDIUM
MEDIUM	MEDIUM	MEDIUM
HIGH	MEDIUM	HIGH
LOW	HIGH	HIGH
MEDIUM	HIGH	HIGH
HIGH	HIGH	HIGH

membership score computed for the rule. If there are more than one machine elements, the final machine element selection for downstream processing is left to the user discretion. After the user chooses a machine element, failure mode and originally used material input are obtained.

6. After the three critical parameters are obtained the material substitution follows the sequence of steps 1-9 in case 1 in identifying the candidate materials. Also the confidence on the final candidate material selection may not be 100%. It depends on the final confidence on the identified machine element.

4.2.4. Case 4 – Originally used material is not known

- Machine element – known

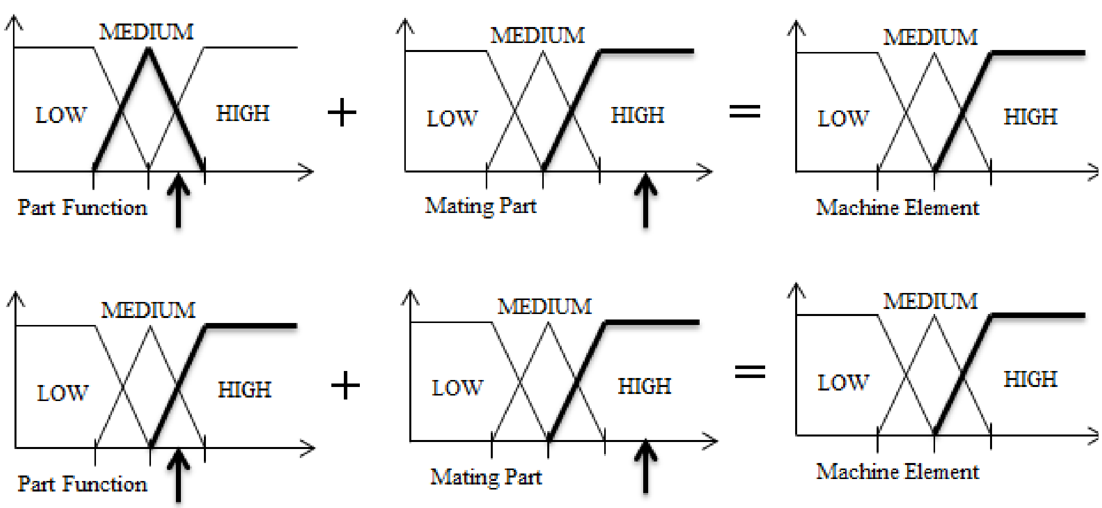

Figure 17: Rule selection for Machine element identification

- Failure Mode – known
- Originally used material – not known

In this scenario if the originally used material is not known, there are two methods for obtaining the material property values. Generally all the engineering materials can be grouped into material classes such as carbon steels, stainless steel, and aluminum alloys etc… Even if the actual material is not known and if the existing material can be identified as one of the material classes, the average material property values for the material class can be used. The confidence percentage in classifying the material into one of the classes is directly used as safety factor for downstream calculations. If the material cannot be classified into a material class, then a low-fidelity structural analysis can be performed to obtain stress values. The user is prompted to input the CAD geometry of the part and also specify the load values and locations. If the input geometry is an assembly of machine elements then equivalent boundary conditions can be applied. First for the given boundary condition, the dominant load is identified. Based on the section properties of the overall shape, for the worst combination of loads, critical stress hot spot regions are identified and stress values are estimated. The confidence percentage in estimating the loads and their locations is used as safety factor for downstream calculations. Once the material property values are obtained, the material substitution follows the sequence of steps 1-9 in case 1 in identifying the candidate materials.

4.2.5. Case 5 – None of the important parameters are known

- Machine element – not known
- Failure mode – not known
- Originally used material – not known

In this scenario, the machine element, the part failure mode or the originally used material is not known. This is the worst combination of all the above four scenarios which is indicated graphically in Figure 10. The logic in case 2 is followed in identifying the failure modes using the fuzzy logic. The logic in case 3 is followed in identifying the machine element. The logic in case 4 is followed in obtaining the material property values. Once all of the cases above are executed and the machine element, failure mode and the material property values are identified the material substitution process follows the steps in case 1 for identifying the candidate materials. In this case however the confidence on the final candidate materials is a product of the final confidence percentage in the machine element, failure mode and property values identified.

CHAPTER 5

MATERIAL SUBSTITUTION: SOFTWARE IMPLEMENTATION

A part of the objective of this research is to automate the process of material substitution for legacy engineered systems as part of the LSE testbed. In order to automate the processes mentioned above a software system is implemented. The software primarily has two parts: the front-end Graphical User Interface (GUI) and the back-end database. The architecture of the software is represented in Fig 18.

The material substitution software architecture is based on the generic model-view-controller (MVC) architecture. The MVC architecture is commonly used in large projects and is popularly used in software systems that involves database. Generally, software without any architecture has the GUI code and the business logic code intertwined. This is generally fast and easy to develop but has its disadvantages in debugging, testing and future development. The MVC architecture however is a framework that separates the business logic from the GUI so as to facilitate debugging, testing, future development and other benefits that are beyond the scope of the discussion. The architecture consists of three parts

1. Model – is the business logic. Here the business logic API is developed for several input scenarios. It assumes that the necessary parameters are available

