

Building a Fuzzy Logic based Tool for E-Readiness Measurement

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ABSTRACT

Firstly, this paper presents fuzzy logic based approaches for building a tool for measuring e-readiness of a country. This paper proposes fuzzy logic for realizing the measuring tool as fuzzy logic allows processing of heterogeneous indicators and imprecise values assigned for them. The tool is constructed by using one or more fuzzy logic based inference engines. Secondly, due to the problems in constructing pure fuzzy logic based inference engines, this paper also proposes some hybrid techniques for performance improvement; the hybrid techniques combines fuzzy logic with array-based logic.

Keywords: Fuzzy logic, array-based logic, hybrid inference system, e-readiness, e-government

1. INTRODUCTION

The e-readiness value of a country indicates how healthy the economy is and how attractive it is for investors. Investing in countries with higher e-readiness values will usually give higher and more secure returns.

There are many tools in use for measuring e-readiness. These tools make use of different parameters that are classified under a number of categories such as: infrastructure, access, applications and services, economy, use of the Internet, skills and human resources, e-business climate, pervasiveness (per capita usage), etc; Ifinedo and Davidrajuh (2005) provides a comprehensive coverage on the tools in use for measuring e-readiness.

1.1 E-Readiness Measurement

All the existing tools for measuring e-readiness use Figure-of-Merit (FOM) equation (Davidrajuh, 2005). A generalized FOM equation for e-readiness measurement features a series of indicators with corresponding weights (indicator-weights). The indicators are grouped into sectors; the sectors have different weights too (sector-weights). The sectors are further grouped

into blocks; each block is assigned a block-weight. Hence, an indicator is multiplied by up to three different weights (Davidrajuh, 2005).

There are two major problems in using FOM equation for e-readiness measurement:

1. Imprecise data: The first problem with the FOM equation is that values provided for indicators must be precise. However, in reality, the values provided for the same indicators by various sources differ considerably; this means, the indicator values are imprecise.
2. Inhomogeneous data: The second problem with the FOM equation is that all the indicators are assumed homogenous taking values on the same scale (e.g. 1-5). However, in reality, indicators are not homogenous. For example, an indicator may require Boolean answer (yes or no), or a multi-valued answer (within next twelve months are you planning to buy a personal computer, mobile phone, Internet access, any of these, or all of these) or linguistic quantifiers (such as many, most, at least, about, etc.).

FOM equation cannot be used to obtain an overall value (e-readiness measure) from a set of values for heterogeneous indicators. In addition, FOM equation is too sensitive to the imprecise values provided for the indicators. Hence, existing tools measure e-readiness based on limited homogeneous set of indicators only. This paper proposes use of hybrid inference engines that can process heterogeneous indicators; in addition, the hybrid inference engines can also cope with imprecise values assigned to the heterogeneous indicators.

In this paper: Section-2 presents fuzzy logic based inference engines for measuring e-readiness. Section-3 presents hybrid (fuzzy logic + array-based logic) techniques for improving performance of the inference engines for measuring e-readiness.

2. USING FUZZY INFERENCE SYSTEM (FIS)

This section explores the use of fuzzy inference system (FIS) for measuring e-readiness. Since fuzzy logic works well with imprecise data (Klir and Yuan, 1995) and with heterogeneous data sets (Yager and Kacprzyk, 1997; Yager and Zadeh, 1991), it can be used to realize inference engine for measuring e-readiness. However, there is a problem in utilizing fuzzy logic for this purpose; the problem is the large number of the fuzzy rules (Ross, 2004). The maximum number of fuzzy rules needed in a FIS is equal to (Tsoukalas and Uhrig, 1997): $\prod_{i=1}^n c_i$, where n is the number of indicators, and c_i is the number of linguistic labels for the i th input variable. For example, if we were to realize the tool by Bui et al (2003) using a FIS, assuming each of the 52 indicator has at least 3 linguistic values (let say 'high', 'moderate', and 'low'), then the maximum number of fuzzy rules needed is 3^{52} .

