FUZZY CONCEPTS IN PAEDIATRICS [†]

9.1. Introduction

In medical domain in general, and in paediatric domain in particular, doctors frequently have to take decisions based on vague and imprecise knowledge which can be called inexact knowledge which comes from our linguistic articulations. Fuzzy logic and fuzzy set theory has been proposed as a convenient framework for dealing with such vague, linguistic articulated knowledge. This chapter presents ideas on a research direction incorporating an outline of some fuzzy concepts in paediatrics in order to design a powerful expert system which needs to take into account such fuzzy concepts. It is also intended to present fuzzy knowledge based prototype systems as applications of the theory.

To understand the meaning of the term "**fuzzy**", we may take the weight of a baby as an example. The weight of a baby can be expressed by different vague linguistic articulations such as **good**, **bad**, **satisfactory** etc., instead of exact numeric measurements. Such linguistic articulations like **good**, **bad** or **satisfactory** are fuzzy terms (values) for the variable weight. These terms have shades of meaning. For example, the weight of many babies may be described as **satisfactory** but their exact measurements may differ markedly. Terms like **good**, **satisfactory** etc., do not assume a simple unique value but a range of values. The boundaries of such linguistic articulations are not sharp but fuzzy which essentially means that the decision path from **satisfactory** to not **satisfactory** is a gradual progression which has no sharp boundary. Moreover, if the weight of a baby is decreased by some grammes only, he / she can retain the value **satisfactory**.

Our real-life reasoning systems often use some inexact knowledge of fuzzy form leading to some rational decisions. However, as the knowledge itself is inexact, the derived decisions can not be exact but approximate, having a good rationality.

In about 30 years of its existence, fuzzy set theory has been used in many areas including engineering, business, mathematics, psychology, management, semiology, medicine, image processing and pattern recognition. Its applicability and usefulness

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[†] This is based on the publications [Proc. xxx Annual Conv. of CSI; 9 -12 Nov 1995, 258-267, Hyderabad; Proc.3rd. Int. Conf. on Cognitive Systems (ICCS'97) 13-15th Dec 1997, vol.2, 627- 636, Delhi; and VIVEK: a Quarterly in Artificial Intelligence, vol.11, no.1, 1998, 3-15] of the author.

are increasing interestingly in diverse fields. In chapter 7, we had a discussion in this connection. Concentrating on medical domain, fuzzy logic has previously been used in a number of knowledge based systems [1-7]. For paediatric problem domain Ong and Qiu-He [8] report on interesting application. Here, the investigators have applied fuzzy logic for the diagnosis of convulsions in children. Using only symptoms (without CSF test) of twenty five patients to make diagnosis, their system achieved an accuracy of 92% compared to 67.7% on the average as observed from the doctors' diagnosis in similar conditions [9]. However, in our opinion, the potential of fuzzy logic has not been exploited at length to cover different aspects of the paediatric domain. This motivated us to explore such possibility of use of this logic in paediatric problem domain.

In the next section, we discuss the basics of fuzzy logic and fuzzy set theory. Section 9.3 presents fuzzy concepts in neonatal problem domain. In section 9.4, a fuzzy knowledge based consultation system (Prototype 2.0) has been presented using Appendix A. In section 9.5, we present a fuzzy knowledge based neonatal resuscitation management system(Prototype 3.0). In the last section, we draw our conclusion.