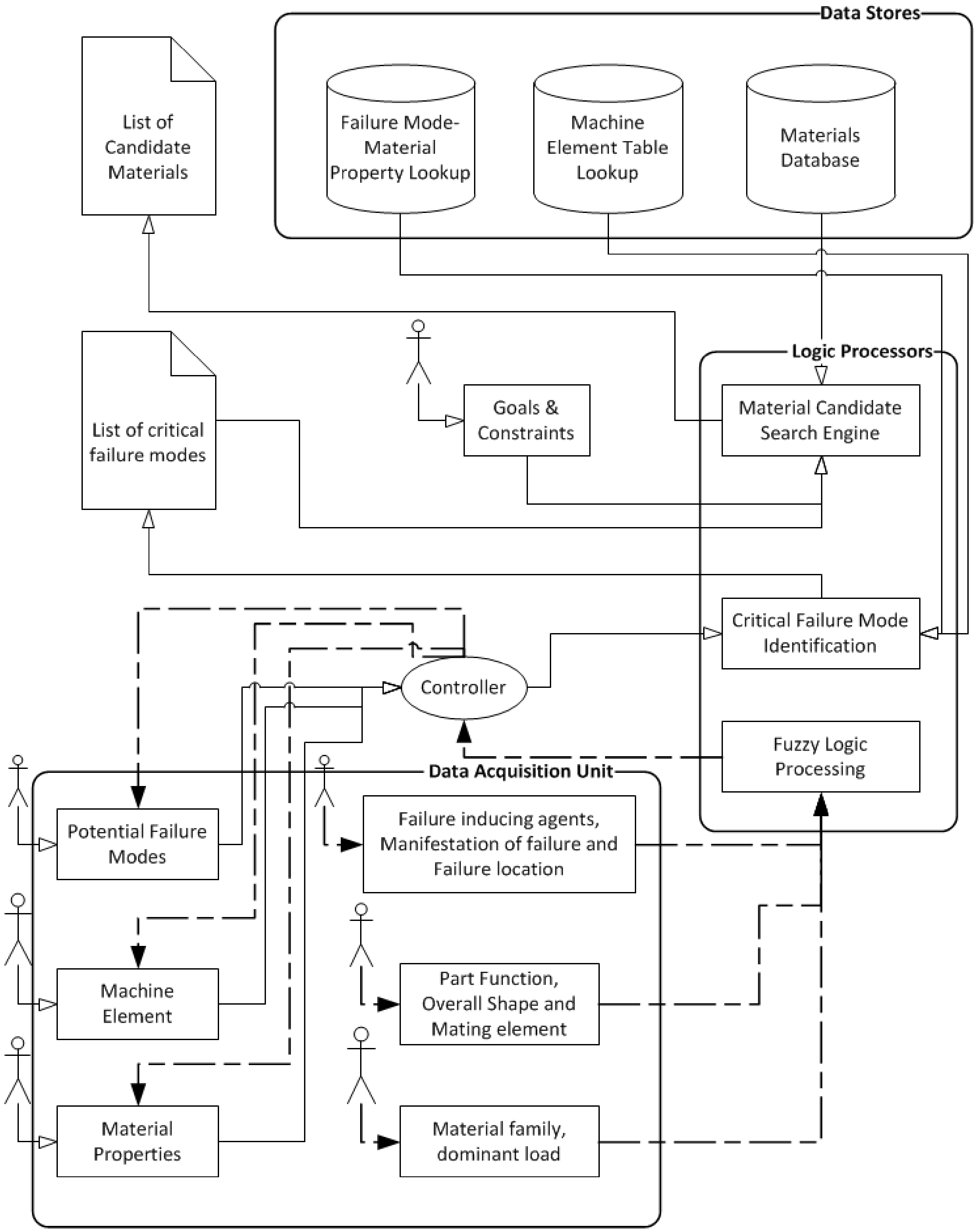

Figure 18: Material substitution software architecture

and produces the output based on the values of the input parameters. Function calls in the API are made by the controller. This module also includes the data stores such as material database as in this case.

2. View – is the GUI. This part has no business logic and is unaware of the background processes. The main emphasis is on presentation of data and posing the right questions to get the right input.
3. Controller – is the interface between Model and View. This can be a package of files or just one single file that controls the flow of data between the Model and View. This part is unaware of the actual data and its only function is to switch control between different modules based on the input process routes chosen by the user.

The main advantage of MVC architecture is that it allows the modules to be developed independent of each other. The database is developed using Microsoft Access Database (.mdb) and the GUI of the software is developed using Microsoft Foundation Classes (MFC). The software is developed using the object oriented C++ language using Microsoft Visual Studio 2005 IDE.

Based on the discussion from chapter 2, 3 & 4 it is evident that any material substitution for legacy engineering involves three parts: – Data acquisition, Logic processing and Candidate selection. Each of the sections and the implementation is discussed in the following sections.

5.1. Data extraction

Data extraction is crucial to any legacy system engineering tool because the success of the tool lies in the quality of information obtained during this step and sets the benchmark for all successive computations and comparisons. Referring the Figure 10 in chapter 4, we can see that there are several input parameters to be obtained based on the user's availability of the information. Predominantly there are 5 different modules of input:

1. Failure mode input
2. Machine element input
3. Original material input
4. Goals and Target input
5. Constraints input

A toolbar in the fig 19 shows different icons for different input modules.

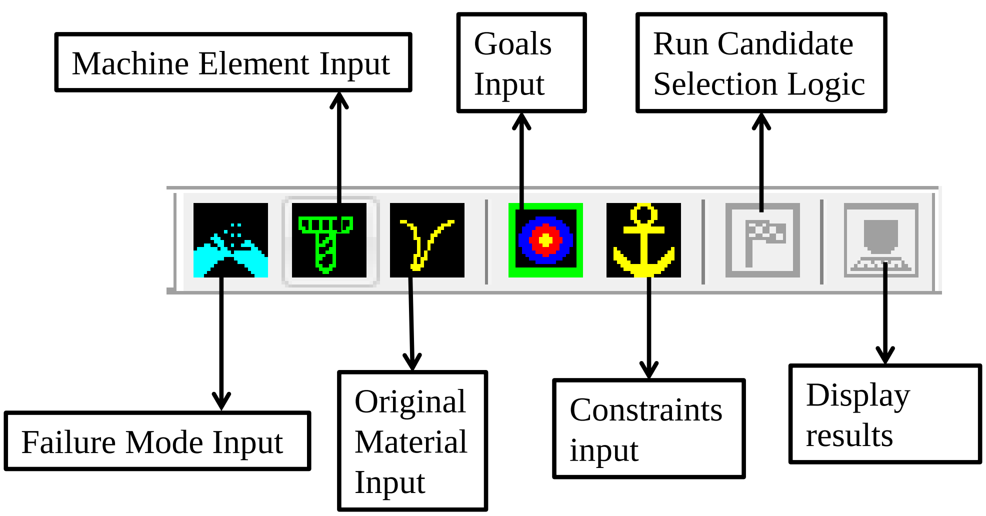

Figure 19: Material Substitution Toolbar

When the user clicks on failure mode input icon or the machine element input icon, a message is prompted to check if he knows the actual failure mode or the machine element. If the user wants to input the failure mode or the machine element directly then dialog boxes as the one shown in figure 20 are displayed for user input. Failure mode input, machine element input and the original material input material are mandatory if the user wishes to input them directly. If the user needs the software to identify the failure mode or the machine element for the user, then a dialog box with alternative parameters that are used in identifying the failure mode or the machine element as shown in Figure 21 is shown. For each of the alternative input parameter the user is also prompted for the confidence % input that will be used in downstream fuzzy logic processing. By default the slider

