Manufacturing Flexibility Measurement: A Fuzzy Logic Framework

Nikos C. Tsourveloudis and Yannis A. Phillis

Abstract—**Flexibility is recognized as an important feature in manufacturing. This paper suggests a knowledge-based methodology for the measurement of manufacturing flexibility. We claim that flexibility is an inherently vague notion and an essential requirement in its measurement is the involvement of human perception and belief. Nine different flexibility types are measured, while the overall flexibility is given as the combined effect of these types. Knowledge is represented via IF⟨fuzzy antecedents⟩THEN⟨fuzzy consequent⟩ rules, which are used to model the functional dependencies between operational characteristics such as *setup time* and *cost, versatility, part variety, transfer speed* etc. The proposed scheme is illustrated through an example.**

Index Terms—**Approximate reasoning, flexibility types, fuzzy logic, manufacturing flexibility, measurement.**

I. Introduction

As globalization of markets raises competitive pressures, one essential requirement for the survival of organizations is their capability to meet competition. Market needs cause unceasing changes in the life cycle, shape, quality, and price of products. Manufacturing flexibility is an effective way to face up to the uncertainties of this rapidly changing environment and it is defined as the ability to absorb various disturbances which occur in production systems, as well as the ability to incorporate and exploit new technological advances and work practices. Taking full advantage of flexibility presupposes a clear definition together with the formation of a unified system to model and quantify the concept. Reading the relevant literature, one could observe overlappings in the dimensions and types of flexibility as well as a lack of a universal measurement scheme [1], [2]. It is common belief, however, that flexibility is a multidimensional notion which is connected with almost all levels of an organization.

The measurement of manufacturing flexibility has continued to be a major challenge to researchers. Numerous efforts have been reported which can be categorized by the aspect of flexibility they measure or by the approach used to determine flexibility. There are measures which concentrate on economic advantages [3], [4], the effects on decision making [5], or the quantification of certain performance indices and operational characteristics of flexibility [6], [7]. From a methodological point of view, measures have been proposed in the context of information theory [8], [9], graph theory [10], mathematical programming [11] and Petri nets [12]. Extensive literature review of manufacturing flexibility can be found in [1] and [2].

Flexibility is a desirable property of production systems which quite often is presented as a panacea to numerous practical problems. The development of flexibility measures is extremely useful in order to exploit the benefits of a flexible system. By utilizing these measures, decision makers have the opportunity to examine different systems at different flexibility levels. This objective seems elusive, unless measures provide a direct and holistic treatment of flexibility components. It is essential to remember that flexibility is an outcome of not only technological achievement, advanced organizational and managerial structure and practice, but also a product of human abilities, skills, and motivations. As manufacturing systems are operated and managed by people, it is necessary to record and utilize human knowledge and perceptions about flexibility in its measurement. This requirement is clearly documented in several works [13], [14].

Regardless of the structure of each measure, it is important to establish basic principles which should be satisfied by any flexibility measure. In our view, any practical flexibility metric should work as follows.

1) Focus on specific flexibility types from which overall flexibility measures will be derived. The observable parameters for each measure should be specified together with the derivation methodology.
2) Allow flexibility comparisons among different installations.
3) Provide a situation specific measurement by taking into account the particular characteristics of the system.
4) Incorporate the accumulated human knowledge.

In this paper, we describe a new approach for measuring manufacturing flexibility, in which all parameters needed in the various steps of the quantification procedure are represented by words and the overall flexibility is given by their synthesis. The system we propose uses expert knowledge and consists of an implementation of fuzzy logic methods and terminology to assess manufacturing flexibility. Fuzzy logic was first introduced in flexibility measurement in [15] and [16], and was discussed further in [17].

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The paper is organized as follows. Section II reviews various flexibility types and emphasizes the necessity of a knowledge-based approach to measure flexibility. In Section III, we discuss the measurement of the overall manufacturing flexibility within an approximate reasoning schema. In Section IV, the fuzzy IF-THEN rules and variables needed to model *machine, routing, material handling, product, operation, process, volume, expansion*, and *labor* flexibilities, are formulated. The proposed methodology is illustrated through an example and comparisons of three manufacturing systems. We conclude in Section V indicating future research objectives.

II. Flexibility Types and Knowledge-Based Measurement

Manufacturing flexibility is a vague notion, exhibiting a polymorphism that makes quantification a difficult exercise. For the sake of analysis, flexibility has been categorized into several distinct types. In one of the first systematic classifications, eight flexibility types were identified [18], which still form the basis of understanding the various facets of the concept. Several flexibility types have been suggested subsequently which may be summarized without significant oversights as follows.

Machine flexibility deals with the ease of making changes among the operations required to produce a number of products. It is measured by the number of operations that a workstation performs and the time needed to switch from one operation to another.

Routing flexibility is the ability of a production system to manufacture a part using several alternative routes in the system and it is determined by the number of such potential routes and back-up machinery in case of breakdowns.

Material Handling System flexibility is the ability of a transportation system to move efficiently several part-types from one point to another. It can be measured by the number, diversity, and transportation time of workpieces.

Product flexibility is the ease with which the part mix can be changed in order to manufacture or assemble new products. Quantitatively it is measured by the time or the cost needed to switch from one part mix to another.

Operation flexibility of a part refers to the ease of changing the sequence of the operations required to manufacture this part and it can be measured by the number of different operation sequences the part may be produced.

Process flexibility measures the ability of a manufacturing system to produce several part-types without reconfigurations. An index of this flexibility is the number of part-types that can be simultaneously processed by the system.

Volume flexibility is the ability of a system to operate profitably at different throughput levels. It is quantified by the range of volumes at which the system runs profitably.

Expansion flexibility refers to a system's capability to be modular and expandable. It can be measured by the time or cost required for the system's expansion to a given capacity.

Labor flexibility is the ease of moving personnel to different departments of an organization and it is achieved by the aptitude of multi-trained staff to carry out a wide variety of tasks.

Direct measures of flexibility utilize operational parameters which determine the flexibility type in contrast to measures that focus, for example, on the economic or performance consequences of flexibility. Certain points require additional attention when we develop direct measures. The functional parameters can be studied in different hierarchical levels and, usually, demand data that are not easily quantifiable such as the rerouting ability of a material handling system. Sometimes flexibility parameters cannot be accurately defined, as for example the versatility of a workstation. In addition, a sufficient synthesis method of the operational parameters of flexibility is lacking. One of the reasons for this is that the parameters involved in the measurement of each type are not homogeneous. For instance, in the measurement of machine flexibility one should combine not only the changeover time with the number of operations the machine performs but also with data concerning physical characteristics of the workparts, such as weight, geometry etc. Another difficulty which stands in the way of measurement is the lack of a one-to-one correspondence between flexibility types and the physical characteristics of the production system. As a result, we have inconsistent behavior of some parameters in the measurement of flexibility [19], [17] such as concurrency and synchronization. An example of parameter inconsistency can be found in the measurement of routing flexibility, where the ability to absorb malfunctions may be attributed either to redundant similar machinery or to versatile workstations, which substitute dedicated machines that have broken down.

