CHAPTER 11

A FUZZY, KNOWLEDGE-BASED NEONATAL RESUSCITATION MANAGEMENT SYSTEM †

11.1. Introduction

Neonates are considered as a high risk group of paediatric problem domain since more than 50% of total infant mortality in India occurs during first month of life. For the proper management of neonatal problems highly skilled Paediatricians or Neonatalogists are required. But, however, for a developing country like India, there are some socio-economic problems in this regard. In India, Paediatricians and specially Neonatalogists are a scarce commodity. The situation is more grave for rural regions. It might have been better if one such human expert be appointed at each and every health centre in our country and which may not be simply feasible. To mitigate the lack of proper human experts, a computer aided consultation system in an ES framework may be considered as a graceful alternative. This automated system may be used by a general medical practitioner to have expertise advice. Starting from MYCIN, a good number of attempts have been made to develop different expert systems / knowledge based systems in medical domain. But, however, in our opinion, the potential of fuzzy logic has not been exploited at length to cover different aspects of the paediatric domain. By far the greatest use of fuzzy logic has been in control applications. This motivated us to explore such possibility of use of the logic in paediatric domain, in particular, for neonatal resuscitation management.

In section 11.2, we have provided the system analysis part of the development process. Sections 11.3 and 11.4 present the fuzzification of system state input variables and fuzzification of system state output variable respectively. Inferencing process has been described in section 11.5. Section 11.6 provides the performance evaluation of the system. In the last section, we draw our conclusions.

11.2. System analysis

The goals of neonatal resuscitation are to prevent the morbidity and mortality associated with hypoxic-ischemic tissue (brain, heart, kidney) injury and to re-establish adequate spontaneous respiration and cardiac output [1].

---

† This is based on the publication [Proc. 3rd. Int. Conf. on Cognitive Systems (ICCS'97) 13-15th Dec 1997, vol.2, 627- 636, Delhi] of the author.

Different levels of resuscitation are required depending on the signs and symptoms of a newborn as observed by a medical practitioner. In general, APGAR-score [1] is used for resuscitation management. This scoring system uses five main components such as **muscle tone of limbs**, **heart rate**, **respiratory effort**, **reflex stimulation** and **colour**. Although doctors are used to dealing with precise numeric data in respect of some factors, for example, heart rate, there is nevertheless considerable uncertainty with these factors. Much of the knowledge as gathered by doctors may have shades of meaning (fuzzy). For example, heart rate, say 95/min may belong to two regions but with different possibility values as depicted in fig.11.1.

