MYOCARDIAL INFARCTION DIAGNOSIS USING FUZZY-EXPERT APPROACH

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ABSTRACT

A fuzzy expert system is a system which incorporates fuzzy sets and/or fuzzy logic into its reasoning process and/ or knowledge representation scheme. It allows the knowledge to be encoded in a form that reflects the way experts think about a complex problem. Since fuzzy expert approach model imprecise information, it improves the cognitive modelling of the problem and therefore makes it more powerful. The Expert system and fuzzy logic have their own significant capabilities; hence the combination of both technologies that form a fuzzy-expert system or a hybrid system could increase the systems performance (Herrmann, 1996). This paper presents the use of such technologies in the system known as FEMInS. The system assists the general medical practitioners in handling heart attack cases that have been referred to them. Unlike conventional expert systems, FEMIns implemented the fuzzy logic technique in its inference engine. Since fuzzy logic can be used for prediction, and expert system can provide explanation and reasoning, the combination of both fields is able to cope with the problems of uncertainty and provide the explanation of the results to the user. FEMIns demonstrates that both fuzzy logic and expert system complement rather than complete with each other.

Keywords: expert system, fuzzy logic, hybrid system, expert fuzzy system, artificial intelligence.

1.0 INTRODUCTION

Computational intelligence has been used to solve many complex problems by developing intelligent systems. It has been applied in various fields such as engineering (Abdullah *et al.*, 2003), business (Abdul. Aziz *et al.*, 2003; Siraj *et al.*, 2003), medicine (Sharkey *et al.*, 1998; Siraj *et al.*, 2002) and economics (Siraj and Mat Junoh, 2001). Many of the early efforts to apply computational intelligence to medical reasoning problems have primarily used rule-based systems (Szolovits *et al.*, 1988). In traditional rule-based approach, knowledge is encoded in the form of antecedent-consequent structure such that when new data is encountered, it is matched to the antecedent classes of each rule. Those rules where antecedent match a data exactly are fired, establishing the consequent clauses. This process continues until a desired conclusion is reached, or no new rule can be found.

Expert systems have been developed to solve a wide range of problems. In medical diagnosis, such programs are typically easy to create because their knowledge is catalogued in the form of if-then rules. However, in real-life situations, there is considerable degradation of performance due to the presence of both ambiguity and incomplete information as well as inadequate modelling of the diseases by the rules (Mitra *et al.*, 2000). On the other hand, fuzzy logic and fuzzy set theory provide a good framework for managing uncertainty and imprecision in medicine (Halim *et al.*, 1990; Dounias, 2003) and have been successfully applied to a number of areas (Watanabe, 1994). It was felt that a fuzzy logic based expert system would offer more realistic and acceptable interpretation (Garibaldi and Ifeachor, 2000).

Since expert system and fuzzy logic have their own significant capabilities, the combination of both technologies that form a fuzzy-expert system or a hybrid system could increase the systems performance (Herrmann, 1996). The increased popularity of hybrid intelligent systems is due to the extensive success of these systems in a wide range of real-world complex problems The computational intelligent components such as machine learning, fuzzy logic, neural network, genetic algorithms, or other intelligent heuristics provide hybrid systems with complementary reasoning and searching methods that allow the use of domain knowledge and empirical data to solve complex problems (Dounias, 2003). This paper presents the use of such technologies in the system known as FEMInS. The system serves as an assistant to general medical practitioner in handling heart attack cases that have been referred to them. Unlike conventional expert system, FEMIns implemented the fuzzy logic technique in its inference engine. Since fuzzy logic can be used for diagnosing, and expert system can provide explanation and reasoning, the combination of both fields is able to cope with the problems of uncertainty and provide the explanation of the results to the user. FEMIns demonstrates that both fuzzy logic and expert system complement each other rather than compete with each other.

2.0 FUZZY EXPERT MYOCARDIAL INFARCTION SYSTEM

Computational intelligence tools and techniques have been successfully applied to medical and biomedical applications. In many cases, hybrid combinations are capable of describing an approximate reasoning for these domains (Dounias, 2003). Dounias defined hybrid computational intelligence as any effective combination of intelligent techniques. Since the hybrid systems are proved superior to each of their underlying components, therefore these systems provide better problem solving tools. Hybrid systems like fuzzy expert have been investigated very intensively in recent years and several successful applications have been reported in the literature (Butkiewicz, 1997). The success of such hybrid systems was due to their linguistic representations of cognitive observations that yield more informative and reliable interpretations than traditional arithmomorphic representations (Bloch, 2000).