In our view, mathematical models have difficulties in dealing with the direct measurement of flexibility. To accomplish this task it is important to take into account the ideas people have about the quantification of the observable parameters of the notion. Algebraic formulae fail in putting together the various dimensions of flexibility; in much the same manner as in a medical diagnosis, for example, where it is inappropriate to add or multiply clinical symptoms and laboratory test results, to specify how serious a patient's illness is. On the other hand, by a suitable representation of human expertise concerning the combination of the flexibility parameters, we achieve a knowledge-based measurement which overcomes these problems. The key idea is to model human inference, or equivalently, to imitate the mental procedure through which experts arrive at a value of flexibility by reasoning from various sources of evidence. These experts could be managers, engineers, operators, researchers, or any other qualified individual. It has been shown in [15] that experts are capable of estimating flexibility if they know the values of certain relevant parameters. For example, the existence of many alternative production routes for each product, together with on-line rescheduling capability, indicates high routing flexibility. Similarly, if a machine performs a wide variety of operations with small setup times, then the machine level flexibility is high.

Verbal or linguistic values, such as *low, average, about high* and so on, are frequently used by managers and researchers

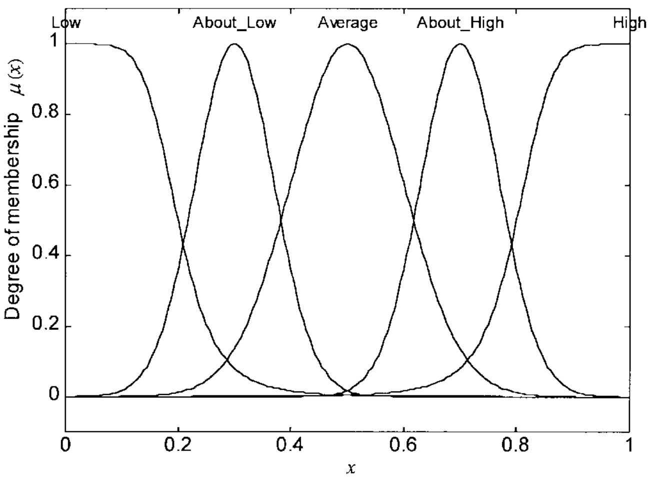

Fig. 1. Typical membership functions for the fuzzy sets: low, about low, average, about high, and high.

to quantify flexibility. This provides an additional motivation for building a knowledge-based system. But knowledge is almost never accurate and is completely contrary to what mathematical models require. Knowledge is ordinarily enmeshed in inexactness and vagueness. Fuzzy logic offers a methodological framework [20] to represent knowledge together with a reasoning procedure whereby the value of flexibility is deduced. Some of these issues are discussed in the following section.

III. Modeling and Measurement of Flexibility

The key idea of our model is the involvement of all distinct types and corresponding operational parameters in the determination of the overall flexibility. This is implemented via multi-antecedent fuzzy IF-THEN rules, which are conditional statements that relate the observations concerning the allocated types (IF-part) with the value of flexibility (THEN-part). An example of such a rule is:

"IF *Routing* flexibility is *Low* AND *Product* flexibility is *Average*
THEN *Manufacturing* flexibility is *About Low*,"

where *Routing, Product*, and *Manufacturing* flexibility are the *linguistic variables* of the above rule, i.e. variables whose values are linguistic, such as, *Low, Average* and *About Low*, rather than numerical. These values are fuzzy sets with certain mathematical meaning represented by appropriate membership functions (Fig. 1).

Fuzzy rules are an efficient way to map input spaces to output spaces, especially when the physical relationship between these spaces is too complex to be described by mathematical models. As the impact of individual flexibility types on manufacturing flexibility is hard to be analytically computed, we devise fuzzy rules to represent the accumulated human expertise. In other words, the knowledge concerning flexibility, which is imprecise or even partially inconsistent, is used to draw conclusions about the value of flexibility by means of simple calculus. In the following, we concentrate on the structure of fuzzy rules and explain the fuzzy formalism that is used toward measurement.

Suppose, that $F_i, i = 1, \cdots, N$, is the set of flexibility types and A_i the linguistic value of each type; then the expert knowledge general rule is

$$\textbf{IF } F_1 \text{ is } A_1 \text{ AND } \cdots \text{ AND } F_N \text{ is } A_N \textbf{ THEN } F_{MF} \text{ is } MF \quad (1)$$

or

$$(A_1 \text{ AND } A_2 \text{ AND } \cdots \text{ AND } A_N) \rightarrow MF \quad (2)$$

where MF represents the set of linguistic values for manufacturing flexibility F_{MF}. All linguistic values A_i and MF are fuzzy sets like those shown in Fig. 1 and defined on base sets X and Y such that $a_i(x)$ and $mf(y)$ denote the membership grades of elements x and y in A_i and MF, respectively. "AND" represents the fuzzy conjunction and has various mathematical interpretations within the fuzzy logic literature. Usually it is represented by the intersection of fuzzy sets which corresponds to a whole class of *triangular* or *T-norms* [21]–[23]. The selection of the "AND" connective in the flexibility rules should be based on empirical testing within a particular installation, as flexibility means different things to different people. Certain criteria for choosing logical connectives are proposed in [24, p. 39].

Let, now, $D = A_1$ AND A_2 AND $\cdots$ AND A_N. Then (2) becomes

$$\textbf{IF } (F_1, F_2, \cdots, F_N) \text{ is } D \textbf{ THEN } F_{MF} \text{ is } MF \quad (3)$$

or $D \rightarrow MF$, where $(F_1, F_2, \cdots, F_N)$ is called the *joint variable* and represents the combined effect of the allocated types of components on flexibility. The fuzzy relation L induced by (3) is

$$L_{D\rightarrow MF}(x, y) = f_{\rightarrow}[d(x), mf(y)] \quad (4)$$

where $f_{\rightarrow}$ is the functional form of the fuzzy implication and $d(x)$ is the membership function of the conjunction D. Equation (4) is the mathematical interpretation of a fuzzy rule and leads to the construction of an implication matrix which maps the fuzzy knowledge described by the rule. One can use any implication and conjunction operators needed to achieve the desirable knowledge representation within a given context. It should be noted, however, that an appropriate "AND" connective should combine the information of all parameters (antecedents) by considering their importance in a given context. In view of this need, operators that do not reflect the interaction of flexibility factors, such as the minimum operator, are not adequate.

The inputs to the described rules, i.e. the assessments of flexibility types, are fuzzy sets which, in general, are different from the A_i's included in the rule base. Consequently the conjunction of these sets differs from D. Manufacturing flexibility is then computed from

$$MF' = D' {}^{\circ} L_{D\rightarrow MF} \quad (5)$$

where $^{\circ}$ represents an *approximate reasoning* procedure [25], MF' is the deduced value of flexibility and D' is the conjunction of inputs. *Fuzzy* or *approximate reasoning* is used to draw a conclusion from an observation that does not match exactly with the antecedents. For example, suppose that we know that

'IF $Routing$ flexibility is Low AND $Product$ flexibility is $Average$
THEN $Manufacturing$ flexibility is *About Low*' (Rule),

but for a given production system we have

'$Routing$ flexibility is $more\ or\ less\ Low$' (Observation).