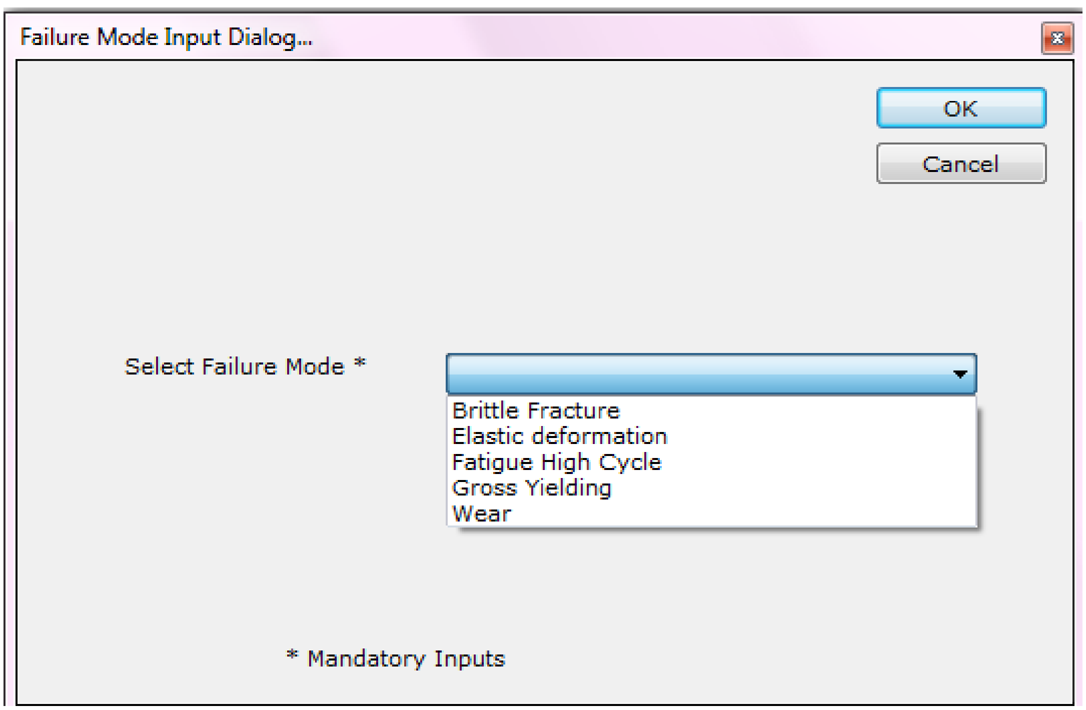

Figure 20: Failure mode input dialog box

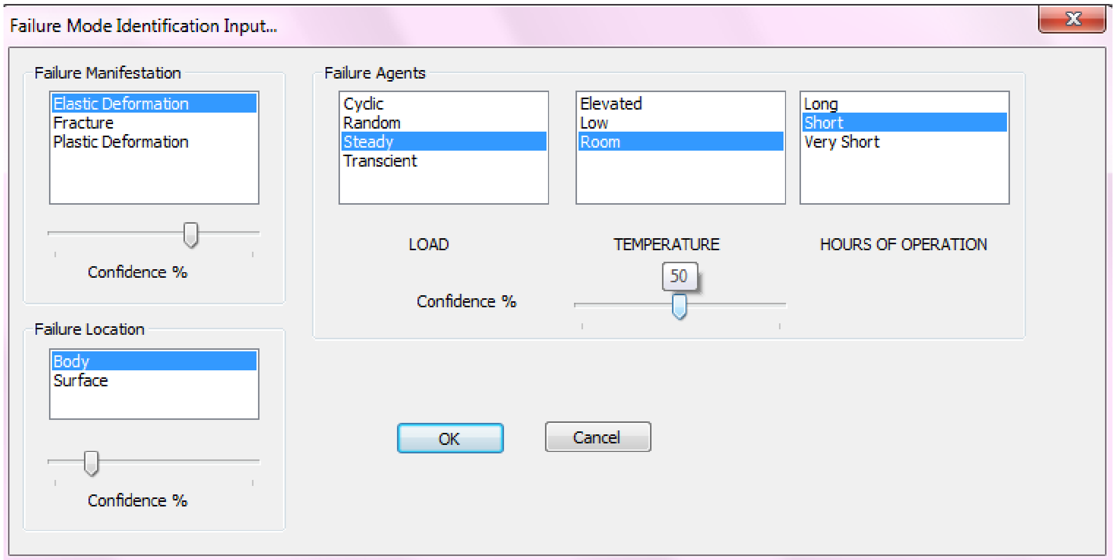

Figure 21: Failure Mode identification input dialog box

for confidence % input ranges from 1-100. After the alternative parameters are input the data is transferred to the fuzzy logic controller for identifying the critical parameter of interest. If candidate critical parameter values are identified the same dialog box as shown in Fig 20 is prompted with the list for final selection. The user is also notified of the confidence % in the resulting output. Once the three critical input parameters are obtained or identified. The user goes on to input the goals and the target % improvement as shown in Fig 22. If there are any user constraints such as cost constraints the user can input them using the constraints dialog box. After all the necessary parameters are input and the values are obtained, the 'run candidate selection logic' icon in Fig 19 is enabled. The icon triggers the candidate selection logic descried in case 1 in chapter 4 and finds a list of candidate material substitutes. If there are no materials found the user is notified. If however candidate materials are found then the display icon in Fig 19 is enabled for the user to view the candidate material substitutes.

Figure 22: Material Substitution Goals Input

5.2. Database and Logical Processor

The logical processor performs three major functions – data validation, fuzzy processing and material candidate search. Several validations are critical before the final candidate selection process logic can be run. For e.g. the input failure mode or the failure mode identified through fuzzy logic processor should be one of the possible failure modes for the machine element specified. If not, the user is notified to verify and re-input the correct data. It also validates dialog box inputs for mandatory input check. If the mandatory input is not available the user is prompted to input with a message box. The fuzzy logic processor mainly performs four functions –

1. Setting up the membership functions to convert the input confidence % to fuzzy member ship value
2. Setting up the fuzzy rules for critical parameter identification.
3. Initiating the rule logic table for combining member functions

4. Defuzzification for combining the rules and identifying the desired critical parameter. It also computes the final confidence % on the identified critical parameter.