There are three major design options to reduce the sheer size of the fuzzy rules base in a 'pure' fuzzy logic based inference system:

1. Dividing the FIS into a multiple number of inference engines instead of a single engine
2. Employing a fuzzy inference method that operates on minimal set of rules
3. Finding a minimal set of input indicators

2.1 Number of Inference Engines

Rather than building monolithic single inference engine with large number of fuzzy rules, the system could be to split into several subsystems, arranged in several layers; the resulting system is a multi engine inference system. The first layer consists of subsystems each taking some of the input indicators as inputs. Thus, each subsystem in this layer computes a partial e-readiness measure, which will then be fed as inputs to the next layer and so on. The inference engine on the last layer, the exit layer, computes a single output as the final e-readiness measure (Davidrajuh and Tvedteras, 2006).

2.2 Fuzzy Inference Method

Three types of fuzzy inference systems could be developed depending on the fuzzy inference method employed by the inference engine (Ross, 2004):

1. Mamdani inference system,
2. Sugeno inference system, or
3. Hybrid Mamdani/Sugeno system.

Mamdani system requires user defined fuzzy rules and fuzzy membership functions. However, Sugeno system only requires input-output trainer data set. Though defining input-output trainer data set is easier than developing fuzzy rules and fuzzy membership functions, it is also a time-consuming and tedious task. Sugeno system is also computationally faster because it does not analyze membership functions. Table-1 summarizes the different types of FIS.

Table 1: Fuzzy inference system types

Inference systems	Remarks
Single engine	Impossible to build due to the exponential number of fuzzy rules
Multiple Mamdani	Input indicators are divided into a number of sets, and these sets are fed into different engines; thus, fewer fuzzy rules are needed
Multiple Sugeno	Same as multiple Mamdani system. But easier to build, as trainer data sets are somewhat easier to construct than the huge number of rules.

2.3 Minimal Set of Input Indicators

The last option for minimizing the number of fuzzy rules is to use a reduced set of indicators. Unlike 52 indicators in Bui et al (2003), the inference system may be designed to intake fewer indicators, say 10, considering the most important indicators and shedding the less important ones.

However, using a minimal of set of indicators can be a hazardous solution, as selection of indicators may drastically influence the output results. For example, Davidrajuh (2005) reveals that even though a case study on Sri Lanka shows a credible e-readiness measure (2.5 on 1-5 scale), the measure conceals many aspects including the domestic digital divide (domestic digital divide is the gap between citizens of a country in knowledge, access, usage, and mastery of ICT and the Internet); this is because, the measure does not include any indicators that can expose the domestic digital divide.

2.4 Deriving a Formula for the Number of Fuzzy Rules

Let us derive a formula for the number of fuzzy rules needed under different fuzzy inference system types: Assuming that all the N number of input indicators is m multi-valued:

- The maximum number of fuzzy rules needed for a single engine FIS is: m^N

However, if the FIS is divided into r layer of subsystems, i th layer containing n_i number of subsystems, then

- The maximum number of fuzzy rules needed for a multi engine FIS is:

$$\left(m^{N/n_1} \times n_1\right) + \left(m^{n_1/n_2} \times n_2\right) + \dots + \left(m^{n_{r-1}/n_r} \times n_r\right)$$

By keeping the ratios (N/n_1 and the subsequent ratios n_i/n_{i+1}) to a small integer (say around 4), the number of fuzzy rules can be reduced drastically.

2.5 Case Study: A Fuzzy Inference System for E-readiness Measurement

Finally, we present a case study on building a fuzzy logic based tool for e-readiness measurements.

2.5.1 Data model for indicator set

First of all, a hierarchical structured data model for indicators is used; the data model is based on Bui et al (2003). The data model consists of three basic building blocks:

1. Demand forces,
2. Supply forces, and
3. Societal Infrastructure

The three basic building blocks are further divided into eight major factors, and each of these major factors has a set of indicators. The major factors and the number of indicators that come under these factors are given below:

Demand forces:

Major factor-1 (Culture, understanding and effectiveness): 4 indicators

Major factor-2 (Knowledgeable citizens): 6 indicators

Supply forces:

Major factor-3 (Industry competitiveness): 7 indicators

Major factor-4 (Access to skilled workforce): 6 indicators

Major factor-5 (Willingness and ability to invest): 4 indicators

Societal Infrastructure:

Major factor-6 (Cost of living and pricing): 3 indicators

Major factor-7 (Access to advanced infrastructure): 10 indicators

Major factor-8 (Macro economic environment): 12 indicators

The data model uses a total of 52 indicators.

2.5.2 Preparing the inputs variables to the fuzzy engine

Figure 1 shows how the input indicators for e-readiness measurement are processed through the system. In figure 1, each indicator is first normalized and then combined to form 8 major factors, before they are fed as input to the fuzzy systems.