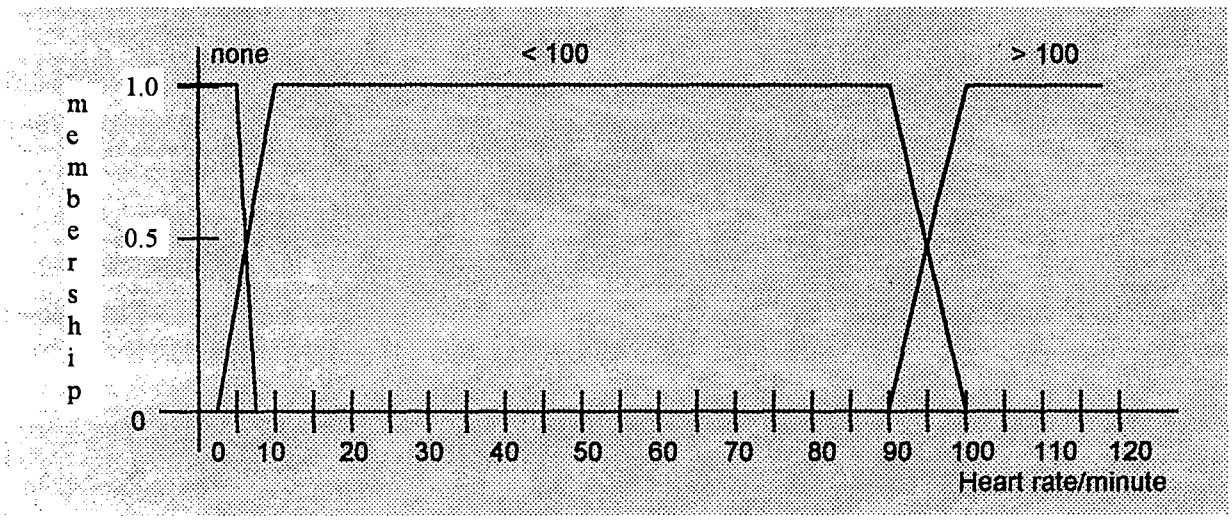

Fig.11. 1 Heart rate

This heart rate 95 per minute might not sharply be defined in strictly one region. For another example, let us consider muscle tone of limbs. In general, flexion is observed at wrist, elbow, shoulder, ancle, knee and hip. It is sometimes difficult to define the value as flaccid or some-flexion or active as depicted in fig.11.2.

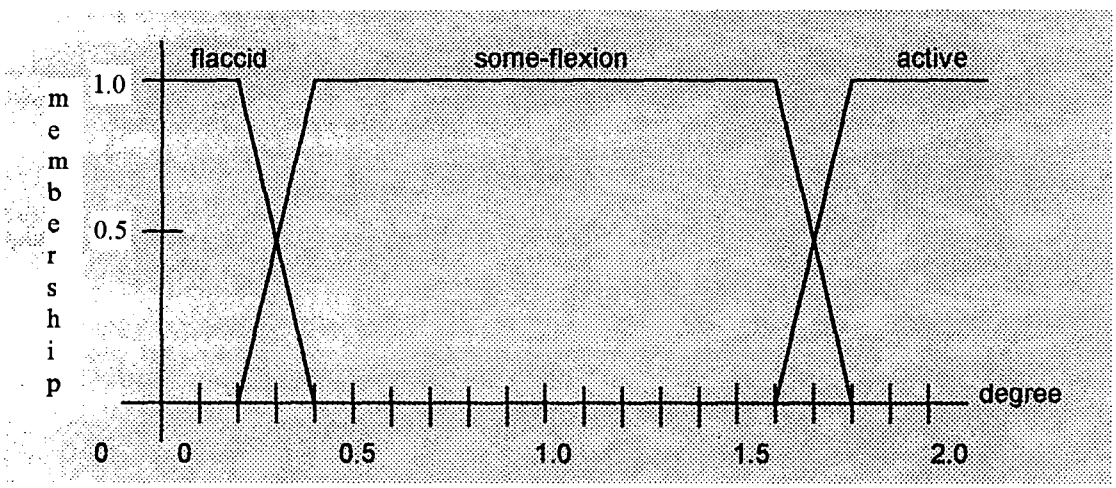

Fig.11. 2 Muscle tone of limbs

Once such fuzzy variables and term sets are defined, the knowledge representation using rules will become easy. For the present problem domain (for a neonate), main linguistic variables and the corresponding term sets may be identified as :

- Muscle tone → {flaccid, some-flexion, actively moving the extremities};
- Heart rate → {none, normal(100-140), low};
- Respiratory effort → {none, slow/irregular, good/crying};
- Reflex stimulation → {noresponse; grimace; cries, coughs or sneezes};
- Colour → {blue/pale, periphery blue and body pink, pink}.

Every member of a term set will be attached to a set of numerical values between 0 and 1 (inclusive) called possibility values or grades of membership in the term set. This fixation of numerical values, obviously, will be done by domain experts. It is, now, important to examine the 'adequacy' of a term set for the problem domain. The question of granularity of representation comes into picture in this context. If we have too few members in a term set, a system may be inadequately descriptive. If we have too many members in a term set, this may lead to unmanageable situation in two important respects. First, large amount of storage space will be required for storing fuzzy tables. Or if one desires to represent such terms using mathematical functions, the number of such functions may be unmanageably high which may lead to reduction of speed of a typical expert system. Second, the associated rules will become cumbersome. One feasible solution of the above problem may be achieved using the concept of '**hedges**' and fuzzy logical operators AND, OR, NOT.

11.3. Fuzzification of system state input variables

In this model, **muscle tone of limbs**, **heart rate**, **respiratory effort**, **reflex stimulation** and **colour** are treated as the state fuzzy variables. Fuzzification of variables lies under the trade-off between precision in resuscitation decision and computation time. Each of the system state fuzzy variables is decomposed into a reasonable number of fuzzy regions following the rules of thumb [2]; that is, an odd number of labels associated with a variable had been chosen. Each label should overlap somewhat between 10% and 50% with its neighbours. The five system input state variables were fuzzified e.g. figures 11.1 and 11.2 where fuzzification of heart rate and muscle tone of limbs are shown respectively. Figures 11.3, 11.4 and 11.5 show the fuzzification of respiratory effort, reflex stimulation and colour respectively.