Step 2 in the fuzzy logic processing above involves querying the database where the tables discussed in chapter 2 and 4 are stored. The database also contains tables with material data. The entity-relationship diagram shown in Fig 23, 24 and 25 contains the major tables and the relationships between them that are used in candidate selection and Fuzzy rule setup. After the input data validation the logical processor tries to identify all the critical failure modes of interest. Once the critical failure modes are identified the key material properties and their values for the originally used material is obtained from database tables. The candidate search engine queries the material database for suitable substitutes

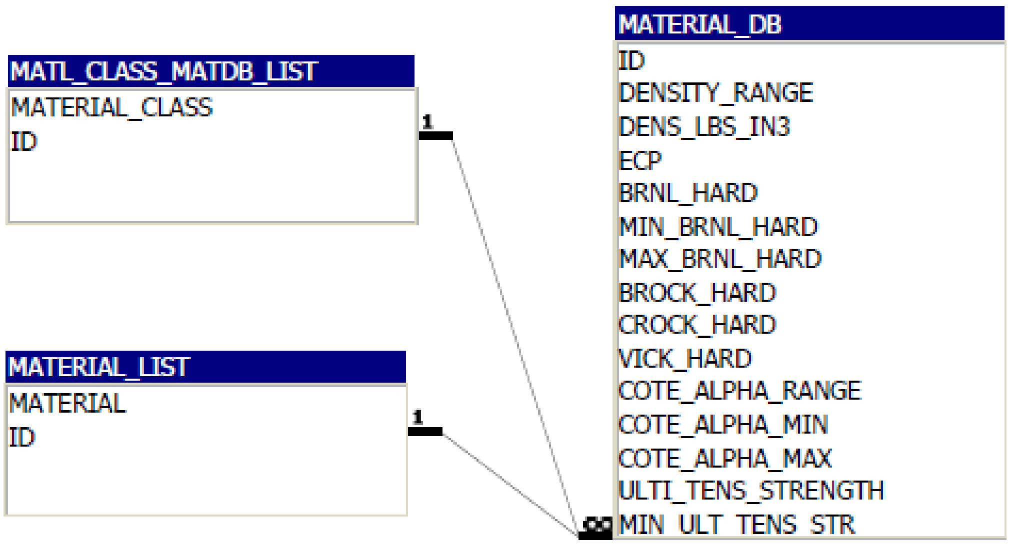

Figure 23: ER diagram of the material property tables

based on the target values calculated from the goals and constraints specified by the user. The queries are executed through the ODBC driver setup using the Windows DSN.