9.2. Basics of Fuzzy Logic and Fuzzy Set Theory

The concept of fuzzy set and fuzzy logic were introduced by Zadeh [10]. Zadeh was working in the field of control engineering. His intention in introducing this fuzzy set theory was to deal with problems involving knowledge expressed in vague, linguistic terms. Classically, a set is defined by its members. An object may be either a member or a non-member : the characteristic of traditional (**crisp**) set. The connected logical proposition may also be true or false. This concept of crisp set may be extended to fuzzy set with the introduction of the idea of partial truth. Any object may be a member of a set 'to some degree'; and a logical proposition may hold true 'to some degree'. Often, we communicate with other people by making qualitative statements, some of which are vague because we simply do not have the precise datum at our disposal e.g. a person is **tall** (we have no exact numerical value at that moment) or because the datum is not measurable in any scale e.g. a **beautiful** girl (for **beautiful**, no metric exists). Here, **tall** and **beautiful** are fuzzy sets. So, fuzzy concepts are one of the important channels by which we mediate and exchange information, ideas and understanding between ourselves. Fuzzy set theory offers a precise mathematical form to describe such fuzzy terms such as **tall**, **small**, **rather tall**, **very tall**, etc. in the form of fuzzy sets of a linguistic variable. To represent the shades of meaning of such linguistic terms, the concept of grades of membership (μ) or the concept of possibility values of membership has been introduced. We write $\mu(x)$ to represent the membership of some object to the set X. Membership of an object will vary from full membership to non-membership :

- $\mu = 0$ for no membership;
- $\mu = 1$ for full membership;
- $0 < \mu < 1$ for partial membership.

Any fuzzy term may be described by a continuous mathematical function or discretely by a set of pairs of values {numeric values of linguistic variable, corresponding grade of membership}.

For example, '**tall**' may be described by a sigmoid as shown in fig. 9.1.

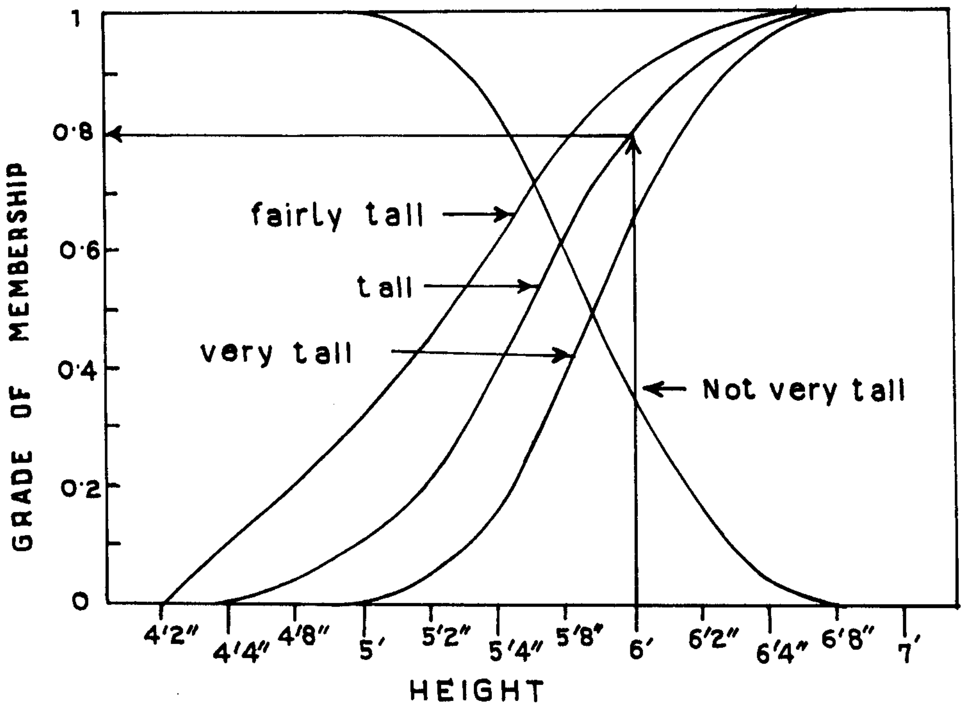

Fig. 9.1 Fuzzy term tall with modifiers

The fuzzy term '**tall**' can also be described by the following fuzzy set :

Height	**Grade of membership**
4'0"	0.00
4'2"	0.00
4'4"	0.01
4'8"	0.04
5'0"	0.10
5'2"	0.20
5'4"	0.38
5'8"	0.62
6'0"	0.80
6'2"	0.92
6'4"	0.98
6'8"	1.00
7'0"	1.00

Every element of the fuzzy set will have its corresponding membership value in this range (fig.9.1). Having the numerical representation of these linguistic terms, one has to define the set theoretic operations of union, intersection and complementation along with their logical counterparts of conjunction, disjunction and complementation which are as follows :

- Union (logical OR) - the membership of an element in the union of two fuzzy sets is the larger of the memberships in these sets.