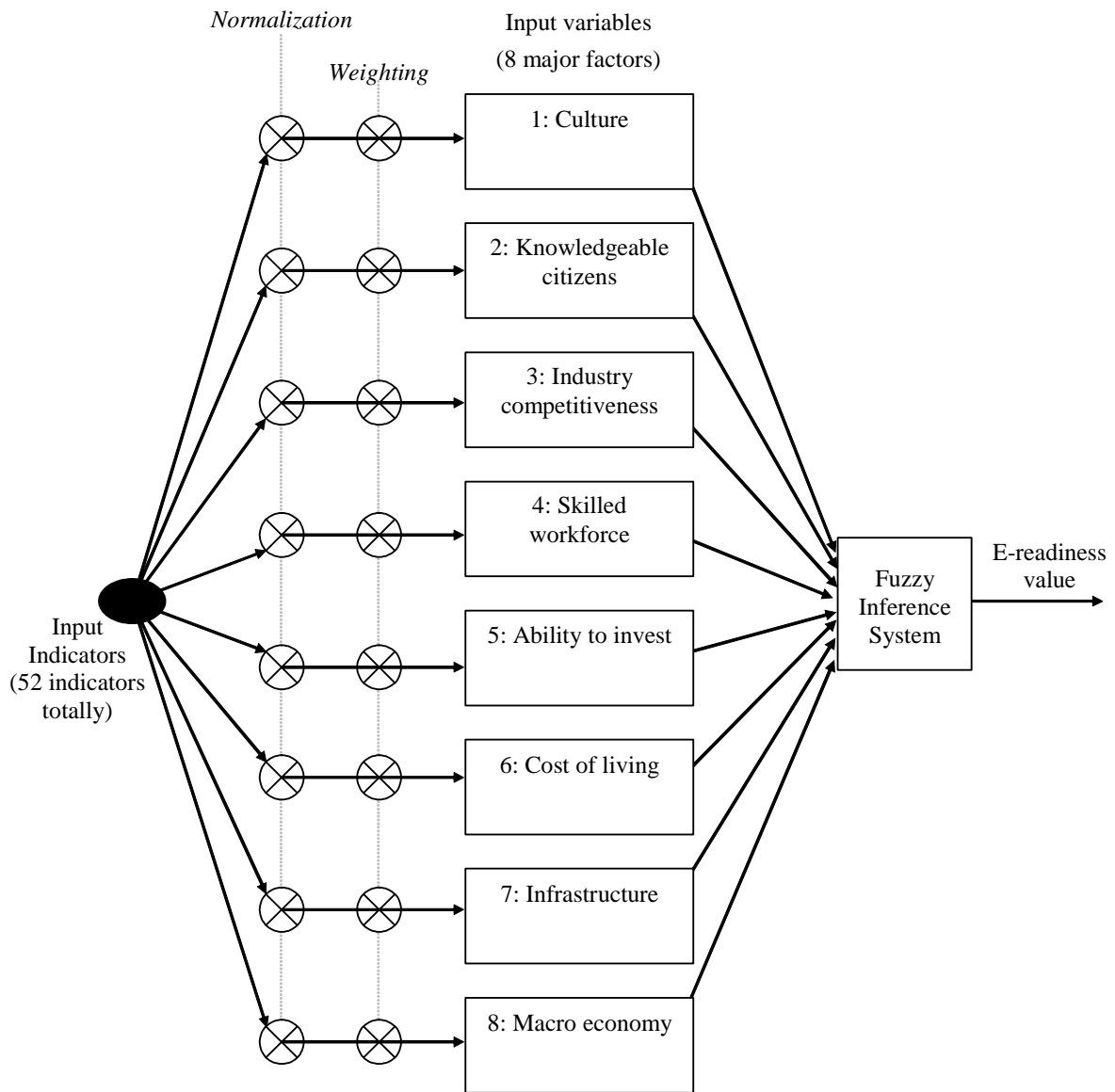


Figure 1: The overview of the fuzzy inference system

Normalization: Each of the inputs may be defined on different scales. Thus, in order to combine them to form main input variables, they must be ‘translated’ to a common scale.

Weighting: Since the variables have different number of input indicators (e.g. culture has 4 input indicators whereas infrastructure has 10 indicators), the indicator values must be also weighted so that all the variables have the same effect on the final output.