By utilizing (5) we are able to compute the value of manufacturing flexibility. In the membership functions domain, this value is given by

$$mf'(y) = d'(x) \circ f_{\rightarrow}[d(x), mf(y)] \tag{6}$$

where, $mf'(y), d'(x), mf(y)$, and $d(x)$ are the membership functions of MF', D', MF, and D, respectively. In (6) we still need the membership function $d'(x)$ which in the previous example was the membership function of the linguistic value "*more or less Low*." Zadeh in [29] has pointed out that if A is a linguistic value characterized by a fuzzy set, then A^k is interpreted as the modified version of the original linguistic value, i.e., fuzzy set, expressed as

$$A^k = \int_X [\mu_A(x)]^k \Big/ x, \qquad x \in X \tag{7}$$

where the integration sign stands for the union of $[\mu_A(x), x]$ pairs and "/" is a marker. For example, *more or less A* is defined as the *dilation operation* which is

$$more\ or\ less\ A = \mathrm{DIL}(A) = A^{0.5} \tag{7a}$$

and "*Very A*" which is the result of the *concentration operation* is given by

$$Very\ A = \mathrm{CON}(A) = A^2. \tag{7b}$$

Using (7) together with the interpretations of negation and the "AND" connective, one is able to formulate the mathematical meaning of composite linguistic terms, such as, "*not very high*" and "*about low but not too low*."

The overall measurement algorithm can be summarized in the following structural steps:

Step 1: Select the implication operator and the "AND" connective: Choose the form and the mathematical meaning of the rules that fit the practical system of interest. Use conjunction operators to interpret the dependencies of flexibility types or parameters.

Step 2: Match the observations (inputs) with the antecedents of the rules.

Step 3: Select and apply an approximate reasoning method: Associate the observations with the available knowledge and compute the value of flexibility.

Details about the selection of operators and reasoning methods will be given in the illustrative example of next section. There, we explain the methodology within the context of the *Compositional Rule of Inference*, introduced by Zadeh in [26]. The *Analogical Reasoning* [27], *Revision Principle* [28], and *Rule Interpolation* [29] are other examples of approximate reasoning algorithms suitable for practical use. In what follows, we present nine flexibility types and define fuzzy rules and linguistic variables for each of them.

IV. Modeling of Flexibility Types

A. Machine Flexibility

A machine is the basic hierarchical element of a production system. Modern machines are equipped with exchange mechanisms for tools and workpieces which enable the machines to perform several operations in a given configuration in short load, unload, and tool exchange times. Machine flexibility (F_M) is the simplest kind of flexibility that can be defined in a manufacturing system and constitutes a necessary building block for the assessment of total flexibility. Although it is mainly determined by the existing hardware, it is quite difficult to be analytically computed. The following parameters are used in the computation of F_M [17]:

1) *Setup* or *changeover time* (S) required for various preparations such as tool or part positioning and release, software changes etc. In many cases machines are controlled by a central computer and the corresponding software changeover time is very small or negligible. The setup time represents the ability of a machine to absorb efficiently changes in the production process and it influences flexibility heavily when the batch sizes are small.
2) *Versatility* (V) which is defined as the variety of operations a machine is capable of performing. It refers to the ability of a machine to change readily between operations or work conditions. Processes with different tools and conditions are also considered to be operations. Versatility may be associated with the physical characteristics of a machine such as the number of motion axes, maximum accuracy, range of cutting speeds, number of fixtures, as well as the quantity and diversity of workpieces on which the machine may operate.
3) Range of adjustments or *adjustability* (R) of a machine which is defined as the size of working space and is related to the maximum and minimum dimensions of the parts that the machine can handle.

These parameters are not independent. A versatile machine, for example, minimizes the time needed for preparations in order to produce a set of parts. Similarly, the size of working space affects the position-and-release time and therefore has an influence on the duration of the setup period. Relations of this kind, although well known, are hard to be analytically defined. Linguistic or fuzzy rules overcome such deficiencies by involving already known facts into the measurement procedure.

Specifically, let T denote the set of linguistic values of concern, such that T_S, T_V, T_R, and $T_{F_M} \in T$ are the linguistic value sets for S, V, R, and F_M, respectively. The rules which represent the expert knowledge on how the variables affect flexibility are of the form

$$\textbf{IF } S \text{ is } T_S \text{ AND } V \text{ is } T_V \text{ AND } R \text{ is } T_R \textbf{ THEN } F_M \text{ is } T_{F_M}, \tag{8}$$

or compactly

$$(T_S \text{ AND } T_V \text{ AND } T_R) \rightarrow T_{F_M} \tag{9}$$

where "AND" denotes fuzzy conjunction, and → is any given fuzzy implication.

B. Routing Flexibility

Routing flexibility (F_R) allows for a quick reaction to unexpected events such as machine breakdowns and minimizes the effect of interruptions of the production process. It is *potential* when part routes are predetermined but parts may be dynamically rerouted during a breakdown, or *actual* when identical parts are processed through different routes, independently of breakdown situations. The benefits of routing flexibility are well understood among researchers but there exists some confusion regarding its definition [1]. Routing flexibility appears in the literature in different guises such as scheduling, operations, process and, more often, manufacturing flexibility. It is achieved when the system consists of interchangeable and multipurpose machines together with a material handling system, rescheduling control software, and redundancy in machines, tools, and processes. These requirements demand a high investment, often making production prohibitively costly.

Routing flexibility is an inherent property of the manufacturing system and it expresses its ability to respond to unanticipated internal changes and variations. We are mainly motivated by the fact that F_R arises from the existence of interchangeable machines, capable of performing similar operations. The ability to handle breakdowns, which is the main characteristic of F_R, exists if each operation can be performed on more than one machines. We recognize that a key prerequisite in measuring F_R is the ability of a machine to substitute for another.

The linguistic variables we define for the assessment of routing flexibility are [17]

1) *Operation Commonality* (C_O) which expresses the number of common operations that a group of machines can perform in order to produce a set of parts.
2) *Substitutability* (S_B) which is defined as the ability of a system to reroute and reschedule jobs effectively under failure conditions. The substitution index may also be used to characterize some built-in capabilities of the system as for example, real-time scheduling or available transportation links. Substitutability is associated with the material handling system and the layout of the machines.

The IF-THEN rules of routing flexibility are of the form

$$\textbf{IF } C_O \text{ is } T_{C_O} \text{ AND } S_B \text{is } T_{S_B} \textbf{ THEN } F_R \text{ is } T_{F_R} \tag{10}$$

or equivalently

$$(T_{C_O} \text{ AND } T_{S_B}) \rightarrow T_{F_R} \tag{11}$$

where the notation in (11) follows that of (9). The same notation is used throughout the remainder of this paper.

C. Material Handling System Flexibility

Limited work has been done in the area of modeling material handling system flexibility (F_{MHS}) measures. In [30], the impact that several types of material handling equipment have on flexibility was explored and linguistic assessments for several flexibility types were reported. These measurements concern equipment of the type of belt and powered roller conveyors, monorails, power-and-free conveyors, towline carts and automated guided vehicles.

The linguistic variables we define for the knowledge-based measurement of material handling flexibility are [17]

1) *Rerouting factor* (B), which indicates the ability of a material handing system to change travel paths automatically or with small setup delay and cost. Rerouting ability is a necessary property for the establishment of routing flexibility.
2) *Variety of loads* (P) which a material handling system carries such as workpieces, tools, jigs, fixtures etc. It is restricted by the volume, dimension, and weight requirements of the load.
3) *Transfer speed* (C), which is associated with the weight and geometry of products, as well as the frequency of transportation.
4) *Number of connected elements* (M) such as machines and buffers.