  μ(A OR B) = max(μ(A), μ(B)) e.g.,
  μ(tall OR small) = max{μ(tall), μ(small)}

- Intersection (logical AND) - the membership of an element in the intersection of two fuzzy sets is the smaller of the memberships in these sets.

  μ(A AND B) = min(μ(A), μ(B)) e.g.,
  μ(tall AND small) = min{μ(tall), μ(small)}

- Complement (logical NOT) - the degree of truth of the membership to the complement of the set is defined as (1 - membership).

$$\mu(\text{NOT } A) = 1 - \mu(A) \text{ e.g.,}$$
$$\mu(\text{NOT tall}) = \{1 - \mu(\text{tall})\}$$

Example :

In fig. 9.1, we may consider two fuzzy sets : **fairly tall** and **not very tall**. The height 5'4" has a grade of membership of 0.62 in the first set, and 0.86 in the second. Thus, the grade of membership in the combined set **fairly tall** AND **not very tall** is min (0.62, 0.86) = 0.62.

The grade of membership in the combined set **fairly tall** OR **not very tall** is max (0.62, 0.86) = 0.86. And, the grade of membership in the set **NOT very tall** = 1 - μ (**very tall**) = 1 - 0.14 = 0.86.

Fuzzy numbers, like ordinary numbers, can be used in different arithmetic operations like addition, multiplication etc. that give another fuzzy number as the result as shown in fig. 9.2.