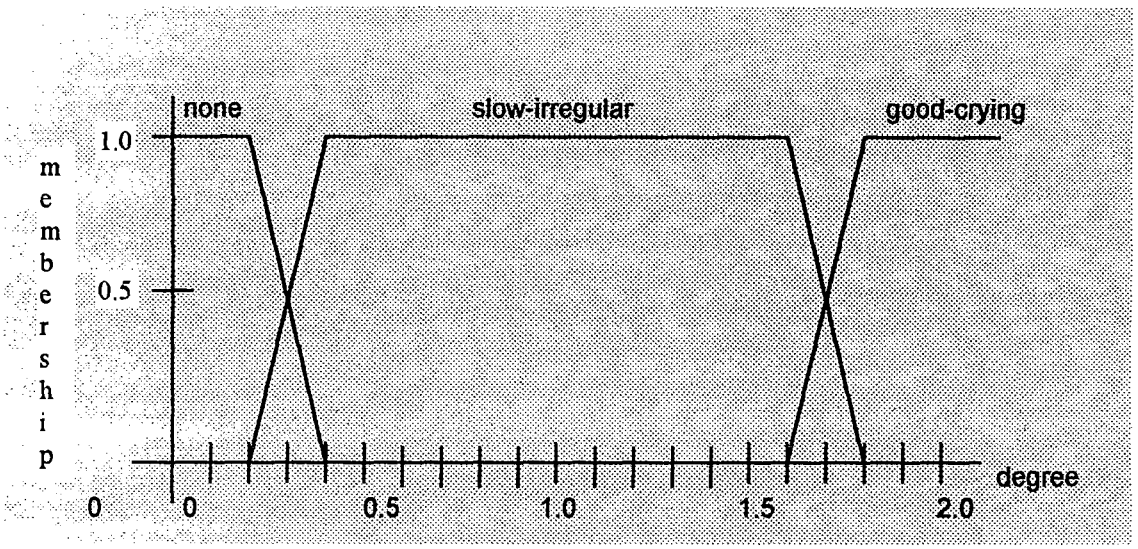

Fig. 11. 3 Respiratory effort

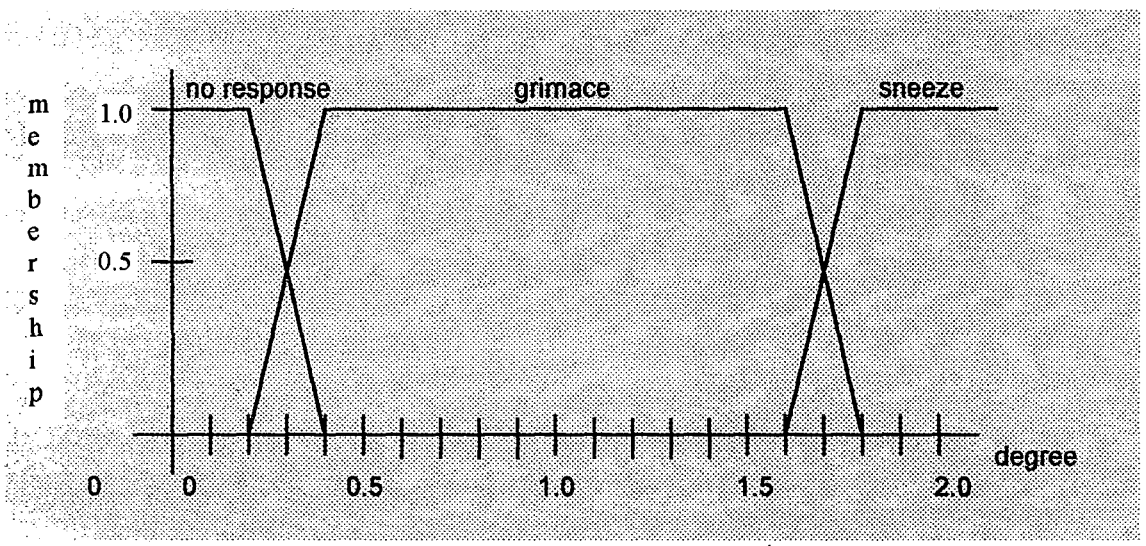

Fig.11.4 Reflex stimulation

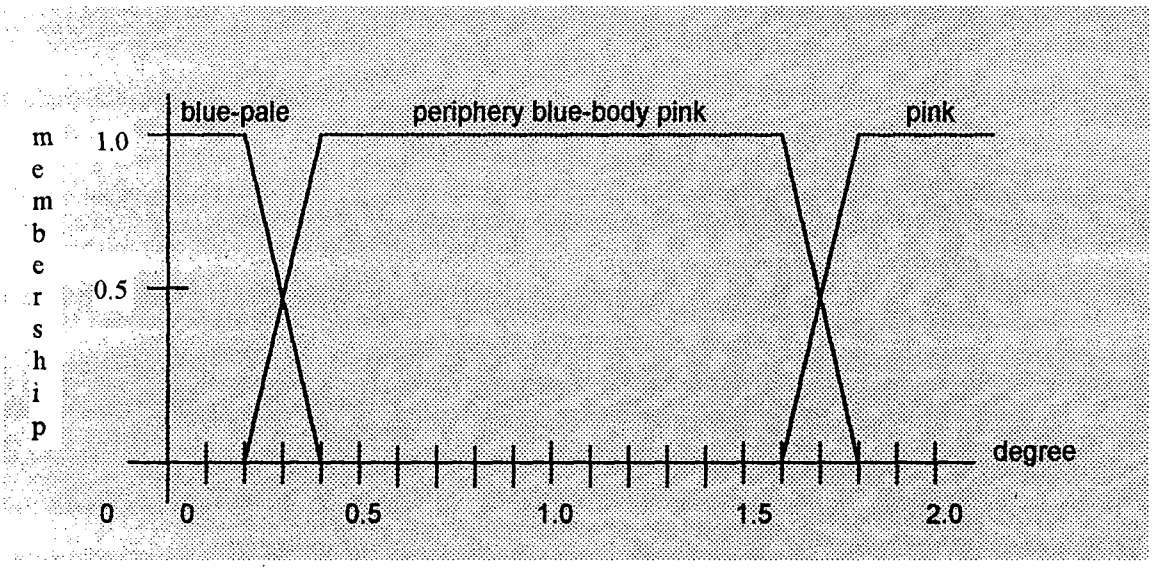

Fig.11.5 Colour

11.4. Fuzzification of system state output variable

The output of the designed fuzzy model is the decision like type I or type II or type III, a neonate has to be undergone. The type I baby should be undergone an immediate resuscitation; Intra-tracheal incubation and Sodium-bi-Carbonate with I V Dextrose solution. For type II baby some resuscitation is needed; e. g. gentle patting at the back; throat suction; Sodium-bi-Carbonate and I V Dextrose solution. And Type III baby should need no resuscitation; only tactile stimulation is sufficient. The system output variable had been fuzzified as shown in fig.11.6.