The general fuzzy rule here is

$$\begin{aligned} &\textbf{IF } B \text{ is } T_B \text{ AND } P \text{ is } T_P \text{ AND } C \text{ is } T_C \text{ AND} \\ &\quad M \text{ is } T_M \textbf{ THEN } F_{\text{MHS}} \text{ is } T_{F_{\text{MHS}}} \end{aligned} \tag{12}$$

or

$$(T_B \text{ AND } T_P \text{ AND } T_C \text{ AND } T_M) \rightarrow T_{F_{\text{MHS}}}. \tag{13}$$

D. Product Flexibility

Product flexibility (F_P) is associated with the number of products that are produced or assembled by the manufacturing system in a given time period. Product flexibility helps the firm respond to demand changes by introducing new products in the market quickly. Parameters pertinent to the measurement of product flexibility are [17]

1) *Part variety* (V_P) is associated with the number of new products the manufacturing system is capable of producing in a time period without major investments in machinery and it takes into account all variations of the physical and technical characteristics of the products.
2) *Changeover effort* (S_P) in time and cost that is required for preparations in order to produce a new product mix. It expresses the ability of a system to absorb market variations.
3) *Part commonality* (C_P) refers to the number of common parts used in the assembly of a final product. It measures the ability of introducing new products fast and economically and also indicates the differences between two parts.

The form of the general production rule is

$$\textbf{IF } V_P \text{ is } T_{V_P} \text{ AND } S_P \text{ is } T_{S_P} \text{ AND } C_P \text{ is } \textbf{THEN } F_P \text{ is } T_{F_P} \quad (14)$$

or compactly

$$(T_{V_P} \text{ AND } T_{S_P} \text{ AND } T_{C_P}) \rightarrow T_{F_P}. \quad (15)$$

E. Operation and Process Flexibility

Operation flexibility (F_O) refers to the capability of producing a part in different ways by changing the sequence of operations which were originally scheduled. It is not a built-in feature of the system but allows for an easier production scheduling and real time rerouting. We define the linguistic variable *number of production sequences* (O_S) for all parts manufactured by the system. For each part, O_S is given by the number of all possible sequences of operations whereby that part may be produced. O_S is restricted by the technological level as much as physical and quality constraints. The general IF-THEN statement relates O_S to operation flexibility as

$$\textbf{IF } O_S \text{ is } T_{O_S} \textbf{ THEN } F_O \text{ is } T_{F_O} \quad (16)$$

or simply, $T_{O_S} \rightarrow T_{F_O}$.

Process flexibility (F_S) is a result of the ability of a manufacturing system to produce different types of products at the same time. Very often it is referred to as *mix, job, variant* and *product-mix flexibility*. It reduces batch sizes and minimizes work-in-process, buffer sizes and inventory costs. Multi-skilled workers who carry out assignments in many workplaces enhance process flexibility. In order to achieve process flexibility, a combination of certain desirable characteristics is needed, for example, a combination of multipurpose machines and fixtures, redundant equipment, material handling devices and process variety. Here the linguistic variables of concern are

1) *Set of part types* (P_S) that can be produced simultaneously or without major setup delays resulting from breakdowns or reconfigurations of large scale
2) *Setup costs* (C_S).

Expert knowledge is represented by

$$\textbf{IF } P_S \text{ is } T_{P_S} \text{ AND } C_S \text{ is } T_{C_S} \textbf{ THEN } F_S \text{ is } T_{F_S} \quad (17)$$

or $(T_{P_S} \text{AND } T_{C_S}) \rightarrow T_{F_S}$.

F. Volume and Expansion Flexibility

Volume flexibility (F_V) is the ability of a manufacturing system to change the production volume and still be able to operate profitably. It can be regarded as the response to demand variations and implies that the firm is productive even at low utilization. It is also associated with the hiring of temporary personnel to meet changes in market demand. The general linguistic rule is

$$\textbf{IF } R_V \text{ is } T_{R_V} \textbf{ THEN } F_V \text{ is } T_{F_V} \quad (18)$$

or $T_{R_V} \rightarrow T_{F_V}$, where R_V represents the *range of volumes* at which the firm is run profitably.

Expansion flexibility (F_E) is the capability of changing the capacity or variety of products easily and economically. Expansion flexibility makes it easier to remove or add equipment of any kind and reduces time and cost required for the manufacture of new products. Expansion flexibility is often equated to a system's modularity and a necessary requirement for its achievement is the existence of material handling systems with flexible traveling routes such as automated guided vehicles. The variables needed for the knowledge-based measurement of F_E are as follows.

1) *Modularity index* (M_D) which represents the ease of adding new machinery to a production system without significant effort and changes.
2) *Expansion ability* (C_E) which is the time and cost needed to increase the capacity to a given level.

The rules are

$$\textbf{IF } M_D \text{ is } T_{M_D} \text{ AND } C_E \text{ is } T_{C_E} \textbf{ THEN } F_E \text{ is } T_{F_E} \quad (19)$$

or $(T_{M_D} \text{ AND } T_{C_E}) \rightarrow T_{F_E}$.

G. Labor Flexibility

Labor flexibility (F_L) is the ease of moving personnel around various departments within an organization [31], [32]. By taking advantage of a flexible workforce, a firm will be able to respond quickly to unexpected work loads that may arise. This type of flexibility also allows the firm to reduce the throughput times of jobs and improve customer service. The linguistic variables we define as labor flexibility level indicators are

1) *Training level* (W). Improved flexibility can be achieved through education and cross-training programs. Horizontal training programs aim at developing skills for performing a wide variety of different tasks, rather than increasing specialization of work. Specialization is in conflict with labor flexibility. Each worker learns how to perform a number of tasks in different departments instead of only the one to which he/she was initially assigned. As a result, workers who have access to many departments increase the firm's capability to face unanticipated events. High training level implies high labor flexibility. A completely flexible worker can perform all tasks or operate all machines in each department of a firm.
2) *Job rotation* (J). It is related to training and expresses the frequency with which the workers are transferred to new work positions, under normal conditions. Job rotation increases the possibility of fast reaction to an unscheduled situation and, therefore, contributes to flexibility. An additional benefit of job rotation is that it broadens the knowledge of the personnel, enabling them to obtain a global vision of the company's objectives.

The fuzzy rules can be written as

$$\textbf{IF } W \text{ is } T_W \text{ AND } J \text{ is } T_J \textbf{ THEN } F_L \text{ is } T_{F_L} \quad (20)$$

or $(T_W \text{ AND } T_J) \rightarrow T_{F_L}$.