The development of FEMInS (an acronym for Fuzzy Expert Myocardial Infarction System) was based on the combination of two computational intelligence techniques, namely the expert system and fuzzy logic. FEMInS has been developed to help the general medical practitioner to diagnose heart attacks based on early symptoms. Since the users of the system are definitely someone from the medical domain, therefore, jargons or medical terms are used while running through the system. Fuzzy logic has been implemented in FEMInS in order to handle the uncertain information. Since fuzzy logic can be used for diagnosing, and expert system can provide explanation and reasoning, the combination of both fields is suitable for medical domain system, which generally needs to cater for the problems of uncertainty and provide explanation of the results to the user.

The system is intended to serve as an assistant to medical practitioners in order handle heart attack cases that have been referred to them. The medical practitioner will question the patients, and the answers given will be entered into the system. The system analyses the symptoms and predicts the risk of getting heart attack of the specified patient. The risk, which is presented in terms of percentage will be calculated using fuzzification and defuzzification technique. All the details regarding consultation are stored in a database for further reference. An overview of FEMInS system is shown in Figure 1.

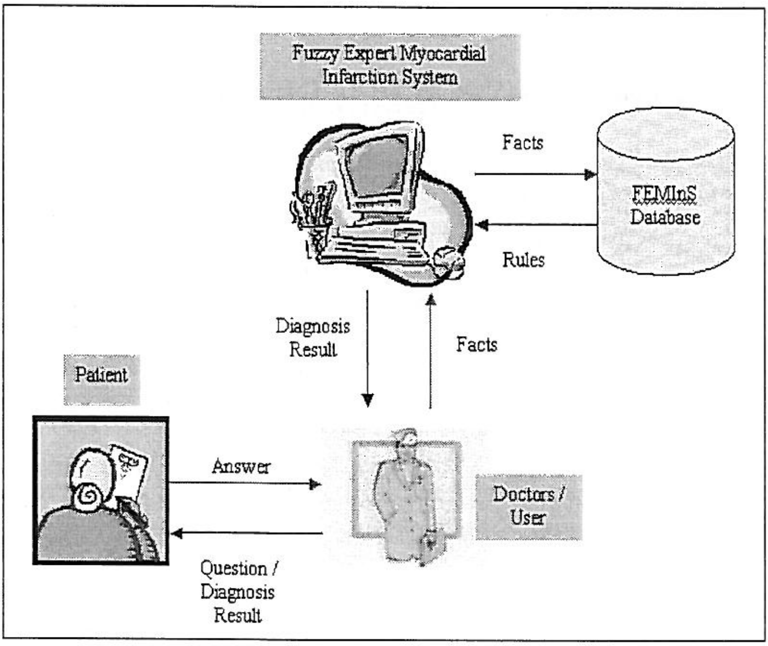

Fig. 1: An overview of FEMInS

2.1 Knowledge Acquisition and Representation

Based on the research, a few domain selections have been identified, which are Myocardial Infarction (Heart Attack), cancer disease and gynecology. Among the listed selections, the heart attack problem has been identified as one of the most crucial problems in the medical domain since the disease really needs to be diagnosed by experienced cardiologists, the number of whom is small in Malaysia. Realizing the problem and opportunity existing as a result of the shortage of experts, heart attack has been chosen as the domain of this study.

During the first interview, the expert briefly discusses the common factors of getting heart attack and a common way to diagnose it. After the first meeting, the information that has been gathered was analyzed carefully. This is to ensure that all the information is useful to the development of the system and no unimportant idea is included in the script. The second interview concentrates on refining of the problem and the rules that have been briefly constructed. Each heart attack factor is discussed further in order to extract relevant rules.

Information that has been verified and gathered through the knowledge acquisition process are interpreted and filtered to map with the system's requirement. Unnecessary information has been excluded. The information is then analyzed and presented in suitable forms of knowledge representation.