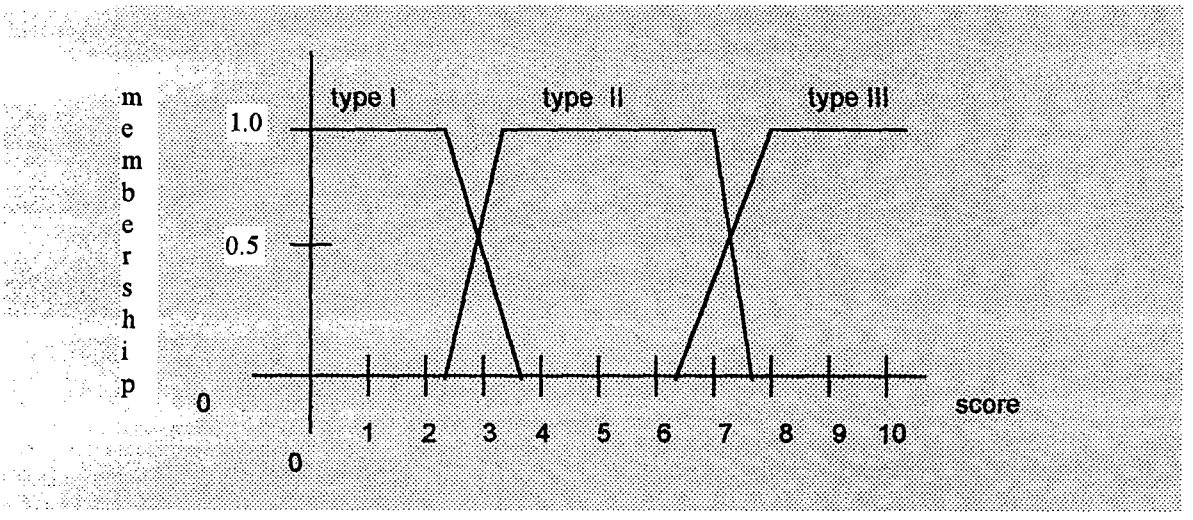

Fig. 11. 6 Fuzzification of system output variable : resuscitation.

11.5. **Inferencing process**

Since fuzzy sets are defined for each system state variable, a fact supplied by the user will have a membership for each fuzzy set. As the fuzzy sets in the system are defined by arbitrary **{value, membership}** pairs, a particular fact may require interpolation between defined pairs. Some of the membership grades so determined might not be appropriate due to their small numeric value. In order to eliminate undesired effects, a fuzzification threshold is introduced, in this case 0.2, in the line of [3,4]. Only calculated membership ≥ 0.2 are used in the process of inferencing.

We concentrate on fuzzy rule based approach :

If < fuzzy proposition >, then < fuzzy proposition >,

where the fuzzy proposition are of the form, "p is Q" or "p is not Q", p being a scalar variable and Q being a fuzzy set associated with that variable. Generally, the number of rules is related to the number of system state input variables. For our case, we have five such variables each of which is divided into three fuzzy regions leading to total of 243 fuzzy rules comprising the fuzzy knowledge base. Knowledge acquisition was done from a domain expert employing interview techniques. Architectural components of the system are shown in fig.11.7.