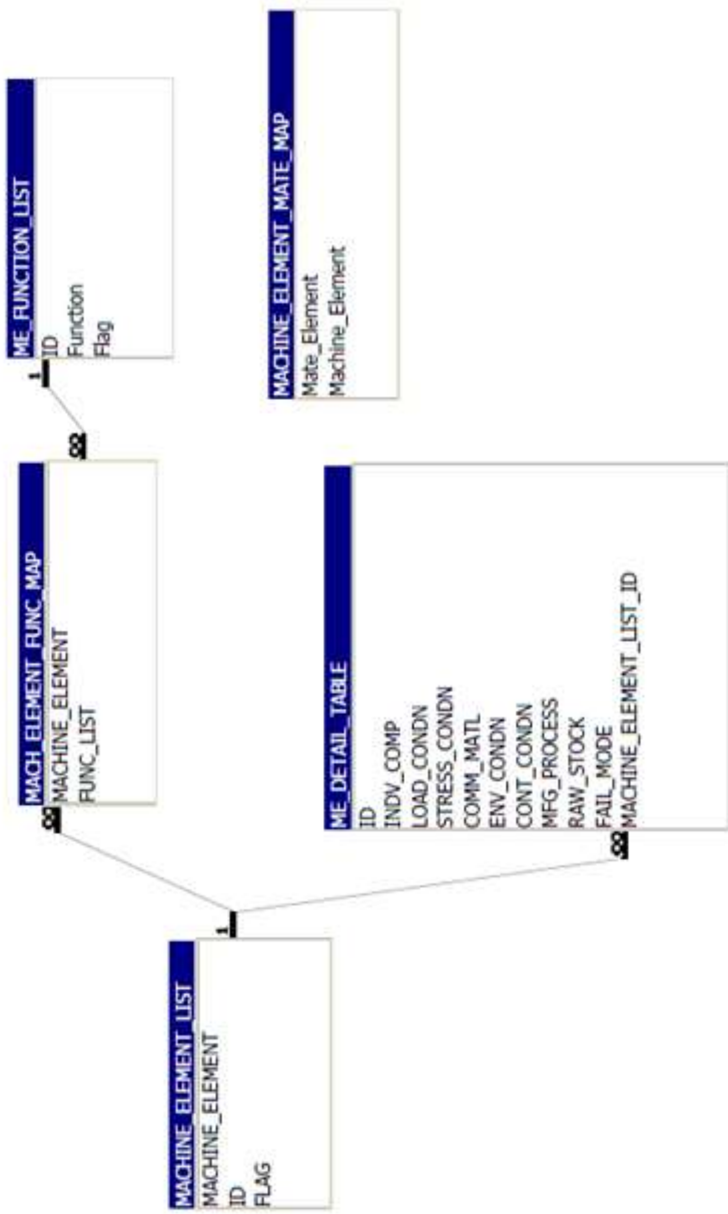

Figure 24: ER diagram of machine element tables and maps

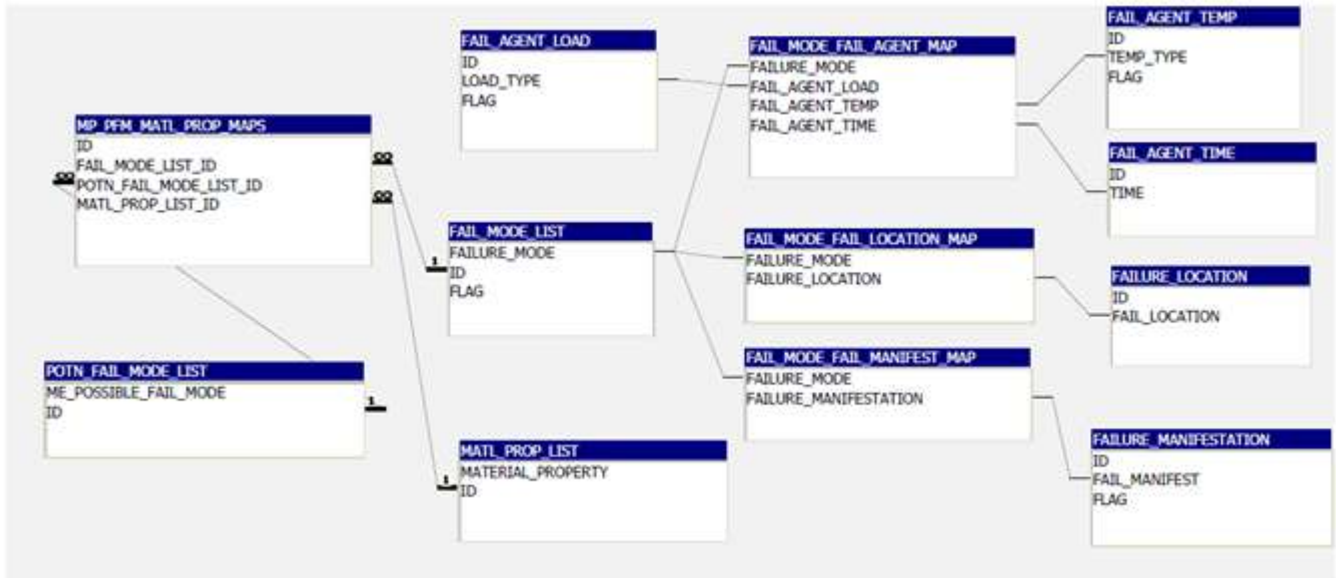

Figure 25: ER diagram of failure mode tables and maps

CHAPTER 6

CASE STUDIES

In order to evaluate the effectiveness of a knowledge based system, we need a valid set of case studies that can endorse the rules and algorithms implemented in the system perform all the desired functions. The effectiveness of the system can be measured in two ways. Intrinsically the number of attempts the user takes to identify the correct failure mode of the part or the machine element or the material property before proceeding to find the candidate materials is a measure of the effectiveness of the fuzzy rules. Extrinsically the candidate materials identified can be evaluated against the expert selection. The material substitution for legacy engineered parts is a knowledge based system that is meant to work on data that has varying degree of uncertainty. For ex: Data extracted from OEMs are more reliable than data that is extracted from a failed system. From section 2.3 it was also clear that even within extraction techniques uncertainty can vary. Case studies are chosen to evaluate both the intrinsic effectiveness and the results are compared with expert opinion for extrinsic effectiveness.

Example 1: Pressure Vessel

Pressure vessels, from the simplest aerosol-can to the biggest boiler, are designed, for safety, to yield or leak before they break. Small pressure vessels are usually designed to allow general yield at a pressure still too low to cause any crack the vessel may contain to propagate (“Yield before break”). With large pressure vessels, safe design is achieved by ensuring that the smallest crack that will propagate unstably has a length greater than the thickness of the wall ("leak before break") [4 (Ref 6.11)]. The objective is to find lightweight alternatives for low carbon steel pressure vessels.

Parameters:

This is the simplest of cases where all the three important parameters are known. The machine element is given to be pressure vessel and the originally used material is given to be low carbon steels. Brittle fracture and Yielding are two possible dominant failure modes depending on the size of the vessel.

Process:

1. The equivalent machine element for pressure vessel in the list of machine elements in the database is pressurized cylinders. For the given machine element, we refer the machine element reference table and obtain a list of potential failure modes.
2. From table 12 the potential failure modes are Yielding, Brittle fracture/Ductile Rupture, Fatigue, Stress corrosion cracking and creep. The failure modes are classified into two types – primary and secondary. The primary failure modes are the most probably failure modes and hence the dominant failure modes.
3. For smaller pressure vessels the failure mode of concern is brittle fracture and for larger pressure vessel yielding is the failure mode of concern. Both

Table 12: Machine Element reference table for Pressure vessels

Machine Element	Load Conditions	Stress Condition	Commonly used materials	Environment Conditions	Potential Failure Modes
Pressurized Cylinder	Tensile Loads; Thermal Loads (in certain cases) - fatigue loading	Hoop Stresses ; Radial Stresses	Carbon and Low-alloy steels, High alloy steels, non-ferrous alloys, cast iron, and ferritic steels	High Temperature, Corrosive Fluids	Primary: Yielding, Ductile Rupture / Brittle Fracture Secondary: Fatigue (Low cycle, Thermal or Corrosion), Stress Corrosion Cracking, Creep and Fatigue

these failure modes are primary failure modes and hence are the critical failure modes.

4. For the critical failure modes, we refer the failure mode and material property mapping (table 2) to obtain the material properties corresponding to the failure modes.
5. The critical material property for yielding is “Tensile Yield strength”. The critical material property for brittle fracture is “K_{IC}”.
6. The originally used material specified is low carbon steel, which is one of the commonly used materials for pressure vessel from table 12. We obtain the original material property values for the given material.
   a. Yield Strength – 20305 psi – 348090 psi
   b. K_{IC} – 60100- 74600 psi(in)$^{1/2}$
7. The objective is to find lightweight alternatives for low carbon steels. Hence “Improving strength/Reduce weight” is the ratio of interest.

8. Let us consider the case of yielding failure and so for a 10% target increase in the (σ_y/ρ) ratio several candidate materials are identified. A shortlist of the materials of interest is shown in table 13.

Table 13: Candidate materials for lightweight pressure vessels

Material Class	Material
Aluminum	2014 -T6,6262-T9,2011 - T8,2011 -T3,2219 -T62,6066-T6,5052-H38,3004-H38
Ultra High strength steels	Ultrahigh-strength Steel for Structural Applications
Stainless Steel	Precipitation-hardened grades, Nitrogen-strengthened grades, T S20000 Series Stainless Steel
Steel	Air hardened steel, Mold steel, Maraging steel

Verification:

Some of the major candidate groups identified in [4 (Ref table 6.20)] are Stainless steels, Low alloy steels, Copper, Aluminum alloys and Titanium alloys. Verifying with table 13, we can see that some Aluminum alloys and Stainless steel alloys are identified. Aluminum alloys are commonly used in very light applications such as pressure tanks in rockets and Stainless steel is commonly used in nuclear pressure vessels. Hence the results match the expert opinion and the identified candidates are substitutable.

Example 2: Materials for Ball Joints (incompatible machine element and failure mode)

Ball joints are commonly used in automobile applications. It two linkages and allows rotation but no translation. Ball joints are commonly made of steel. If brittle fracture is one of the part failure modes, the objective is to find lightweight alternatives for the given material.

Process:

1. For the given machine element, we refer the machine element table and identify a list of potential failure modes.
2. From table 14, the potential failure modes are wear, corrosion and corrosion fatigue.
3. Brittle fracture is not one of the primary or secondary potential failure modes of ball joints.
4. Hence an error message “Machine Element cannot undergo the Failure Mode specified. Please Re-enter the Machine Element or Failure Mode

Table 14: Machine element reference table for Ball Joints

Machine Element	Load Conditions	Stress Conditions	Commonly used materials	Environment Conditions	Potential Failure Modes
Ball Joints	Axial Loads (tension or compression loaded suspensions); Torsional loads	Cyclic Hertzian contact Stress	Carbon Steel or Alloy Steel	Corrosive Environment	Primary: Wear , Corrosion Secondary: Corrosion fatigue

data!" is displayed.

Example 3: Materials for Splines (Ambitious targets)

Splines are common machine element that is used to mate shafts with other machine elements such as gears. For one of the dominant failure modes, the objective is to identify lighter candidate material substitutes, if the originally used material is a titanium alloy.

Process:

1. For the given machine element, we identify a list of commonly used materials and a list of potential failure modes.
2. From table 15, the potential failure modes are Fatigue, Wear and Force-induced elastic deformation.