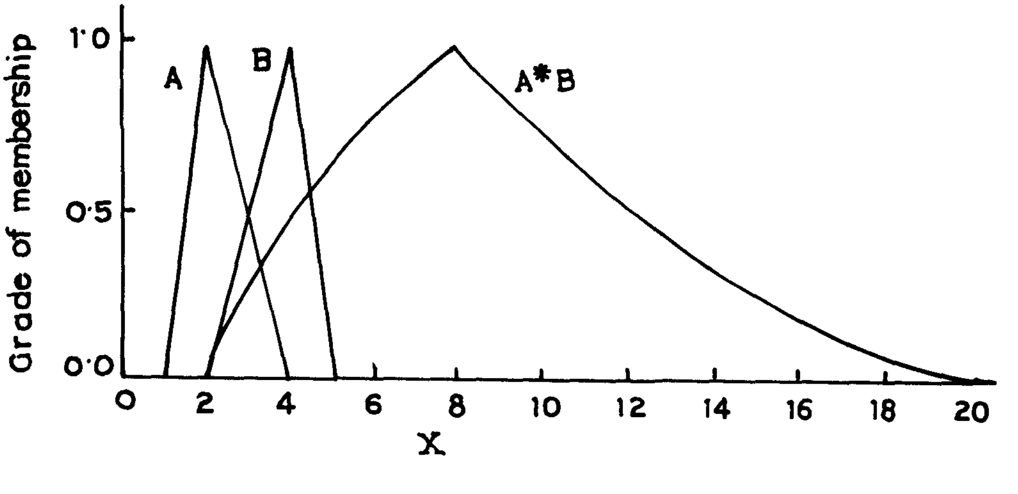

Fig. 9.2 Multiplication of two fuzzy numbers

Moreover, some fuzzy modifiers or 'hedges' such as **very**, **around**, **rather**, **quite**, **fairly**, **extremely** are common in our real-life knowledge-transfer. One can obtain the possibility distribution of a fuzzy concept like **very tall** or **fairly tall** by applying arithmetic operations on the fuzzy set of the basic fuzzy term **tall**. Power factors are a simple and convenient way for the required arithmetic operations since the grade of membership of a fuzzy set falls in the interval [0,1]. For example, we can calculate the possibility values of each height in the fuzzy set representing the fuzzy concept **very tall** by taking the square of the corresponding possibility values in the fuzzy set of **tall** (fig.9.1). Similarly, we can tackle the situation for **fairly tall** by using the square root operation on fuzzy set **tall** (fig.9.1). If one wants to generate fairly tall but not very tall, the following procedure may be followed. First we generate the set **fairly tall** by taking the square root of **tall**; then the set **very tall** by squaring **tall**; then the set **not very tall** by negating the set **very tall**. Finally, we take the intersection of these two sets (representing **but** by the **and** operation) producing the final set.

Possibly much human reasoning is based on the concepts of implications which states that :

IF antecedent THEN consequent.

For example,

IF X is A THEN Y is B.

If **antecedent** is true, **consequent** will also be true. This is **modus ponens** inference. However, there are other ways of reasoning from implications such as **modus tollens** and **hypothetical syllogism**. **Modus tollens** is based on the reasoning from data about Y to a conclusion about X. In **hypothetical syllogism**, an implication relating X to Y is combined with an implication relating Y to Z to yield an implication relating X to Z. Researchers in fuzzy logic have explored fuzzy versions of all of these, but only modus ponens has seen applications in expert systems. The present author, obviously, will continue discussion using **modus ponens** approach.

Often human knowledge is expressed in such a way that antecedent and / or consequent may contain fuzzy and / or crisp values. The following table may be considered valid :

Antecedent	Consequent
crisp	crisp
crisp	fuzzy
fuzzy	fuzzy

Note here that for 'fuzzy A' degree of truthness of B should not be greater than that of A. Fuzzy logic allows both the antecedent and consequent to be fuzzy propositions. These fuzzy propositions comprise statements involving linguistic variables, which will have shades of meaning or varying degrees of truth. An antecedent of any rule may be a simple clause (or atomic propositions) or may be a combination of number of clauses connected via the fuzzy logical operators AND, OR, NOT AND and NOT OR. For examples :

Example 1.

IF

Rhythms (sleep and meals) of a baby is satisfactory

THEN

Growth of the baby should be good.

Example 2.

IF

Production volume is high

AND

Flexibility is high

THEN

Variety is high [11].

Recently, however, some researchers [8] have suggested an extension to the basic conjunctions of AND and OR by incorporating the ADD and REL conjunctions for the linkage of premises in conventional rules.

Now, we have a fact 'Rhythms of a baby is highly satisfactory' which matches with the rule as stated in above example 1. We have to find out the corresponding conclusion which will be reflected from the consequent section of the rule. The fuzzy concepts satisfactory and good can be modeled by a fuzzy relation R, represented by a matrix. Let F_1 and F_2 be the fuzzy sets representing the concepts satisfactory and good, respectively. One can obtain the fuzzy relation R [12] by performing some fuzzy operations on F_1 and F_2 , expressed as vectors. Different approaches have been proposed to compute the fuzzy relation R. One may use the Cartesian product $F_1 \times F_2$ to get the mapping or relation $R(F_1 \rightarrow F_2)$.

The fuzzy concept highly satisfactory can be represented by a fuzzy set F, which we may obtain by applying an arithmatic operation (a square operation in this case) on F_1 . The fuzzy set C representing the effect or conclusion after the application of the said fact can be deduced by applying a fuzzy operator called composition operator (denoted by 0) on F and R i.e.,

$$C = F \; 0 \; R$$

A number of forms for composition operator has been suggested to compute C. Most of the developers of expert systems prefer the **max-min** composition rule of Zadeh [13]. Obviously, the vector C will indicate very good and the conclusion growth of the baby should be very good will be drawn.