2.2 System Design and Development

As in conventional expert system, FEMInS can be divided into four major components. They are knowledge base, working memory, inference engine and user interface (see Figure 2). Unlike conventional system, input and output variables to FEMInS are fuzzy variables

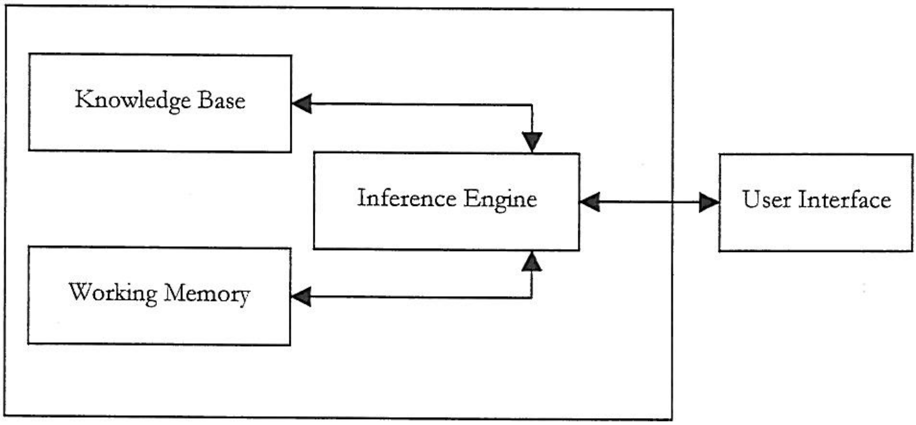

Fig. 2: Components of FEMInS

The process of diagnosing heart attack was divided into four main sections, which are History of Presenting Illness (HOPI), Personal Medical History (PMH), Personal and Social History (PSH) and Diet History. Based on 17 different symptoms, a total of 17 inputs to the system were generated. The distribution of the inputs is shown in Figure 3.

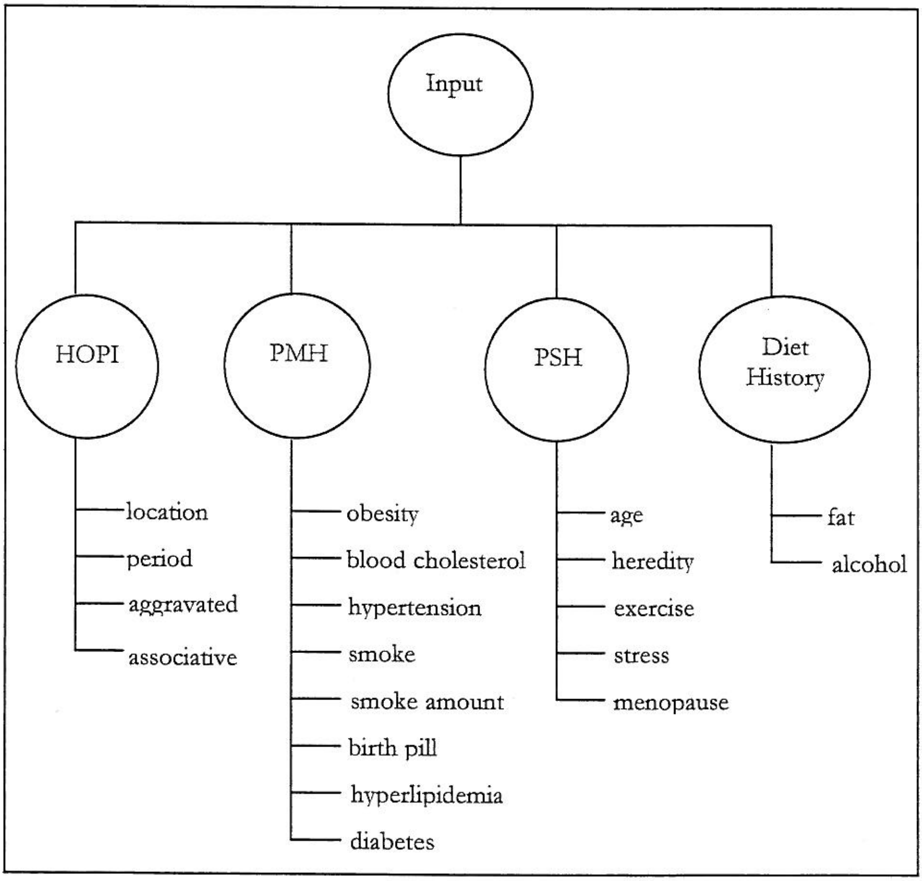

Fig. 3: Inputs of the system

It is important to note that every patient might get a slightly different set of questions, depending on his/her previous answer or personal profile. For example, questions regarding menopause will only be asked if patient is female with age above 50. Questions regarding smoke amount will only be asked if patient indicates that he/she smoked in the previous question. Birth pill question also will only be asked to a female patient.