Table 15: Machine element reference table for Splines

Machine Element	Load Conditions	Stress Conditions	Commonly used materials	Potential Failure Modes
Splines (Shafts)	Fluctuating Torque; Fluctuating Moment	Cyclic Hertzian contact stress	Steel (ANSI 1020 -1050) Bronze or Stainless steel (corrosive environment);Case hardened steel (when used as journal or sleeve in bearings)	Primary: Fatigue, Wear Secondary: Force induced Elastic Deformation.

3. The dominant failure mode of interest is Wear. Referring the failure mode and material-property mapping (table 2), the critical material properties corresponding to wear failure mode is Hardness.
4. The hardness values for the originally used beta-titanium alloy material ranges from 290-485 BHN.
5. For the objective of finding lighter candidate material substitutes, the target increase is 30%.
6. Executing the material substitution logic, an error message “Sorry there are no materials matching the criterion. Please change the combinations and try again!!!” is displayed.

Inference:

To start with the originally used material is a titanium alloy. Titanium alloys have very high strength/weight ratios of all common metals. So the material is specified is by default very strong and very light. The objective specified is to find materials that have higher strength/weight ratios and the target % increase is 30. The combination of the originally specified material and the target increase is too ambitious for any other materials to satisfy and hence the error message.

Example 4: Materials for flywheel

Flywheels store energy. Small ones found in children's toys are made of lead. Old steam engine flywheels are made of cast iron [4 (Ref 6.6)]. Steel flywheels are used in nuclear reactors. The flywheels on nuclear reactor coolant pump motors provide inertia to ensure a slow decrease in coolant flow in the event of loss of power; thus preventing fuel damage due to the reduced coolant flow [24]. At over speed operation of the pumps, the flywheel disintegrates and produces large missiles. The objective is to identify candidate material substitutes to avoid catastrophic failure.

Process:

1. The machine element is given as flywheel and the original material is steel. The only other important parameter is the failure mode which is not known.
2. Since the part failure mode is not known, the first step in the process is to identify the failure mode using fuzzy logic.
3. If failure mode is not known, then failure descriptors such as failure manifestation, failure agents and failure location help in identifying the failure modes.
4. The flywheel disintegrates into large missiles and so clearly fracture is the failure manifestation. Also the failure location can be classified as body failure. Flywheels generally experience a cyclic load. Since the component

is used in a nuclear reactor, the temperature conditions may be higher than room temperature but because the flywheel is used with a coolant pump the conditions may not be as high. It is observed that when the pumps exceed the normal speed, the flywheel bursts and within a speed limit the flywheels are safe. It can be concluded that when the speeds exceed a limit, the fracture is instantaneous.

5. For each of the input failure manifestation, failure agents and failure location, a specific confidence % value needs to be input. Since the failure manifestation and failure location is very visible the confidence in the input is as high as 80%. The identified time of operation before failure is very short. But the load type and the temperature conditions are not known for certain. Thus a confidence of 55% is input.
6. The first step in the fuzzy logic process is to convert the input confidence % to fuzzy membership values.

$$\mu_n = \left| \begin{array}{l} \text{LOW:} \begin{cases} 1 \text{ if } X_n \leq 30\% \\ \dfrac{70\text{-}X_n}{70\text{-}30} \text{ if } X_n > 30\% \end{cases} \\ \text{HIGH:} \begin{cases} \dfrac{X_n\text{-}30}{70\text{-}30} \text{ if Xn} < 70\% \\ 1 \text{ if } X_n \geq 70\% \end{cases} \end{array} \right.$$

$$\therefore \mu_{\text{Manifestation}} = [\text{HIGH},1] \ (\text{for } X_{\text{manifestation}} = 80\%)$$

$$\mu_{\text{location}} = [\text{HIGH},1] \ (\text{for } X_{\text{location}} = 80\%)$$

$$\mu_{\text{agents}} = \left[\text{LOW}, \frac{70\text{-}55}{70\text{-}30}\right], \ \left[\text{HIGH}, \frac{55\text{-}30}{70\text{-}30}\right] \ (\text{for } X_{\text{Agent}} = 30\%)$$

$$=> [\text{LOW},0.375],[\text{HIGH},0.625]$$

7. The next step in the process is to setup the output failure mode member function. Referring table 6 (a), the list of possible failure modes are Brittle Fracture and Fatigue high cycle.
8. The list of possible failure modes is then crosschecked to match with input in tables 6(b) & (c). Brittle fracture matches the failure location but the fatigue does not. Brittle fracture also matches the failure agent combination of (cyclic load, low temperature, and very short time) but fatigue only matches the cyclic load failure agent description. Thus for the failure mode member function with two categories (LOW and HIGH) the corresponding failure modes are (LOW = Fatigue, HIGH = Brittle fracture).
9. The next step in the process is to combine the input and output fuzzy member functions in mamdani type rules. Referring the rule logic table 7 for failure mode identification the two rules combination are
    a. If FM is HIGH and FA is LOW and FL is HIGH then Failure is HIGH – R1
    b. If FM is HIGH and FA is HIGH and FL is HIGH then Failure is HIGH. – R2

(Where FM is Failure manifestation, FA is Failure agent and FL is Failure location and R1 & R2 are rules 1 & 2).

10. The next step in the process is to compute the output fuzzy membership scores for rules 1 and 2. Since Product/Sum norm is used, the membership score for

$$R1=\left(\mu_{Manifestation}*\mu_{Agent}(LOW)*\mu_{location}\right)=(0.375*1*1)=0.375$$

$$R2=\left(\mu_{Manifestation}*\mu_{Agent}(HIGH)*\mu_{location}\right)=(0.625*1*1)=0.625$$

11. The final step in the fuzzy logic process is to defuzzify and obtain the failure mode and confidence% on the corresponding failure mode identified. The rule scores are R1 [HIGH, 0.375] and R2 [HIGH, 0.625]. We use the maximum value method to defuzzify. The maximum value is thus 0.625 corresponding to R2. Thus the failure mode corresponding to HIGH category from step 8 is brittle fracture and the confidence % in the identified failure mode is greater than 50% but lesser than 70%.
12. The material substitution process after identifying the part failure mode is similar to example 1 where all the three important parameters are known.
13. Referring the machine element table 3 for flywheels, the potential failure modes of flywheels are ductile rupture/brittle fracture, fretting fatigue. Thus brittle fracture/rupture is one of the critical failure modes.
14. Then referring the failure mode and material property mapping in table 2, the critical material property corresponding to brittle fracture is $K_{IC.}$
15. Then material property value for the originally used steel (AISI 1000 series) material is obtained from the material database. The objective is to

find lighter and stronger candidate substitute materials. The target increase is specified at 20%.