9.3. **Fuzzy Concepts in 'NEONATES' Problem Domain**

The knowledge base(s) used by a typical computer-based expert system often comprises vague, linguistic rules as articulated by domain experts, i.e., Paediatricians in the field of paediatrics. Moreover, the basic facts on which the reasoning process starts may also often comprise such vague, linguistic articulations. In designing an expert system with fuzzy uncertainty / inexactness for a problem domain, one has to identity, first, the linguistic variables for the domain. Next, one has to define the term set of fuzzy sets which adequately covers the spaces of the domain. The members of a term set are linguistic terms characterising the corresponding linguistic variable. Once such fuzzy variables and term sets are defined, the knowledge representation using rules will become easy. For example, for the present problem domain (for a neonate), some main linguistic variables and the corresponding term sets may be identified as :

- General status → {Healthy, sick};
- Birth weight → {SGA, AGA, HGA};
- 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. For example, if we are talking about '**general status**' of a baby, the term set {**healthy, sick,**} may be considered as our primitive term set for the linguistic variable '**general status**'. Other fuzzy terms like **fairly healthy**, **very healthy**, **not very healthy** etc. can be derived from the members of primitive term set. Now, we are in a position to generate a fuzzy set to represent a complete phrase 'fairly healthy but not very healthy'. Fig.9.3 illustrates the required intermediate fuzzy sets to generate fairly healthy but not very healthy. This kind of analysis may be useful in assessment of a patient by a doctor. For example, a baby with respiratory distress or convulsion may be analysed in this manner for further management i.e. whether the baby needs hospitalization with or without intensive care, may be kept for observation or may be advised for domiciliary treatment.

The above concepts and ideas have been used in developing a prototype system for neonatal resuscitation management which has been considered in section 9.5. In the next section, we now present a fuzzy consultation system (Prototype 2.0) for the present problem domain based on Appendix A.

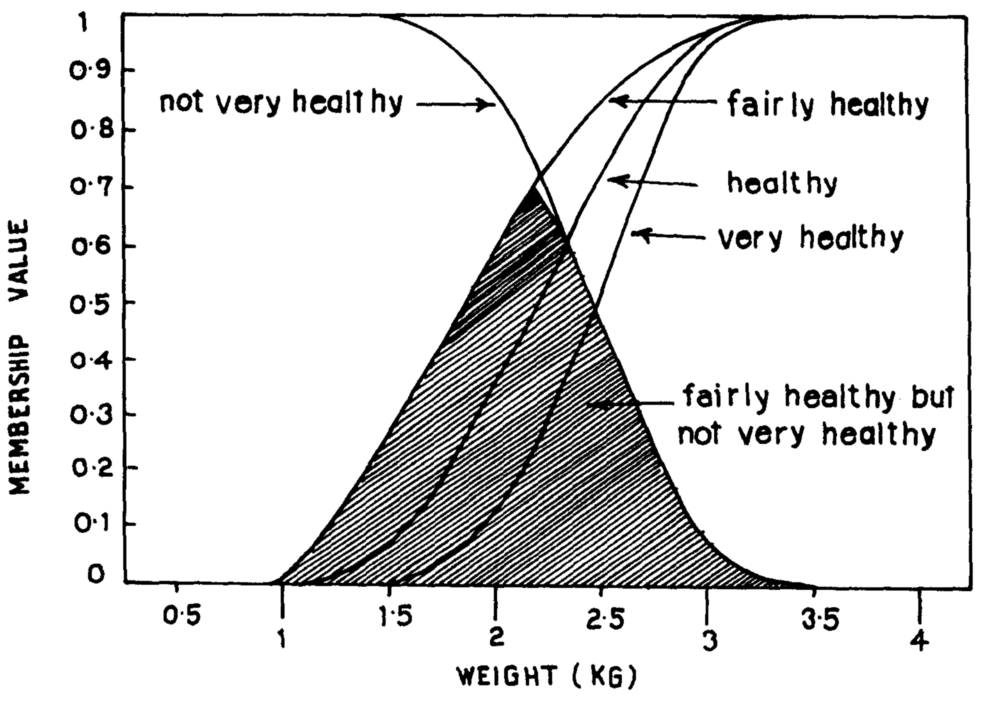

Fig. 9.3 Generating fairly healthy but not very healthy.