It should be noted that the nine types of flexibility we have discussed here are not unique. Moreover, the proposed list of

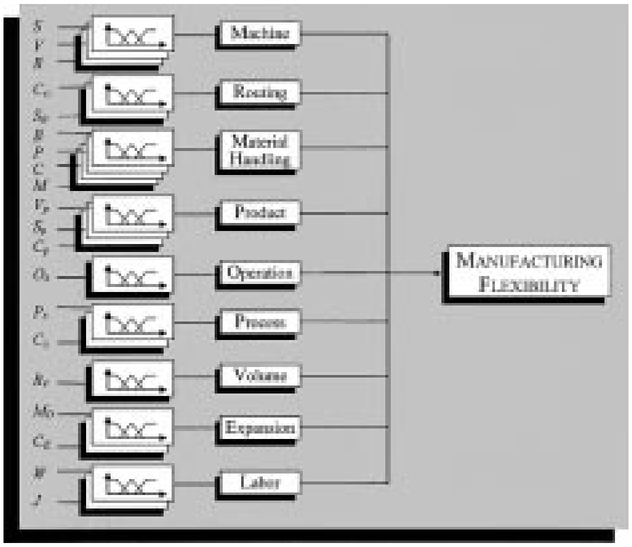

Fig. 2. Fuzzy assessment of manufacturing flexibility.

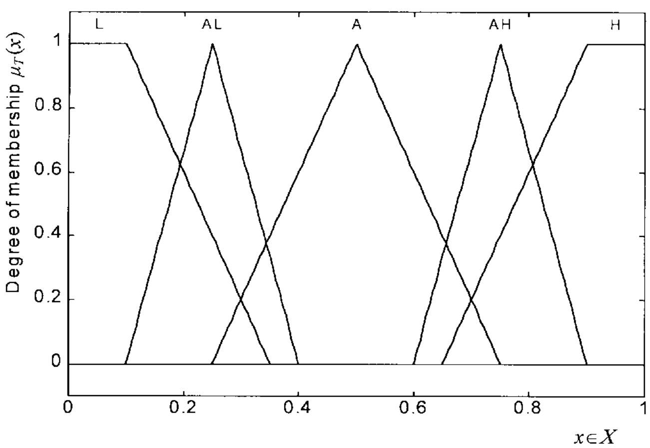

Fig. 3. Membership functions of the linguistic values: L = low, AL = about low, A =average, AH = about high, and H = high.

attributes used in measurement is not exhaustive. Managers may wish to define different types and attributes that fit better to their needs. The only restriction is that the relation between flexibility types and operational components should be presented via fuzzy rules.

H. An Example

In the previous section, we discussed the fuzzy formulation of nine flexibility types which are observed in various hierarchical levels. Fig. 2 is graphical representation of the proposed methodology, where manufacturing flexibility is given as the logical synthesis of all types.

Suppose, now, that for a given manufacturing plant we have five linguistic variations of the variables involved in the fuzzy rules, namely, *Low* (L), *About Low* (AL), *Average* (A), *About High* (AH), and *High* (H). Their membership functions in X are denoted by μ_T: $X \rightarrow [0,1]$, where $T = \{L, AL, A, AH, H\}$. For simplicity and without loss of generality, we define the membership functions in the unit interval [0, 1], as shown in Fig. 3.

TABLE I
LINGUISTIC DATA FOR EACH FLEXIBILITY TYPE

Types of Flexibility	Variables	Observed Values
Machine (F_M)	Setup (S)	*About Low*
	Versatility (V)	*Average*
	Adjustability (R)	*Low*
Routing (F_R)	Operation Commonality (C_O)	*Very High*
	Substitutability (S_B)	*About High*
Material Handling (F_{MHS})	Rerouting Factor (B)	*High*
	Load Variety (P)	*About High*
	Transfer Speed (C)	*Average*
	# of connected Elements (M)	*High*
Product (F_P)	Part Variety (V_P)	*About High*
	Changeover Efforts (S_P)	*Low*
	Part Commonality (C_P)	*More or less Average*
Operation (F_O)	# of Production Sequences(O_S)	*Very Low*
Process (F_S)	Part types (P_S)	*Average*
	Setup Cost (C_S)	*More or Less Low*
Volume (F_V)	Range of Volumes (R_V)	*Low*
Expansion (F_E)	Modularity Index (M_D)	*Low*
	Expansion Ability (C_E)	*Average*
Labor (F_L)	Training Level (W)	*About Low*
	Job Rotation (J)	*About High*

By representing the discrete membership functions of the linguistic values with $\mu_T(x)/x, x \in X$, where $\mu_T(x)$ is the membership grade of point x, we have

$$\mu_L = Low = [1/0, 1/.1, 0.7/2, 0.5/.25, 0.2/.3, 0/.4]$$

where, for example, 1/0 means that 0 belongs to *Low* with membership grade 1. Similarly

$$\begin{aligned} About\ Low &= [0/.1, 0.7/.2, 1/.25, 0.7/.3, 0/.4] \\ Average &= [0/.25, 0.2/.3, 0.6/.4, 1/.5, 0.6/.6, \\ &\quad 0.2/.7, 0/.75] \\ About\ High &= [0/.6, 0.4/.65, 0.7/.7, 1/.75, 0.7/.8, 0/.9] \\ High &= [0/.65, 0.2/.7, 0.5/.75, 0.7/.8, 1/.9, 1/1]. \end{aligned}$$

We assume that for the given production system we have the observations of Table I.

Let us now consider the case of routing flexibility to illustrate the measurement schema. The observation O, given by Table I is

O: Operation Commonality is $Very\ High\ (VH)$
AND Substitutability is $About\ High\ (AH)$

which compactly can be written as O: C_O is VH AND S_B is AH or more simple as O: VH AND AH. It is known [26] that for the fuzzy modifier "*Very*" holds that

$$Very\ H = H^2 \text{ or equivalently } \mu_{VH}(x) = \mu_H^2(x), x \in X$$

and consequently

$$Very\ High = [0/.65, 0.04/.7, 0.25/.75, 0.49/.8, 1/.9, 1/1].$$

The rule with which observation O matches best is

$$\text{IF } C_O \text{ is } H \text{ AND } S_B \text{ is } AH \text{ THEN } F_R \text{ is } H$$

or compactly

$$H \text{ AND } AH \rightarrow H. \tag{21}$$

The above rule contains the information we use to deduce the value of routing flexibility because its antecedents (C_O

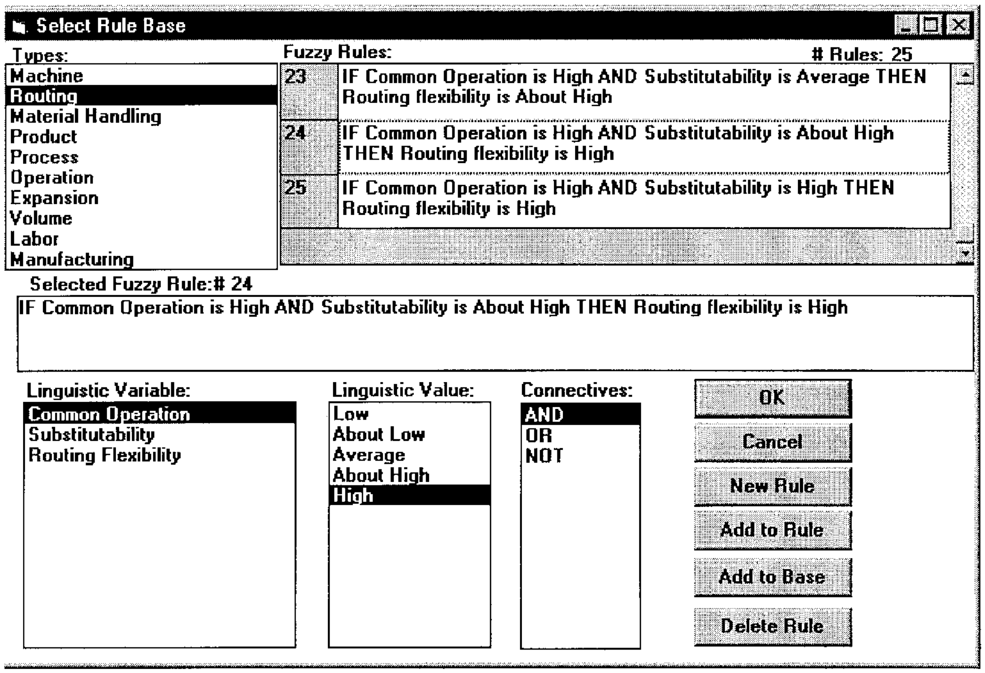

Fig. 4. Software implementation of the proposed methodology: the *Select Rule Base'* dialog box.