A synchronized number of 3 linguistic variables is being used for all inputs; except for inputs with yes/no answer. Listed below are the linguistic variables for each of the inputs in PSH section.

Age € { Young, Middle age, Old }
Heredity € { Negative, Medium, Positive }
Exercise € { Lack, Medium, Enough }
Stress € { Low, Medium, High }
Menopause € { Yes, No }

A trapezoid membership function graph has been used to represent each fuzzy input variable.

In the PSH section, since there are three linguistic variables for each of variables, three confidence values will be generated at a time. The process of getting the confidence value for each of the inputs and linguistic variables is as illustrated below.

```
'-------------------------------------------
' fuzzifying the inputs into confidence value
'-------------------------------------------

Public Sub Fuzzification()

    cf(variable_number, 1) = FuzzyZ(real_value, current_range(1), current_range(2))
    cf(variable_number, 2) = FuzzyDelta(real_value, current_range(3), current_range(
    cf(variable_number, 3) = FuzzyS(real_value, current_range(6), current_range(7))

    x1 = Max(cf(variable_number, 1), cf(variable_number, 2), cf(variable_number, 3),

End Sub
```

Fig. 4: Fuzzification code

The fuzzification is performed by calling the respective function in the program by referring to the type of graph that is represented by each of the linguistic variables for each input value. For example, by referring to Figure 4, for *young* a Z-type graph has been used, so the function *FuzzyZ* has been called accordingly. As for *middle age* a function *FuzzyDelta* has been called since the variable used this type of graph. The same goes to *old* linguistic variable, which has an S-type graph, and the function *FuzzyS* has been called.

The second phase of developing fuzzy system is fuzzy inference, where the evaluated input values are combined in rule sets. Some of question evaluations require a hierarchical model structure and the combination of rules was performed multiple times. In general, the inference engine acts as a mechanism that produces the diagnosis results. The inference engine will take the input from user through user interface and put it into the working memory after it has gone through fuzzification and fuzzy inference phase. It will then match the information in working memory and knowledge base. It also has explanation utility, which enables it to give an explanation to user of why a question is being asked and how the system arrived to the conclusion. The general flow of FEMInS generated by the inference engine is illustrated in Figure 2.

There are two levels of output being defined in this system. First level outputs are HOPI, PMH, PSH and Diet History. After the set of questions for each section have been asked, the system will generate the output for the respective section. Second level output, which is also the final output of the system, is Heart Attack that is stated in terms of percentage. The first level output will act as the input for the second level of fuzzification, hence producing Heart Attack percentage as final output. The relationship between the outputs is shown in Figure 5.

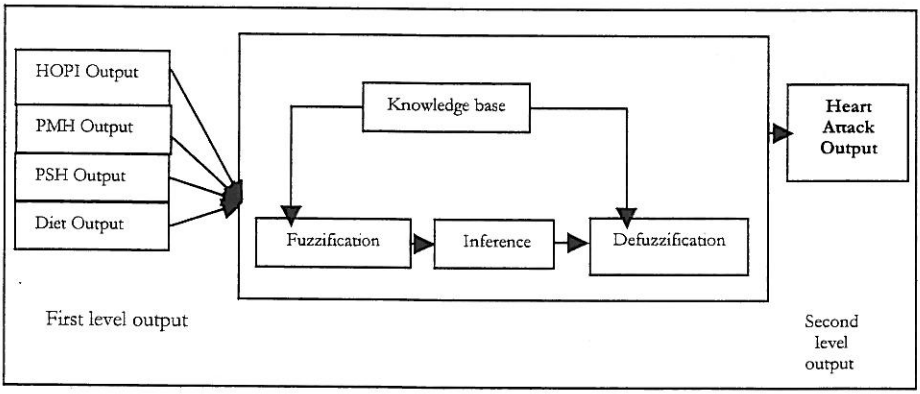

Fig. 5: First and second level output relation

A synchronized number of 3 linguistic variables is being used for all outputs. Listed below are the linguistic variables for each output.