9.4. **Prototype 2.0**

This version deals with some fuzzy concepts in terms of linguistic articulations. The architectural components of our modified system is shown in fig. 9.4. The knowledge base (KB) consists of two parts : static part and dynamic part. The static part is relatively fixed over time. The dynamic part is capable of adding new facts or facts can be removed from the KB as when required. The inference engine uses LTKB and STKB to infer new facts. It has two well-known functions : inference and control. Backward reasoning process has been used here which favours the needs of the application domain. The inference engine uses depth-first scanning but with an 'improved back tracking' using some control rules provided that sufficient domain knowledge is available. A user interacts with the system with the user interface of the system. Through this module different queries are served by the system initiated by the inference engine. The fuzzification and defuzzification required for user supplied linguistic terms (fuzzy) and that required for fuzzy knowledge rules extracted from domain experts are governed by control section of the inference engine. The total review management is transparent to the user through this particular module. All accesses by a user to KB and review management module are through inference engine. However, logical access is presented through broken line of fig. 9.4.

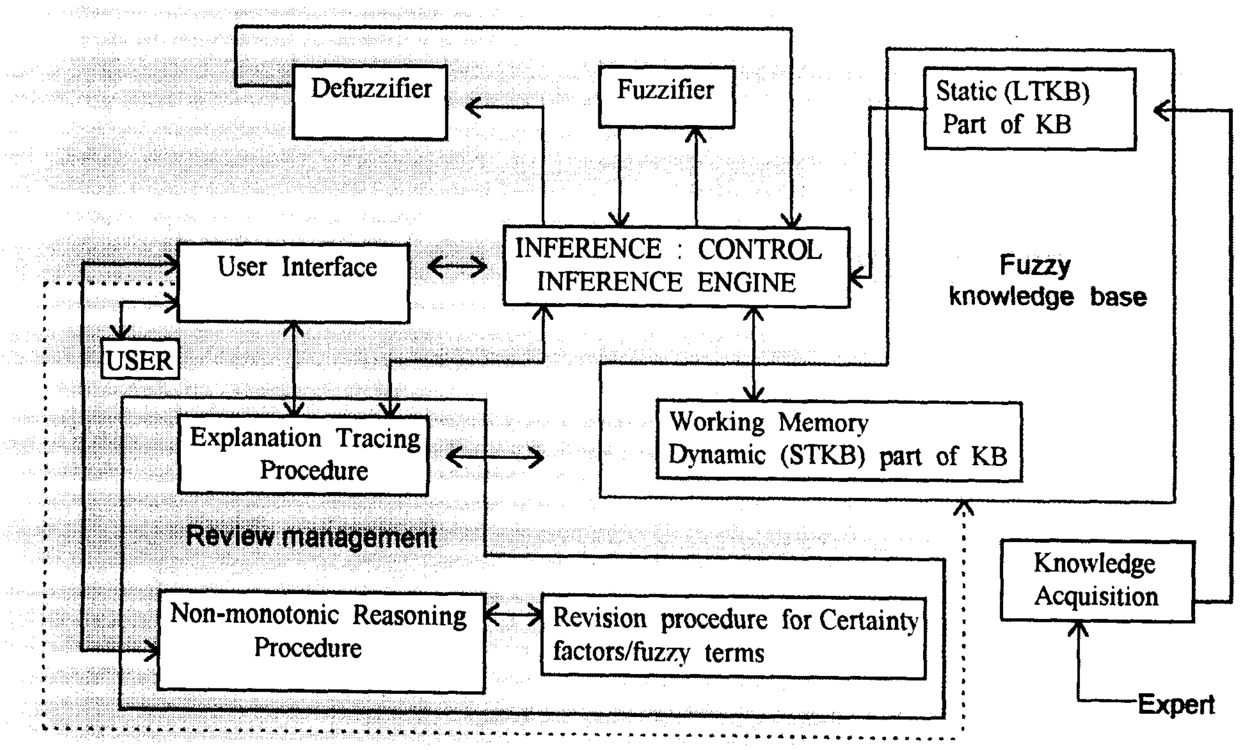

Fig. 9.4 System architecture

9.4.1. A typical consultation session

The following presents an excerpt from a typical consultation session with the system. The objective of this excerpt is to highlight some of the important features of the system. It is a menu-driven system.