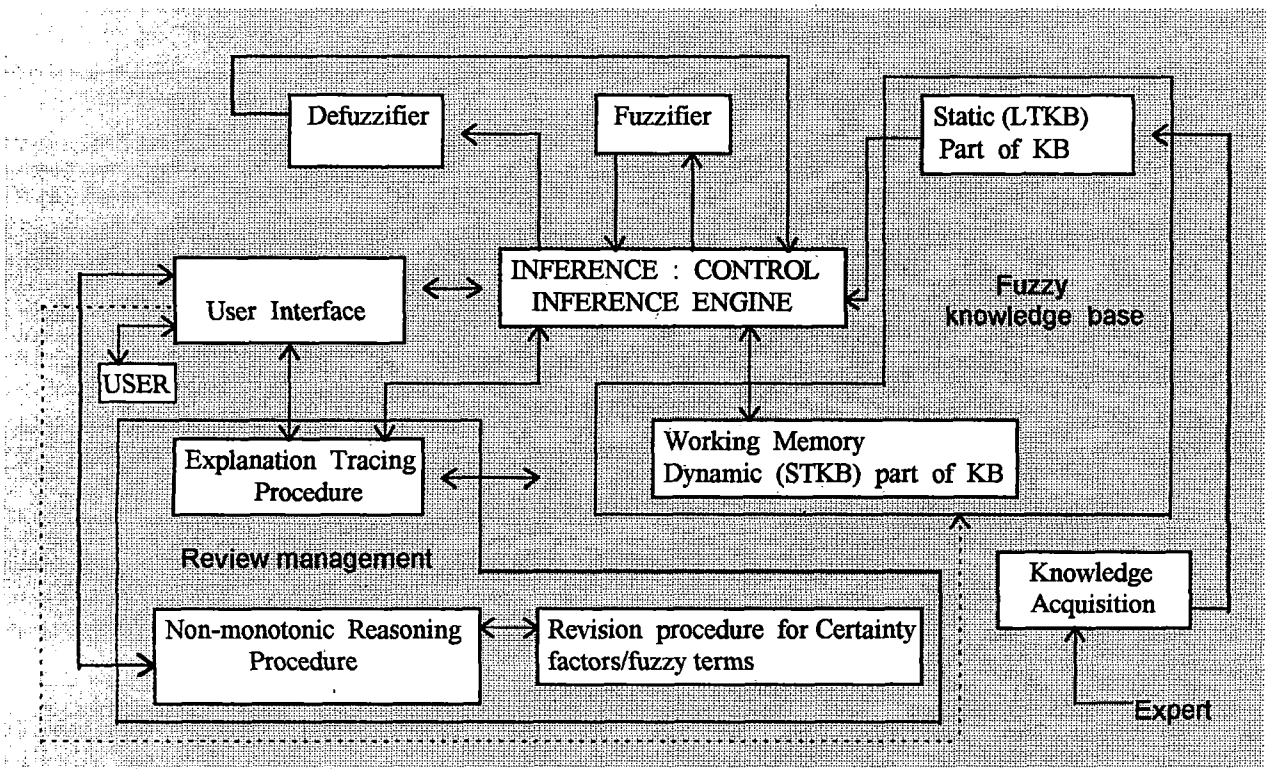

Fig. 11. 7 System architecture

A total of 32 combinations as input are used for knowledge base scanning. Different rules may be activated at the same time and combination of their outputs is then defuzzified to compute the resuscitation status.

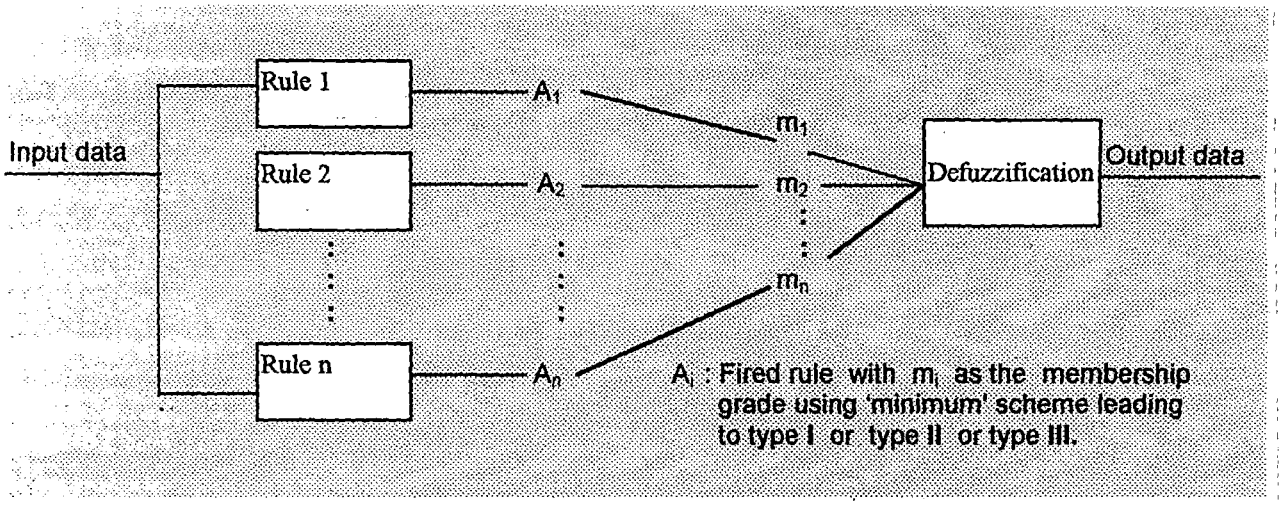

Fig. 11. 8 Inferencing and defuzzification.

Fig. 11.8 shows the inferencing and defuzzification process due to multiple rules. The 'maximum' method of defuzzification has been applied in the model [5]. This simply means that from among the fuzzy rules for the input set, the one with the largest membership grade is used to interpret the conclusion. There can be a number of conclusions according to the knowledge base, input values and defuzzification procedure and so, for presentation to the users, they are ordered by the 'degree of truth'. Thus the results of the defuzzification procedure is a list of suggestions sensible for the resuscitation procedures. The system has been developed using Tubo-prolog running under MS-DOS. The static and dynamic knowledge base features of Turbo-prolog facilitates the implementation. It is a compiled language providing a better runtime response. Prolog is amenable to problems that treats objects and their relationships. For this reason some people refer Prolog as one object-oriented language [6]. One can easily identify the rules (objects) fired. In addition, the O-O nature of Prolog enables it to be applied within the context of the prototyping paradigm for software engineering.