is H AND S_B is AH) are closer to the observation (C_O is VH AND S_B is AH) than any other rule in the rule base. In Fig. 4, a part of the routing flexibility rule base is shown within a software tool for measuring flexibility that was first discussed in [15].

The minimum operator, which usually represents the intersection of fuzzy sets, does not allow for any compensation among those sets. For example, if the connective "AND" is represented by the minimum operator in the statement "H AND L," then $\mu_{H\text{AND}L}(x) = \mu_{H\wedge L}(x) = 0$, which does not reflect the way managers merge the information of these given values. In contrast, we are convinced that the "AND" connective in the expert rules should take values between those given by the classical intersection and union. By taking the convex combination of the union $\cup$ and intersection $\cap$ for the antecedent of (21), we have

$$\mu_{H\text{AND}AH}(x) = (1-\gamma)\mu_{H\cap AH}(x) + \gamma\mu_{H\cup AH}(x) \\ x \in X, \gamma \in [0,1] \tag{22}$$

where γ is the grade of compensation and indicates where the actual operator is located between the classical union (full compensation, $\gamma = 1$) and intersection (no compensation, $\gamma = 0$) of the connected sets [33]. Intersection and union are represented by the minimum ($= \wedge$) and maximum ($= \vee$) operators, respectively, and for $\gamma = 0.4$, (22) yields

$$H \text{ AND } AH = [0.16/.65, 0.4/.7, 0.7/.75, 0.7/.8 \\ 0.4/.9, 0.4/1],$$

where, for instance $0.16/.65 = 0.6(0 \wedge 0.4)/.65 + 0.4(0 \vee 0.4)/.65$.

The discrete membership of the observation O is VH AND $AH = [0.16/.65, 0.304/.7, 0.55/.75, .5734/.8, 0.4/.9, 0.4/1]$ where for example, $0.5734/.8 = 0.6(049 \wedge 0.7)/.8 + 0.4(0.49 \vee 0.7)/.8$. Fig. 5 presents the membership function of observation O for several γ values. Adjusting the γ-parameter, one can regulate the impact of either C_O or S_B have on routing flexibility.

In order to achieve meaningful inference and since all the linguistic values we use are normal fuzzy sets ($\exists x$ such that $\mu(x) = 1$), the normalized membership of the observation O is computed. That is

$$VH \text{ AND } AH = [0.279/.65, 0.53/.7, 0.96/.75, 1/.8 \\ 0.696/.9, 0.696/1]$$

where, e.g., $0.279/.65 = 0.6(0 \wedge 0.4/0.5734)/.65 + 0.4(0 \vee 0.4/0.5734)/.65$ with 0.5734 the highest membership grade of the non-normalized membership function. The implication operator selected is a function of the conjunction $\mu_{H\text{AND}AH}(x), x \in X$, and the consequent $\mu_H(y), y \in Y$, over $X \times Y$, which in the membership domain is given by

$$L_{H\text{AND}AH\to H}(x,y) \\ = L_{\to}(x,y) = (1 - \mu_{H\text{AND}AH}(x)) \vee \mu_H(y). \tag{23}$$

From (23) we compute the *relation matrix*, that is

$$L_{\to} = \begin{bmatrix} .84 & .84 & .84 & 1 & 1 \\ .6 & .6 & .7 & 1 & 1 \\ .3 & .5 & .7 & 1 & 1 \\ .3 & .5 & .7 & 1 & 1 \\ .6 & .6 & .7 & 1 & 1 \\ .6 & .6 & .7 & 1 & 1 \end{bmatrix}$$

where, for example, $L_{\to}(0.65, 0.7)$ corresponds to the first-row-first-column digit and it is given by (23) as follows: $L_{\to}(0.65, 0.7) = 1 - \mu_{H\text{AND}AH}(0.65) \vee u_H(0.7) = (1 - 0.16) \vee 0.2 = 0.84$.

The value of routing flexibility is inferred by applying Zadeh's *compositional rule of inference*, which is the most

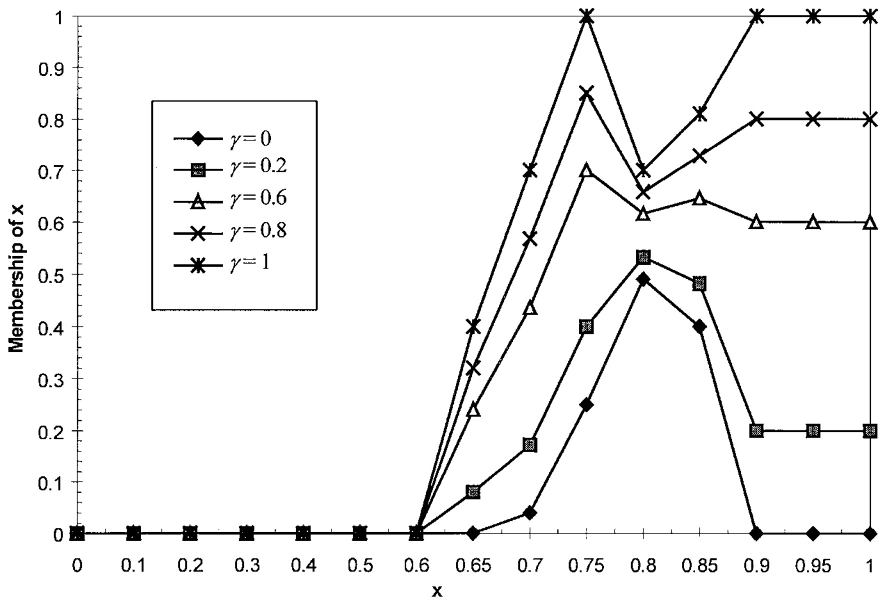

Fig. 5. The membership function of $O = VH$ and AH for various values of y parameter.

frequently used approximate reasoning method. It is described by the following inference pattern:

$$\begin{array}{ll} O\text{: } VH \text{ AND } AH & \text{(Observation)} \\ \text{Expert rule: } (H \text{ AND } AH) \rightarrow H & \text{(Existing Knowledge)} \\ \hline F'_R\text{: } O^\circ L_\rightarrow & \text{(Conclusion)} \end{array}$$

where $^\circ$ denotes the max-min composition defined by Zadeh [29] as

$$F'_R = \max(O \wedge L_\rightarrow) \tag{24}$$

which gives the membership function of routing flexibility

$$F'_R = [0.6/.7, 0.6/.75, 0.7/.8, 1/.9, 1/1]$$

where, for instance, the grade of membership of point 0.7 is

$$0.6 = (0.279 \wedge 0.84) \vee (0.53 \wedge 0.6) \vee (0.96 \wedge 0.3) \vee (1 \wedge 0.3) \vee (0.696 \wedge 0.6) \vee (0.696 \wedge 0.6).$$