A CONSULTATION SYSTEM FOR CHILD GROWTH AND DEVELOPMENT

MAIN MENU

Addition of records and consultation
Previous record with reference number
Printing record with reference number
Read records
Updation
Delete records
Dos
Exit

Enter Command

CAUTION : PRESENT PROTOTYPE NOT FOR MEDICAL USE

Considering the first menu, the particulars like name, age, parents' name etc about the child have to be supplied along with the values of different activities to be examined in terms of CF / fuzzy values. We get the following analysis :

Reference No.: c22/8/95basam43	Age : up to One Year
Activity	CF/Fuzzy Values On 2/8/95
Axial Muscle Tone	Good
Muscle Tone of Limbs	Very good
Spontaneous Gestures	Very good
Gripping	Good
Relation	Good
Emotional & Social Development	Almost poor
Language	Almost poor
Rhythms	Very good
EEG	Good

ABNORMAL ACTIVITIES
Emo_Social_Development
Language

Press a Key

SUMMARY

Total No. of Activities : 9

VERY GOOD : 3 GOOD : 4 ALRIGHT : 0 UNKNOWN : 0
ALMOST POOR : 2 POOR : 0 POOREST : 0

EXPERT CONCLUSION : GROWTH IS ALMOST NORMAL

Press a Key

If then compares with the previous values, if required, and then offers an advice as follows :

COMPARISON WITH PREVIOUS RECORD

Growth increasing in 80% cases.
The variation upto 10% has been neglected.

CONCLUSION :
The growth of the baby is expected to be normal

Press a Key

ADVICE

Please take care of the following activities of Basudev

Axial Muscle Tone
Emotional & Social Development
Language

Press a key

9.5. **Neonatal Resuscitation Management : An Application (Prototype 3.0)**

9.5.1. **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 [14].

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 [14] 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 neverthless 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. 9.5.