The power of a fuzzy system lies in the fact that a fuzzy rule can replace many conventional rules. The power of this system lies in the ability to deal with crisp as well as non-crisp values (fuzzy) of input. Moreover, the fuzzy inference process allows input to be inaccurate to some degree or missing but still produces sensible results in contradiction to traditional knowledge based systems where output heavily depends on absolutely contradiction free knowledge.

11.6. **Performance evaluation**

Lastly, performance evaluation should be produced. As a matter of fact, it is to some extent difficult to establish the degree of performance owing to the non-availability of experimental results in the classical sense. As a preliminary test of the system's performance, we put here the following example data as input using the fuzzy knowledge base :

(A) **Crisp values** (input)

Muscle tone of limbs = 0.2;
Heart rate per minute = 80;
Respiratory effort = 0.7;
Reflex stimulation = 1.7;
Colour = 1.7

Decision (output) : The patient probably has to be undergone with type II resuscitation with the membership 0.5.

$$[(\min(m_{MTL}(0.2), m_{HRT}(80), m_{RES}(0.7), m_{RST}(1.7), m_{COL}(1.7)$$
$$= \min(1.0, 1.0, 1.0, 0.5, 0.5)$$
$$= 0.5]$$

(B) **Combinations of fuzzy and crisp values** (input)

Muscle tone of limbs = 0.2;
Heart rate per minute = low;
Respiratory effort = 0.7;
Reflex stimulation = 1.7;
Colour = periphery-blue-body-pink.

Decision (output) : The patient probably has to be undergone with type II resuscitation with the membership 0.5.

(C) **Fuzzy values** (input)

Muscle tone of limbs = flaccid;
Heart rate per minute = low;
Respiratory effort = slow_irregular;
Reflex stimulation = grimace;
Colour = periphery-blue-body-pink.

Decision(output) : The patient probably has to be undergone with type II resuscitation with the membership 1.0.

The expert confirmed that the decision suggested by the system were reasonable for the given input data and knowledge base. However, more realistic case studies should be produced to validate the system more accurately. Explanation tracing facilities are to provide how the system reaches a decision.

In order to validate the system more accurately, the results of twenty-one case studies are now produced. The results suggested by a domain expert were compared with those suggested by our system. The system has an accuracy of 95%.

11.7. **Conclusions**

In this chapter, the development and implementation of a fuzzy knowledge-based neonatal resuscitation management system has been described. This application area of paediatric domain provides a variety of vague and uncertain knowledge. This knowledge was identified to be appropriately modelled with a knowledge base using fuzzy concepts. This chapter provided the required system analysis, fuzzification of system state input variables and system state output variables. Next, the inferencing procedure was described. The performance was evaluated using some practical case studies available from two domain experts engaged in Hospital and / or Nursing homes.

The fuzzy system produces sensible results for both the cases of the nature of input values (fuzzy or crisp and / or a combination of fuzzy and crisp values). The author is re-affirmed with the belief that the decision making in this particular domain is suitable for modelling with fuzzy logic. More case studies are planned in order to validate the system further.

We conclude that both knowledge acquisition and use are facilitated by the naturalness of the fuzzy logic. Once the fuzzy variables and sets were defined, the knowledge representation using rules was easy. We are with the opinion that fuzzy logic offers a convenient way of expressing vagueness and uncertainty; and the implementation of fuzzy knowledge based system is both convenient and practical.

References

1. Waldo. E. Nelson. Text Book of Pediatrics. 15th edition, 1996, Book 1, W. B. Saunders Company; Bangalore.

2. E. Cox. Fuzzy Fundamentals. IEEE Spectrum; October, 1992, 58-61.

3. E. H. Shortliffe and B. G. Buchanan. A mathematical model inexact reasoning in medicine. Math. Biosci.; 23, 1975, 351-379.

4. C. P. Schründer, J. E. Galletly and J. R. Bicheno, A fuzzy, knowledge-based decision support tool for production operations management. Expert Systems; vol.11, no.1, 1994, 3-11.

5. I. Graham and P. L. Jones. Expert Systems : Knowledge, uncertainty and decision. Chapman and Hall; 1988.

6. R. S. Pressman. Software Engineering - A Practitioner's Approach. 3rd edn., McGraw Hill; New York, 1992.