HOPI € { Low, Medium, High }
PMH € { Low, Medium, High }
PSH € { Low, Medium, High }
Diet € { Low, Medium, High }
Heart Attack € { Low, Medium, High }

Based on justification by the experts, sets of rules have been defined. For each pair of inputs, a fuzzy associative matrix (FAM) table will be constructed. For example, for input age and heredity of PSH, a FAM table is constructed. The table is built based on the rules that have been specified by the expert. FAM table of input age and heredity is shown in Table 1.

Table 1: FAM table of input age and heredity

Age / Heredity	Young	Middle Age	Old
Negative	Low	Low	Medium
Medium	Low	Low	Medium
Positive	Medium	Medium	High

Based on the table, there are nine rules that can be generated. Listed below are the nine rules:

i) IF age is young AND heredity is negative THEN PSH is low
ii) IF age is young AND heredity is medium THEN PSH is low
iii) IF age is young AND heredity is positive THEN PSH is medium
iv) IF age is middle age AND heredity is negative THEN PSH is low
v) IF age is middle age AND heredity is medium THEN PSH is low
vi) IF age is middle age AND heredity is positive THEN PSH is medium
vii) IF age is old AND heredity is negative THEN PSH is medium
viii) IF age is old AND heredity is medium THEN PSH is medium
ix) IF age is old AND heredity is positive THEN PSH is high

Referring to Table 1, the columns are representing linguistic variables for input age, whereas the rows are representing linguistic variables for input heredity. The intersection of each column and row is the output for PSH.

The objective of the defuzzification phase is to convert the confidence values back to real values that can be understood by the user. In this stage, the respective real values for all the confidence values that we get from the inference rules process will be obtained. It will map the confidence value with its respective membership function graph for outputs (Figures 3.13, 3.14, 3.15, 3.16, 3.17) and obtain the real values for it. The confidence value for output with high label will be compared with the membership function graph of high, and the same goes for normal and low output. Below is the algorithm for the process described above.

```
Public Sub ValueFAM(symptom_temp As String)

    Form2.Adodc9.RecordSource = "SELECT * FROM FAM WHERE symptom LIKE '" & symptom_te
    Form2.Adodc9.Refresh

    For i = 1 To 9

        fam = Form2.Adodc9.Recordset.Fields(i).value

        If fam = "low" Then
            valueW(i) = Defuzzify_Value_Low(w(i), current_range(1), current_range(2))
        ElseIf fam = "medium" Then
            valueW(i) = Defuzzify_Value_medium(w(i), current_range(3), current_range
        ElseIf fam = "high" Then
            valueW(i) = Defuzzify_Value_High(w(i), current_range(6), current_range(7)
        End If

    Next i

End Sub
```

Fig. 6: Defuzzification code

Next, the method of centre of area (COA) has been used to determine the real value of the output. The algorithm for this defuzzification method is

$$U = \frac{\sum_{i=1}^{N} u_i \mu_{out}(u_i)}{\sum_{i=1} \mu_{out}(u_i)}$$

where U is the real value for output, u_i is the real value for the respective output of w1 and so on, and $\mu_{out}(u_i)$ is the respective confidence value for u_i.

In the system, the value of u_i refers to the array *valueW(i)* while value for $\mu_{out}(u_i)$ refers to array w(i). The real output value is obtained by using the above-mentioned formula. This value is presented to the user as the output.

3.0 RESULTS

Previous studies have shown that hybrid systems could increase the system performance (Reilly *et al*, 1996; Buckley *et al.*, 1999; Zhang, 1999). Hybrid fuzzy-neural expert systems have been built before for diagnosis and were able to combine most of their advantages and avoiding some of their disadvantages at the same time (Herrmann, 1995). FEMInS development has demonstrated that fuzzy logic can handle uncertainty better than expert system. This is due to the fact that fuzzy logic uses multi-labels and multi confidence values to reach a conclusion.

Comparing with previous expert system developed in the same domain, FEMInS has shown a better result in term of the output produced. It is more acceptable and logical. Answers from the patients can be accepted in exact form. This can be seen from the various means of getting input from the patient. While conventional expert system usually provide users with only two choices, either Yes or No, FEMInS gives more flexibility to the user to enter the data. Figure 7 shows the interface of FEMInS that require the user to select the symptoms that he experienced from the given list.