2.6.3 Experimentation and results

Three inference systems were developed. The first system consists of a single Mamdani inference engine taking 8 input variables (major factors), giving an output (e-readiness value) in the range [1-10]; see figure 1. For acceptable level of performance, the inference system was programmed with **304** rules in its rule base.

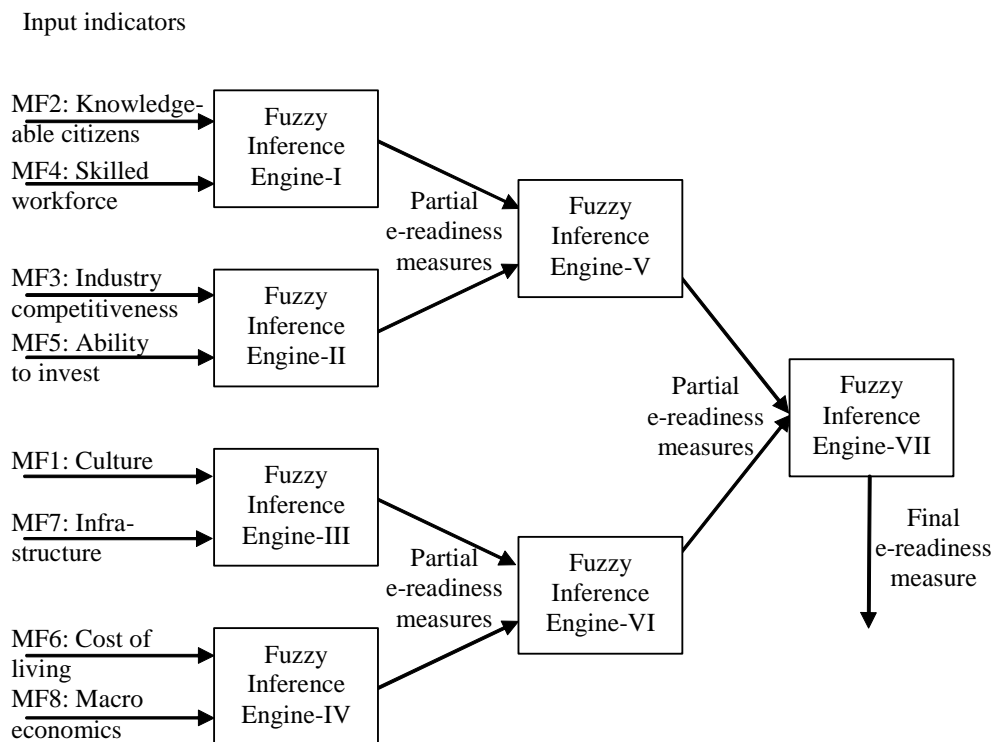


Figure 2: Multi-engine fuzzy inference system

The second inference system is a multi engine Mamdani system consisting of 7 Mamdani inference engines; see figure 2. The system needed a total number of **120** rules (Mamdani-I: 27, Mamdani-II: 27, Mamdani-III: 12, Mamdani-IV: 27, Mamdani-V: 9, Mamdani-VI: 9, and Mamdani-VII: 9)

3. HYBRID TECHNIQUES FOR PERFORMANCE IMPROVEMENT

The previous section pointed out that the major problem with the fuzzy inference system is the huge number of the fuzzy rules. Combining fuzzy logic with an alternative inference mechanism that does not require rules base (e.g. propositional logic (Huth and Ryan, 2000), predicate logic

(Huth and Ryan, 2000), or array-based logic (Davidrajuh, 2000; Møller, 1995)) is a strong option for reducing the number of the fuzzy rules.

Array-based logic can process huge number of logic variables in linear time; interested readers are referred to Møller (1995). Table 2 compares array-based logic with some other well-known logic inference mechanisms.