In practice, a number in [0, 1] may be more preferable than a membership function, in order to represent flexibility. This seems convenient, especially when comparing alternate manufacturing systems. The procedure that converts a membership function into a single point-wise value, is called *defuzzification*. One can choose among various defuzzification methods reported in the literature. Here, by applying the so-called *Center-of-Area* defuzzification method we derive the crisp value of routing flexibility, as follows:

$$def F'_R = \frac{\sum_{i=1}^{5} x_i \mu_{F'_R}(x_i)}{\sum_{i=1}^{5} \mu_{F'_R}(x_i)} = \frac{0.7 \cdot 0.6 + 0.75 \cdot 0.6 + 0.8 \cdot 0.7 + .9 + 1}{0.6 + 0.6 + 0.7 + 1 + 1} = 0.8538. \tag{25}$$

An extensive discussion on the selection of defuzzification methods can be found in [34, p. 132].

For the data of Table I we compute each type of flexibility. The membership function of machine flexibility is

$$F'_M = [0/.25, 0.2/.3, 0.6/.4, 1/.5, 0.6/.6, 0.2/.7, 0/.75]$$

and the defuzzified value $def F'_M = 0.52$

Similarly, we see the calculations at the bottom of the next page. The combined effect of these results is the input to the manufacturing flexibility model. The membership function of the overall flexibility for the system under study is

$$MF = [0.4/.3, 0.6/.4, 1/.5, 0.6/.6, 0.4/.7]$$

and the defuzzified value is $def MF = 0.533$.

I. Flexibility Comparisons

Consider now three manufacturing systems S_1, S_2, and S_3, respectively, that produce similar types of automobile parts. For simplicity, we examine just three flexibility types, namely, *routing*, *material handling*, and *product* flexibility. S_1 consists of four identical horizontal machining centers [Fig. 6(a)], each with a storage magazine of 110 tools. Transportation of materials (pallets, tools, workpieces, etc.) is performed by automated guided vehicles (AGV's) that use photosensors to detect the light that is reflected by a fluorescent paint on the floor. This type of AGV has the advantage of being easily rerouted. The system manufactures five different families of prismatic parts and the production rate is ten pieces per hour. The second manufacturing system [Fig. 6(b)] consists of one horizontal machining center and two vertical turret lathes with automatic tool change and 24-tool storage magazine. The system is capable of producing both prismatic and rotational parts (two-part families of each shape) and a versatile conveyor belt is used for the transportation of products. Two load-unload areas are designated in both sides of the conveyor belt. System S_3 produces a small variety of prismatic and rotational

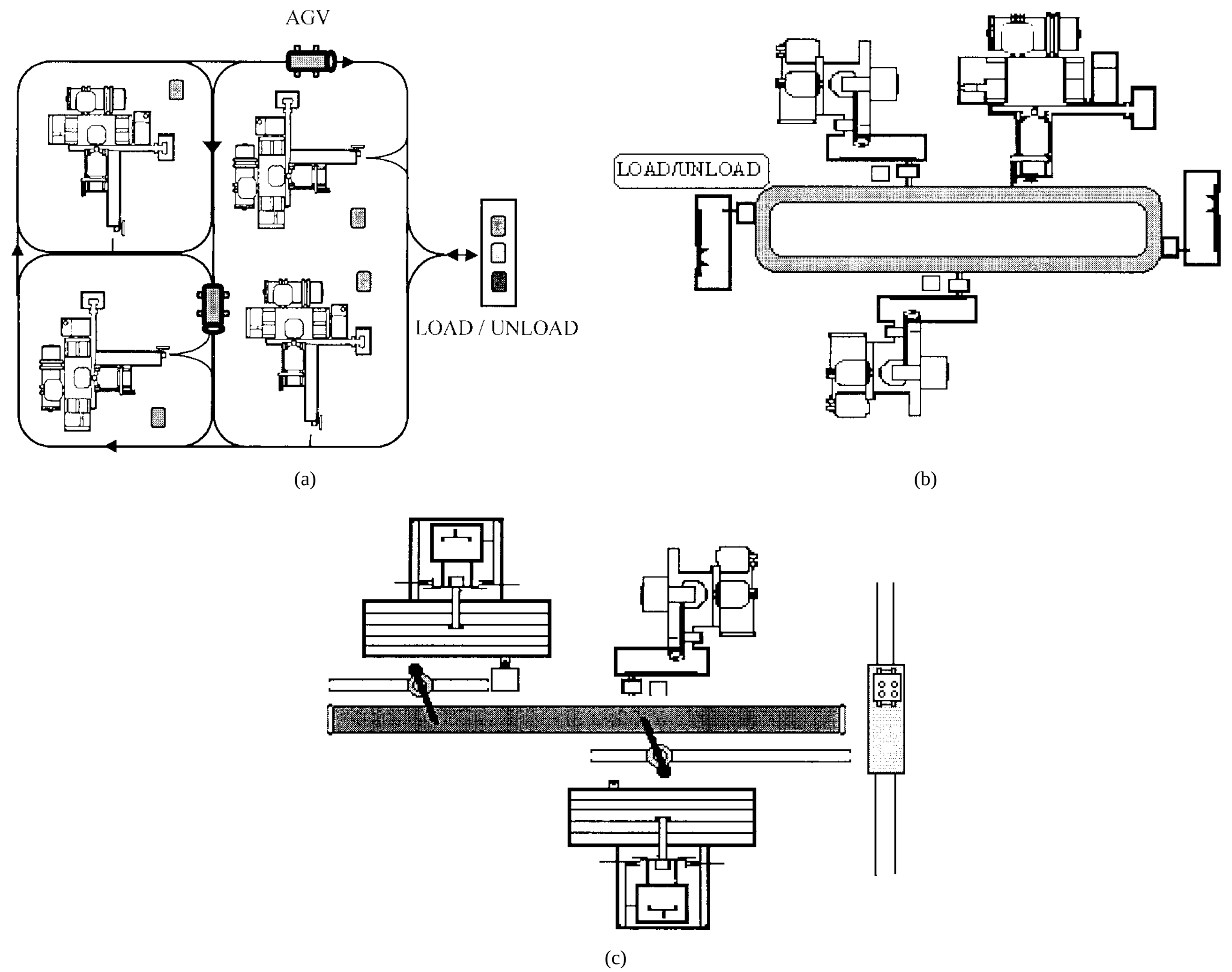

Fig. 6. The manufacturing system: (a) S_1, (b) S_2, and (c) S_3.

parts in high volumes. It consists of two vertical machining centers with a storage magazine of 90 tools which are equipped with robotic arms for loading and unloading workparts and a numerically controlled vertical lathe with four degrees of freedom. Machines are connected via a roller conveyor as shown in Fig. 6(c). Flexibility data for all three systems are summarized in Table II. S_1 is similar to the system analyzed in the previous section. The data for system S_2 are linguistic as well as numerical. *Transfer Speed* and *Operation Commonality* are represented by crisp numbers assuming that the knowledge