16. The identified candidate substitute materials are:

Table 16: Candidate material substitute for flywheel

Material Class	Material
Steel	Low alloy steel, Medium carbon steel
Ultra high strength steels	Ultra high-strength steels for structural applications

Verification:

Flywheels experience centrifugal loading. The design limit is when the centrifugal stresses exceeed the tensile strength (or fatigue strength) [4]. This suggests that fatigue is a probable failure mode. However based on the descriptions of the failure, the failure mode identified was brittle fracture. This agrees with results from [24]. Also alloy steels are commonly used for flywheels in high speed applications and alloy steel is one of the identified material substitutes.

Example 5: Materials for Table legs

Furniture designers, conceive of a light-weight table of daring simplicity: a flat toughened glass supported on slender, un-braced cylindrical legs. The legs must support the top and whatever the weight that is placed on the table without buckling [4 (Ref 6.4)]. The objective is to find lighter alternatives to cast iron that can be machined. The alternative should also be least expensive.

Process:

1. In this example, the failure mode is buckling and the original material is cast iron. Table legs are not one of the standard machine elements. However we can use the fuzzy logic system to identify an equivalent machine element that is similar to table legs in application and identify material candidates for that machine element.
2. So the first step in the process to identify the machine element using the fuzzy logic process. If the machine element is not known, then part function and mating machine elements are used in identifying the machine element.
3. The part function from the problem description can be defined as "Transfer force". A confidence of 90 % is also input with this part function since it is clearly defined. Fasteners are one of the machine elements that definitely mate with the machine element. We also need to put an equivalent machine element that represents a heavy object. Of the list of machine elements engine block is a prospective mating machine element. However the confidence is only 30% due to the guessing of mating machine elements.
4. The first step in the fuzzy logic process is to convert the input confidence % to fuzzy values using fuzzy membership functions.

$$\mu_n=\begin{cases}\text{LOW:}\begin{cases}1 \text{ if } X_n\leq 25\% \\ \frac{50-X_n}{50-25} \text{ if } X_n>25\% \text{ and } X_n<50\%\end{cases} \\ \text{MEDIUM:}\begin{cases}\frac{X_n-25}{50-25} \text{ if } Xn>25\% \text{ and } X_n>50\% \\ 1 \text{ if } X_n=50\% \\ \frac{75-X_n}{75-50} \text{ if } X_n>50\% \text{ and } X_n<75\%\end{cases} \\ \text{HIGH:}\begin{cases}\frac{X_n-50}{75-50} \text{ if } Xn>50\% \text{ and } X_n<75\% \\ 1 \text{ if } X_n\geq 75\%\end{cases}\end{cases}$$

$$\therefore \mu_{PartFunction}=[\text{HIGH},1](\text{for } X_{PartFunction}=90\%)$$

$$\mu_{MatingElement}=\left[\text{LOW},\frac{50-30}{50-25}\right],\ \left[\text{MEDIUM},\frac{X_n-30}{50-25}\right]\ (\text{for } X_{MatingElement}=30\%)$$

$$=>[\text{LOW},0.8],[\text{MEDIUM},0.2]$$

5. The next step in the process is to setup the output machine element member function. The confidence is high in part function input compared to confidence in mating machine elements. Hence referring table 9, the list of potential machine elements for “Transfer force” part function is Chassis, Engine block, Housing and Pulleys. However engine block in itself is a mating machine element and hence it is ignored as candidate machine element.
6. The list of possible machine elements is then cross referenced with table 10 and the input mating machine element – Fasteners and Engine Block. The resulting machine element member function also has three confidence categories (LOW, MEDIUM and HIGH). Chassis mates with both the mating machine elements and so is in HIGH category. Housing mates with only one machine element, fastener and so it is in MEDIUM category and

finally pulleys don't mate with any of the specified machine elements and so it is in LOW category.

7. The next step in the process is to combine the input and output fuzzy member functions in mamdani type rules. Referring the rule logic table 11 for machine element identification the two rules combination are
    a. If PF is HIGH and MME is LOW then ME is HIGH – R1
    b. If PF is HIGH and MME is MEDIUM then ME is HIGH. – R2

(Where PF is part function, MME is mating machine element and ME is resulting machine element and R1 & R2 are rules 1 & 2).

8. The next step in the process is to compute the output fuzzy membership scores for rules 1 and 2. Since Product/Sum norm is used, the membership score for

$$R1=\left(\mu_{PartFunction}*\mu_{MatingElement}(LOW)\right)=(0.8*1)=0.8$$

$$R2=\left(\mu_{PartFunction}*\mu_{Agent}(MEDIUM)\right)=(0.2*1)=0.2$$

9. The final step in the fuzzy logic process is to defuzzify and obtain the machine element and confidence% on the corresponding machine element identified. The rule scores are R1 [HIGH, 0.8] and R2 [HIGH, 0.2]. We use the maximum value method to defuzzify. The maximum value is thus 0.8 corresponding to R1. Thus the machine element corresponding to HIGH category from step 7 is <u>chassis</u> and the confidence % in the identified machine element is greater than 50% but lesser than 75%.

10. Thus a standard machine element equivalent to the non-standard component table legs is chassis. For the identified machine element, referring the machine element reference table 17 for chassis, the list of potential failure modes are Elastic deformation, yielding and buckling.

Table 17: Machine element reference table for chassis

Machine Element	Load Conditions	Commonly used materials	Potential Failure Modes
Chassis	Axial Loads, Bending Loads and torsional loads	Steel, Stainless Steel, Plastics, Aluminum and Magnesium	Primary: Force-induced elastic deformation, yielding, and buckling.

11. The failure mode specified is buckling. Buckling is one of the critical failure modes for chassis. Referring table 2, the critical material properties related to buckling are compressive yield strength and modulus of elasticity. Since the part is not yielding, we are only concerned with modulus of elasticity property.

12. Then material property value for the originally used cast iron material is obtained from the material database. The objective is to find lighter and stronger candidate substitute materials. The target increase is specified at 20%. The constraint to find least expensive alternatives and that can be machined.

13. The identified candidate material substitutes are:

Table 18: Candidate materials for table legs

Material Class	Material
Steel	Carbon steels, alloy steels, hardened steels
Cast iron	White cast iron
Epoxy resins	Molding compounds

Verification:

Chassis systems even though have a much different applications, they essential carry the massive vehicle loads. Also the failure mode specified is one of the potential failure modes for chassis. Thus the equivalent machine element holds good. Also the candidates are some of the commonly used materials in modern table design. It should be noted other materials such as stainless steels, magnesium alloys and titanium were also identified as candidate materials but they were then filtered out due to the specified cost constraints and manufacturing constraint.

Example 6: Materials for spring

Springs come in many shapes and have many purposes: axial spring, leaf springs, helical springs and torsion bars [4 (Ref 6.7)]. Consider a helical coil spring in tension with a steady load, at room temperature. The objective is to find stronger alternative materials that can withstand higher loads. The estimated load increase is considered be 20% that of the normal load conditions. The originally used material is steel.