Table 2: Comparing the logic inference mechanisms

Technology	Property (Relation)	Inference mechanism	Inference cycle time
Propositional	Boolean values	Modus ponus etc.	Slow
Fuzzy logic	Fuzzy rules	Fuzzy rules, membership function	Fast
Array-based logic	Any predicate	Geometry	Fast

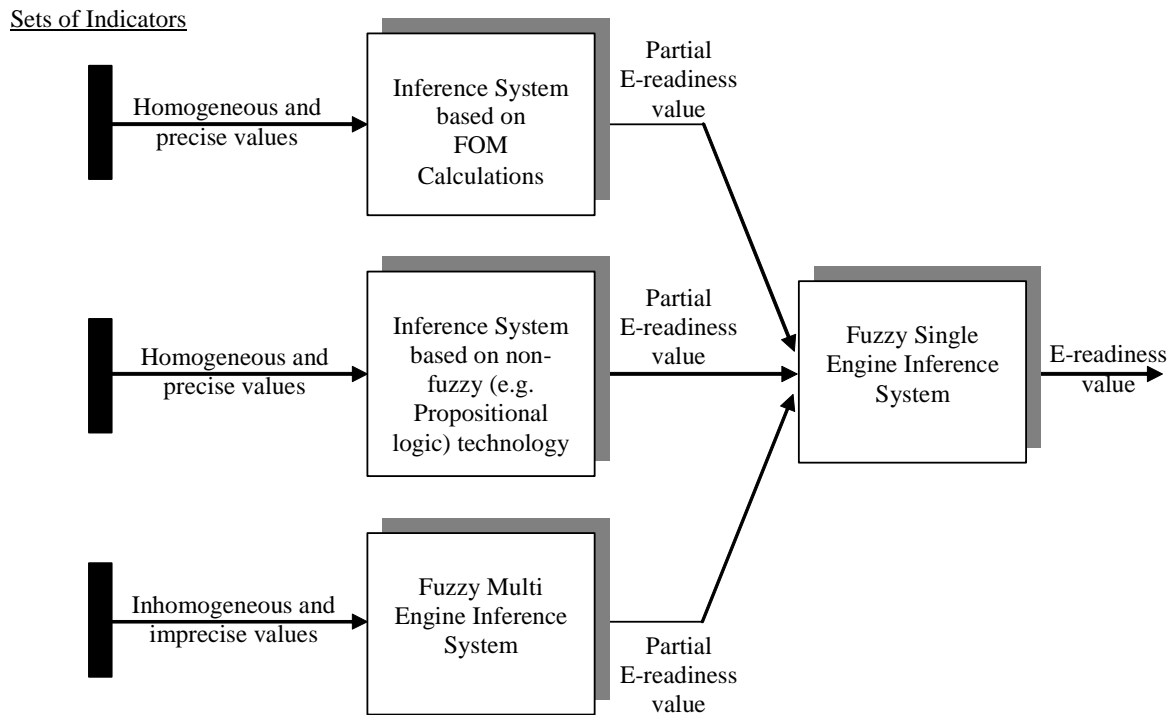


Figure 3: Hybrid Inference System

3.1 Designing a Hybrid System

There are a number of ways a hybrid system can be realized. This section analyses three approaches:

1. Array-Fuzzy parallel engines (independent inference engines with Array-based or fuzzy logic based back-end engine)
2. Fuzzy Arrays (Fuzzy preprocessors, Array-based main inference engine)

3. Array-switched Fuzzy engines

3.2 Array-Fuzzy Parallel Engines

In this hybrid approach, see figure 3, the input indicators are divided into two sets, the first set containing more precise values, and the second set containing less precise (or imprecise) values. The first set of indicators can be processed by a propositional logic based inference system or by FOM calculation. The second set of indicators can be processed by the fuzzy logic based inference system.

In addition to its ability to cope with precise as well as imprecise data, homogeneous as well as heterogeneous data, the main advantage of this hybrid system is the fewer number of fuzzy rules. This is because the system uses fuzzy logic to process only a portion of the input data.

The main difficulty with this approach is that it is not easy to classify the indicators as those that will get precise values, imprecise values, and as homogeneous and heterogeneous. In addition, the inference scheme demands deep understanding of all the mechanisms used, such as FOM, fuzzy logic, and propositional logic.