TABLE II

FLEXIBILITY DATA FOR THE MANUFACTURING SYSTEMS S_1, S_2, and S_3

		S_1	S_2	S_3
Routing (F_R)	Operation Commonality (C_O)	*Very High*	.4	*About Low*
	Substitutability (S_B)	*About High*	*Average*	
Material Handling (F_{MHS})	Rerouting Factor (B)	*High*	*About Low*	*Average*
	Load Variety (P)	*About High*	*About High*	
	Transfer Speed (C)	*Average*	.8	
	# of connected Elements (M)	*High*	*About High*	
Product (F_P)	Part Variety (V_P)	*About High*	*Average*	*Low*
	Changeover Efforts (S_P)	*Low*	*About Low*	
	Part Commonality (C_P)	*About Average*	*Low*	

$$
\begin{aligned}
F'_{\text{MHS}} &= [0/.65, 0.7/.7, 1/.75, 0.7/.8, 0/.9], & def F'_{\text{MHS}} &= 0.75\\
F'_P &= [0/.25, 0.7/.3, 0.7/.4, 1/.5, 0.7/.6, 0.7/.7, 0/.75], & def F'_P &= 0.5\\
F'_O &= [1/0, 1/.1, 0.49/.2, 0.25/.25, 0.04/.3, 0/.4], & def F'_O &= 0.153\\
F'_S &= [0/.1, 0.72/.2, 1/.25, 0.72/.3, 0/.4], & def F'_S &= 0.25\\
F'_V &= [1/0, 1/.1, 0.7/.2, 0.5/.25, 0.2/.3, 0/.4], & def F'_V &= 0.177\\
F'_E &= [0/.1, 0.7/.2, 1/.25, 0.7/.3, 0/.4], & def F'_E &= 0.2516\\
F'_L &= [0/.25, 0.2/.3, 0.6/.4, 1/.5, 0.6/.6, 0.2/.7, 0/.75], & def F'_L &= 0.50.
\end{aligned}
$$

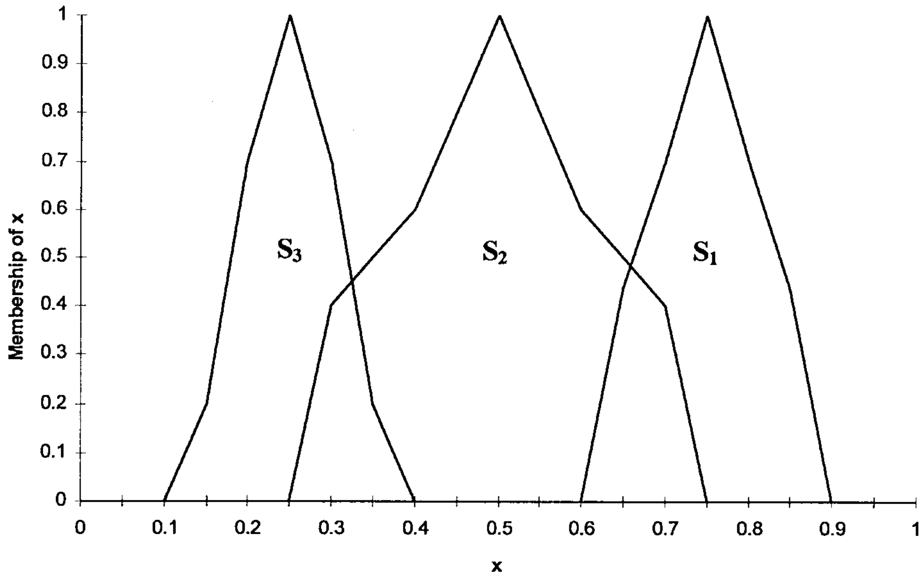

Fig. 7. The membership functions of manufacturing flexibility for the systems S_1, S_2, and S_3.

about these variables is both complete and precise. In such cases, the model uses the membership grades of the crisp inputs, e.g. $\mu_{Average}(.4) = .6$ is the membership grade of .4 and $\mu_{AH}(.8) = .7$ is the membership grade of .8 in "*About High*." For system S_3 the linguistic variations of the flexibility types under study are available. Note that the model does not only accept numerical inputs but also inputs that correspond to a different hierarchical level. The membership functions of values are shown in Fig. 7, and the "AND" connective is the "*compensatory AND*" given by (22) with $\gamma = 0.4$. Furthermore, the whole reasoning procedure is the same as in Section IV-H. The rules that describe flexibility of system S_i, with $i = 1, 2, 3$, are of the following form:

$$\text{IF } F_R^i \text{ is } T_{F_R^i} \text{ AND } F_{\text{MHS}}^i \text{ is } T_{F_{\text{MHS}}^i} \text{ AND } F_P^i \text{ is } T_{F_P^i} \text{ THEN } MF^i \text{ is } T_{MF^i} \tag{26}$$

where $F_R^i, F_{\text{MHS}}^i, F_P^i$, are the flexibilites of system i, and $T_{F_R^i}, T_{F_{\text{MHS}}^i}, T_{F_P^i}$, their fuzzy values. The membership function of flexibility for each system is presented in Fig. 7. Manufacturing system S_1 is more flexible than S_2, which in turn is more flexible than S_3. Applying (24) on the membership functions of Fig. 7, one can clearly see that

$$defMF^1 = 0.75 > defMF^2 = 0.5 > defMF^3 = 0.25.$$

V. Conclusion

Flexibility metrics are difficult to be defined, mainly due to the multidimensionality and vagueness of the concept of flexibility. In this paper, a knowledge-based framework for the assessment of manufacturing flexibility has been presented. The measure incorporates certain operational parameters, their variations and their effect on the value of flexibility. The necessary expertise is represented via fuzzy logic terminology which allows human-like knowledge representation and reasoning.

The measurement framework proposed in this paper is simple in principle and appears to have the following advantages.

1) It is adjustable by the user. Within the context of fuzzy logic, one can define new variables, values, or even rules and reasoning procedures. The model, therefore, provides a situation specific measurement and it is easily expanded.
2) It contributes to coding expertise concerning flexibility through multiple antecedent IF-THEN rules.
3) It provides successive aggregation of the flexibility levels as they are expressed through the already known flexibility types and, furthermore, incorporates types which have not been widely addressed such as labor flexibility.

In the proposed scheme the value of flexibility was given by an approximate reasoning method taking into account the knowledge that is represented by the closest rule to the real observation. An objective of future research is to investigate the influence of more rules on the value of flexibility. An additional topic should be the examination of the relationship between the level of flexibility and the corresponding financial performance of flexibility. The results of such a study will be useful in determining how much flexibility is needed and to what extent it will affect the profitability of a firm.

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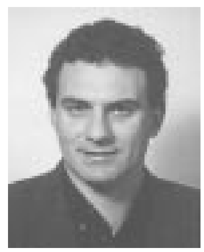

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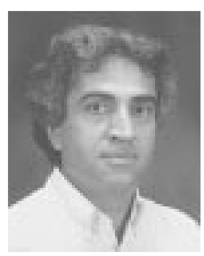

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