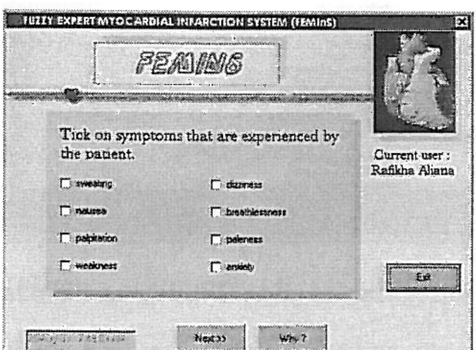

Fig. 7: A snapshot of FEMInS interface

FEMInS offers more realistic and acceptable interpretation of medical data. It allows the results to be presented to medical practitioners in a more natural form. In the output window, the result displayed is the percentage of probability whether patient will have a heart attack or not (see Figure 8).

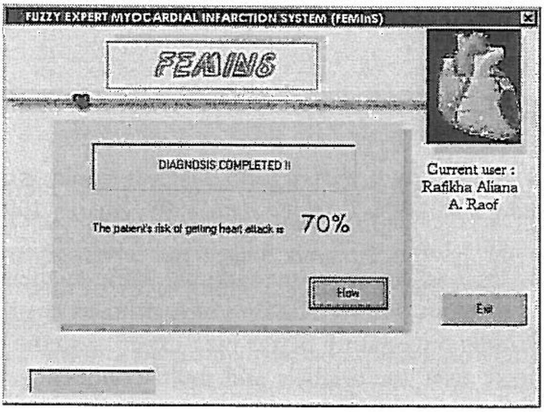

Fig. 8: Output of FEMInS

FEMInS also provides reasonable explanation of how it reaches such a conclusion. A snapshot of the explanation window is shown in Figure 9.

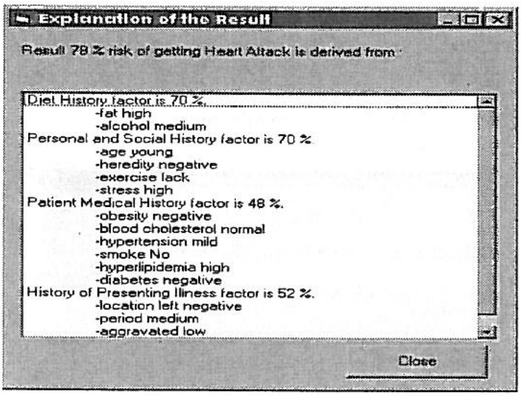

Fig. 9: Explanation Window in FEMInS

A number of advantages can be taken from this fuzzy expert system approach as compared to a conventional expert system. The expert system rules can be acquired in their verbal description and need not be formalized further. Expert can now use terms such as very old, quite young, severely ill and so on when delivering the knowledge. The rules also only needed to be translated into FAM tables, which are more efficient.

FEMInS can be used by doctors to provide a more accurate diagnosis to heart attack. The problem of shortness of the expert system can be overcome because the system will guide the general medical practitioners on the best way to diagnose heart attack. Consultation with the system will create the environment as if the doctor is making the diagnosis with the real expert with the existing of knowledge base that stores all techniques and information captured from the real expert.

A number of advantages can be taken from this fuzzy-expert system approach as compared to a crisp or conventional expert system. Expert rules can be acquired in their verbal description and need not be formalized further. The number of necessary rules also have been reduced since the transition regions of variables are handled by the inference mechanism.

The results from the study demonstrate that the integration of expert system with fuzzy logic allows the prediction to be performed and the explanation to be provided by the system. Therefore, expert system and fuzzy logic techniques complement each other rather than compete.

4.0 CONCLUSION

This study focuses on the software development using hybrid AI technology. Hence, it emphasizes on data acquisition and mapping of uncertainty into fuzzy values, which consists of labels and confidence values. This involves the determination of membership function graph that requires knowledge from medical practitioners. The mapping process is very crucial in this study since if incorrect membership function graph is chosen, the final value yields from the fuzzy logic system would also be incorrect.

For testing purposes, medical practitioners were involved to verify the correct information coded and the correct result evaluated from FEMInS. Although fuzzy logic eases the mapping problem, more programming effort was involved. To this end, fuzzy technique has definitely eased the mapping process. As a result it produces more meaningful information to the user as well as improving the efficiency of handling uncertainty.

FEMInS could be enhanced by integrating the system with other AI technology. Since neural network is a useful tool for prediction, its combination into the system to enhance the power of prediction and diagnosis of the system in the future should be considered.

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