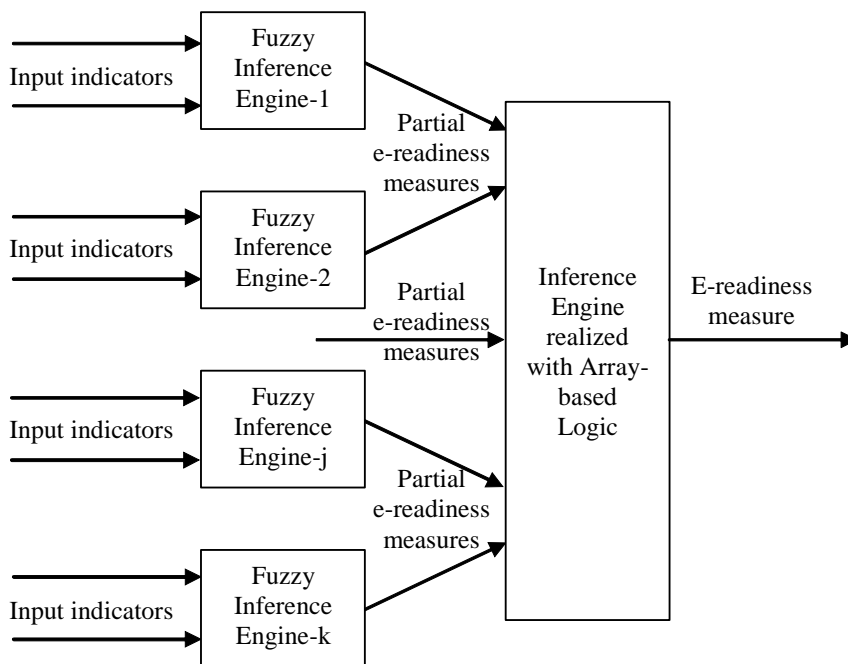


Figure 4: Hybrid fuzzy-array inference system

3.3 Fuzzy Arrays

In this hybrid approach, see figure 4, fuzzy inference engines are used as preprocessors to filter the “impurities” bounded with the imprecise input values. The outputs of the fuzzy engines are then processed by the inference engine realized with array-based logic.

In effect, the hybrid fuzzy-array model has fuzzy logic based inference engines in the first layer, and array-based logic inference engine in the subsequent layers. Thus, the hybrid model copes with any kind of indicators (precise to imprecise, homogenous and heterogeneous) by using fuzzy logic as the preprocessors, and it eliminates the need for large fuzzy rules base by using array-based logic as the main inference mechanism.