Process:

1. The machine element is spring, the originally used material is steel, but the failure mode is not known. This is similar to example 4 and so the first step is to identify the failure mode.
2. The failure mode identification process is done with the help of fuzzy logic. So failure descriptors are used in identifying the actual failure mode of the component. The failure agents are well known to be a (load – steady, temperature – room). The failure hours of operation is determined to be short. Since all of this information is given the input confidence is greater than 80%. The failure manifestation is not clear. There is no fracture or visible plastic deformation and there is no dimensional reduction. Thus the only option is elastic deformation. The deformation is also chosen as a body failure. The failure manifestation is given a 5% confidence since it is derived by method of elimination and failure location is given a 25% confidence.
3. Following the same sequence of steps 5-11 in example 4, the failure mode identified is Brittle fracture. The confidence in the identified failure mode is less than 30% which is alarming.
4. The next step in the process is to obtain the potential failure modes of the machine element specified. Referring table 3, the potential failure modes of springs (brake springs) are Yielding, Fatigue, Corrosion Fatigue,

Fretting Fatigue, Creep, Thermal relaxation, Buckling and Surging (Force-induced elastic deformation).

5. Referring the identified part failure mode with the list of potential failure modes, it is found that the machine element cannot undergo the failure mode specified. Hence the material substitution process is aborted.

Inference:

Some of the primary failure modes of springs are Yielding and Elastic deformation. They do not fail by brittle fracture. Given the input combination of failure agents, yielding and elastic deformation was also found out to be potential failure modes. However owing to very low confidence input in the identified failure manifestation and failure location, the yielding and elastic deformation failure were not deemed to be the probable part failure and the identified failure mode – brittle fracture - is very low in confidence. It suggests that when failure modes are identified with very low confidence it has to be treated with additional care. It suggests that closer inspection of the coil spring is required to verify the failure manifestation and failure location. After inspection, with higher confidence or with additional inputs the right failure mode may be identified with higher confidence. It happens so, that in this case the low confidence failure mode identified is incorrect. However there can be cases where machine elements may undergo the low confidence failure mode but it may not be the actual part failure. Thus output confidence % plays a huge role in downstream decision making process. Similarly, the output confidence in identifying the right machine element is also of critical importance.

Example 7: Materials for rudder sleeves in ships

A ships rudder is supported on a sleeve that slides on the shaft. The rudder sleeve operates under the most unpleasant conditions [4 (Ref 6.17)]. On inspection it was found that dimensional reduction is the main manifestation of failure on the surface of the sleeve. The objective is to identify the right machine element and the right failure mode and find candidate materials that can replace bronze.

Process:

1. This is a worst combination of cases where the failure mode and machine element needs to be identified. Thus there are three steps involved.
    a. Identifying the failure mode
    b. Identifying the machine element
    c. Finding candidate substitutes
2. Case 'a' is similar to example 4 , case 'b' is similar to example 5 and finally case 'c' is similar to example 1 (after cases a & b are executed);\
3. For case 'a', the failure descriptors help in identifying the actual part failure. Dimensional reduction is identified as the main failure manifestation after inspection and so its confidence is very high (98%). The failure location is also identified as surface after measurements and the confidence is also high (75%). There is a very high pressure on the

sleeve, that is random and there is sliding force. The temperature may be low or room but the part fails after a very long time in service. The input confidence is moderate (50%).

4. Thus for this combination of input failure manifestation, failure agent and failure location, the part failure mode was identified to be Wear with over 70% confidence.
5. For case ‘b’, the part function and mating machine element help in identifying the actual standard machine element. The sleeve slides on a shaft and one of the part functions is to constrain motion. The part function is known with certainty but there are additional mating components that cannot be specified. So the part function is given a very high confidence (85%) and the mating machine element is given a lower confidence (60%).
6. Thus for this combination of input part function and mating machine elements, the machine elements identified are (Brakes, Keys, Fasteners, Seals and Plain Bearings) with a confidence less than 75% and greater than 25%. Of all the machine elements identified, Plain bearings best suit the description and function of the component.
7. Thus the failure mode identified is wear, the machine element is plain bearing and the originally used material is bronze. Thus for case ‘c’ the sequence of steps is similar to example 1. For the objective of finding

improved strength and lighter candidate materials for a target 5% increase, the identified candidate materials are:

Table 19: Candidate materials for ship's rudder sleeves

Material Class	Material
Phenolic	General Purpose
Zinc alloys	Zn and Zinc alloys
Nickel alloys	Nickel alloys
Thermoplastics	Polyesters (General purpose)
Steels	Mold steel, AISI 5000
Stainless steels	Precipitation hardened steel

Verification:

The machine element given in [4] is a journal bearing. However for the purpose of demonstration, the machine element descriptions were used and so the machine element identified came out to be the actual machine element. However since several other machine elements were identified along with this machine element and with not so high confidence % the results still need to be treated with care. The failure mode identified as wear with quite a high confidence also corresponds to failure mode discussed in [4]. However of the identified candidate materials the phenolic is the only material suggested in [4]. However stainless steel identified is another candidate material that is commonly used as journal bearings in marine applications. Thus the results correspond to standard bearing selection alternatives for bronze.

CHAPTER 7

CONCLUSION

In this thesis a new knowledge based software system for material selection and substitution is developed. The software is particularly useful for re-engineering legacy engineered systems, where input parameters for material substitution are not clearly defined. However it can also be used for material selection decisions where the design intent is much clear and the input parameters are clearly defined. First a list of parameters such as part function, part failure and originally used material are identified as critical for material selection and substitution. Since design intent is often not clear for LSE systems, such systems only have certain low fidelity parameters such as failure descriptions of the part and hours of operation that can be used in identifying the critical parameters. With the available parameters, extraction methods are identified for obtaining the critical parameters. However extracting data based on only few available parameters involve uncertainty. Fuzzy logic is chosen over other methods to model the uncertainty due to its inherent advantages. Fuzzy member functions are setup to model data imprecision and fuzzy rule sets are setup to model the imprecise dependencies of the data. All the input uncertainty translates to a final candidate confidence for substitution. It is observed that material selection and substitutions are objective driven and hence several goals and constraints are discussed for choosing a new candidate material. Finally, seven case studies are presented to understand the functioning of the knowledge system and the decision making process. The results and their implications are discussed in each of the seven cases.

7.1. Future Work

The existing tool is developed on a material database that has materials and material property data obtained from literature and MatWeb. However new and advanced materials are always being developed, and hence XML based material exchange framework such as MatML [22] needs to be incorporated. With the framework, user can customize the database based on popularly used materials in his field of expertise. The framework can also be customized to add new user specific rules, goals and constraints.

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