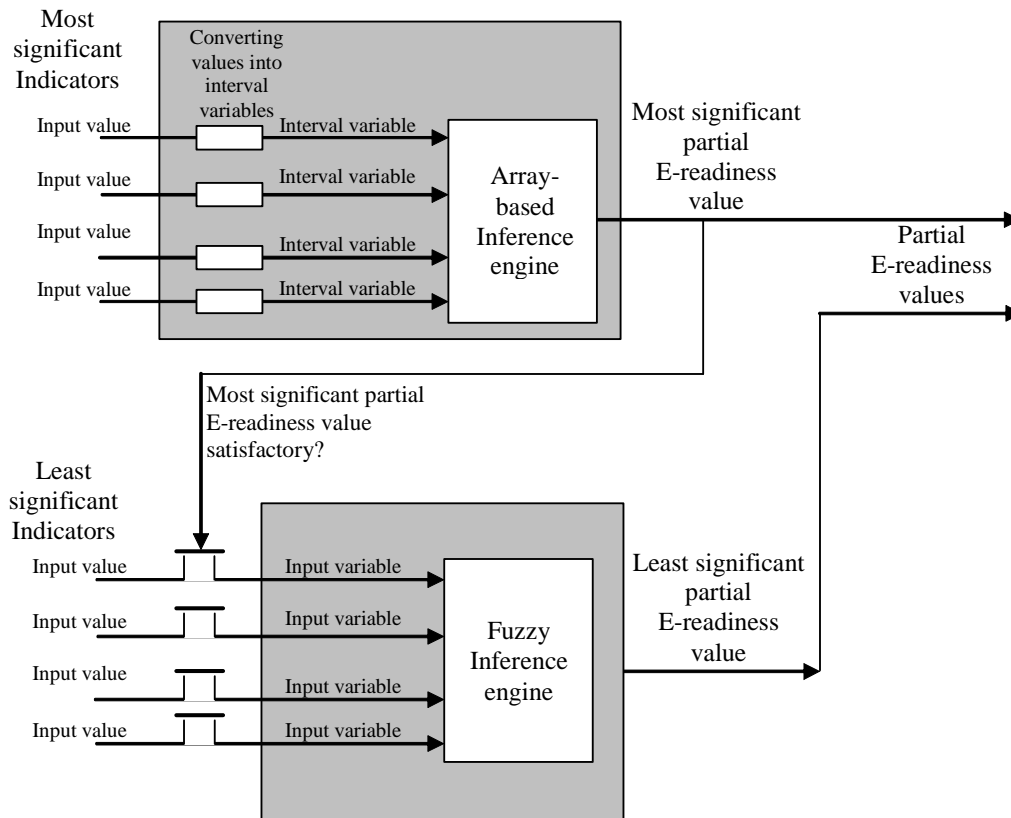


Figure 5: Array-switched fuzzy inference system

3.4 Array-switched Fuzzy Engines

In this hybrid approach, we classify the input indicators into two sets, 1) the set of most important or significant indicators, and 2) the set of least significant indicators.

The input values for the set of most significant indicators are then converted into interval variables and then processed by an array-based inference engine; see figure 5. The input values for the set of least significant indicators are processed by the fuzzy logic based inference engine.

Since the least significant indicators are left to fuzzy logic based inference engine, the inference engine need not be complete, in the sense, it is not necessary to program all the needed fuzzy rules. Hence, the inference engine operates with the minimal number of fuzzy rules.

Though array-based inference engine processes the most significant indicators, the values for these indicators need not be precise, as the engine maps the values into proper intervals. Thus, working with intervals wash-away the impurities attached with the input values.

Another advantage of this hybrid approach is that sometimes it is not needed to run the fuzzy inference system at all: suppose, processing of the most significant indicators results in an unsatisfactory partial e-readiness value, then there is no point in processing the least significant set of indicators. Thus, the fuzzy inference engine is switched on and off depending on whether processing of the most significant indicators results in satisfactory or unsatisfactory partial e-readiness value, respectively.

The main difficulty of this approach is that the input indicators must be divided evenly, into the two sets that are of nearly equal size. If only a few indicators are selected as the important ones, then the rest of the indicators that falls into the least significant set should be processed by a hierarchy of fuzzy logic inference engine (multi-engine FIS) and not by a monolithic single engine FIS. This means, dividing the indicators unevenly into the two sets will not result in a simple solution.

4. CONCLUDING REMARKS

In this paper, we present fuzzy logic based approaches for building a tool for measuring e-readiness of a country. SMEs, large corporations and even governments have used e-readiness measure to gauge investment climate of other countries (Mostafa, 2007; Gonzalez et al, 2007; Zizmond and Novak, 2007; Dwivedi and Lal, 2007). This paper proposes fuzzy logic for realizing the measuring tool as fuzzy logic allows processing of heterogeneous indicators and imprecise values assigned for them. The tool is constructed by using one or more fuzzy logic based inference engines. However, pure fuzzy logic based inference engine demands exponential number of fuzzy rules (aka ‘*combinatorial explosion*’). In order to avoid the problem of combinatorial explosion, we also propose some hybrid techniques; the hybrid techniques combine fuzzy logic with array-based logic.

Conclusion of this work is summarized in table 3. The first approach - hybrid fuzzy/non-fuzzy parallel engines – can process any type of indicators (precise/imprecise, homogenous and heterogeneous). This approach also provides fast and compact inference system. However, the main disadvantage of this approach is that it demands knowledge in diverse issues like Fuzzy logic, FOM, propositional logic, etc.

Table 3: Three different hybrid systems for measuring e-readiness

Hybrid system	Characteristics
Hybrid parallel engine	Advantage: process any type of indicators. Fast and compact inference system. Disadvantage: demands knowledge in diverse issues.
Fuzzy arrays	Advantage: process any type of indicators. Reduced number of fuzzy rules.
Array-switched fuzzy engines	Advantage: no need for complete FIS. Disadvantage: dividing the input indicators into the two sets is not easy.

The second approach is using fuzzy arrays. An inference system made up of fuzzy arrays can also process any type of indicators by using fuzzy pre-processors; the main advantage of this approach is that the number of the fuzzy rules is reduced by using the array-based logic as the main inference mechanism.

In the third approach where array-switched fuzzy engines are employed, the set of most significant indicators is processed by array-based inference engine; fuzzy logic is used process the set of least significant indicators, thus the FIS need not be complete. However, it is not easy to evenly divide the input indicators into the two sets.

Further work: The proposed hybrid techniques for performance improvement were not tested yet. Obvious extension of this work is to build testing prototypes based on the hybrid techniques.

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