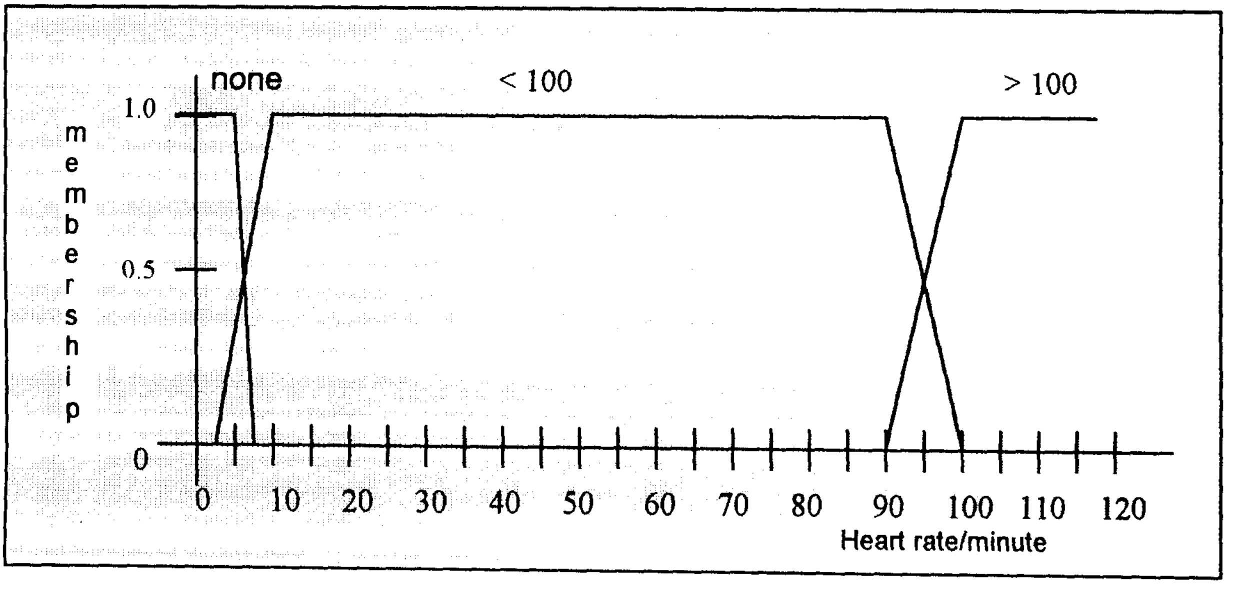

Fig. 9.5 Heart rate

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, ankle, knee and hip. It is sometimes difficult to define the value as flaccid or some-flexion or active as depicted in fig. 9.6.

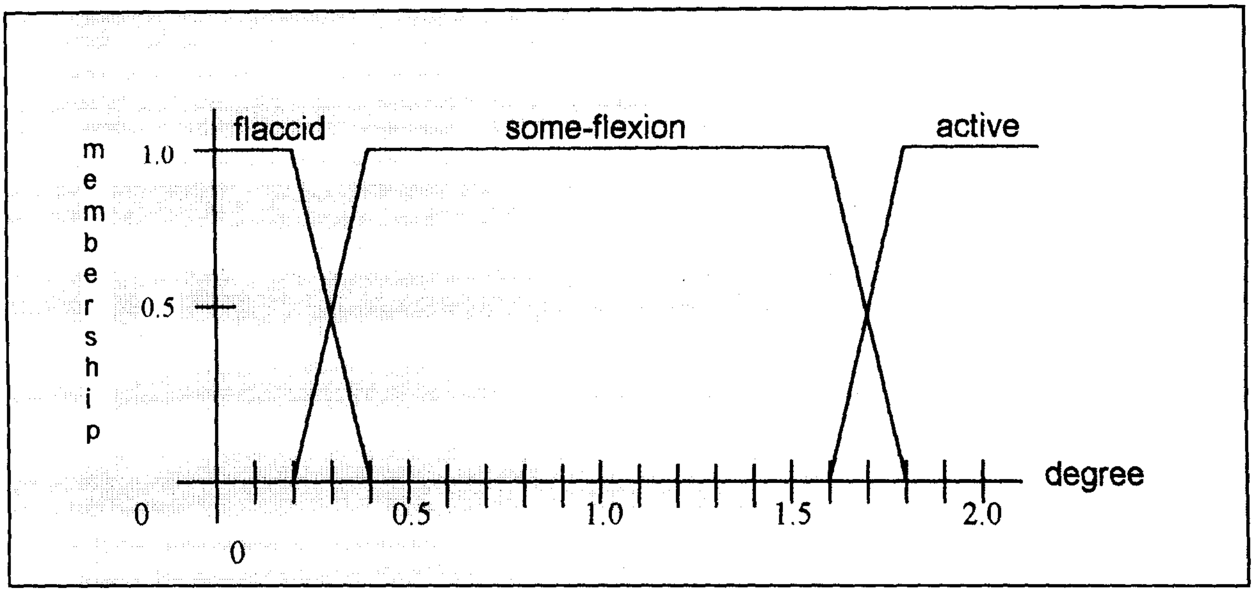

Fig. 9.6 Muscle tone of limbs

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,was done by a domain expert.

9.5.2. **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 [15]; 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. fig. 9.5 and 9.6 where fuzzification of heart rate and muscle tone of limbs are shown respectively. Fig. 9.7, 9.8 and 9.9 show the fuzzification of respiratory effort, reflex stimulation and colour respectively.

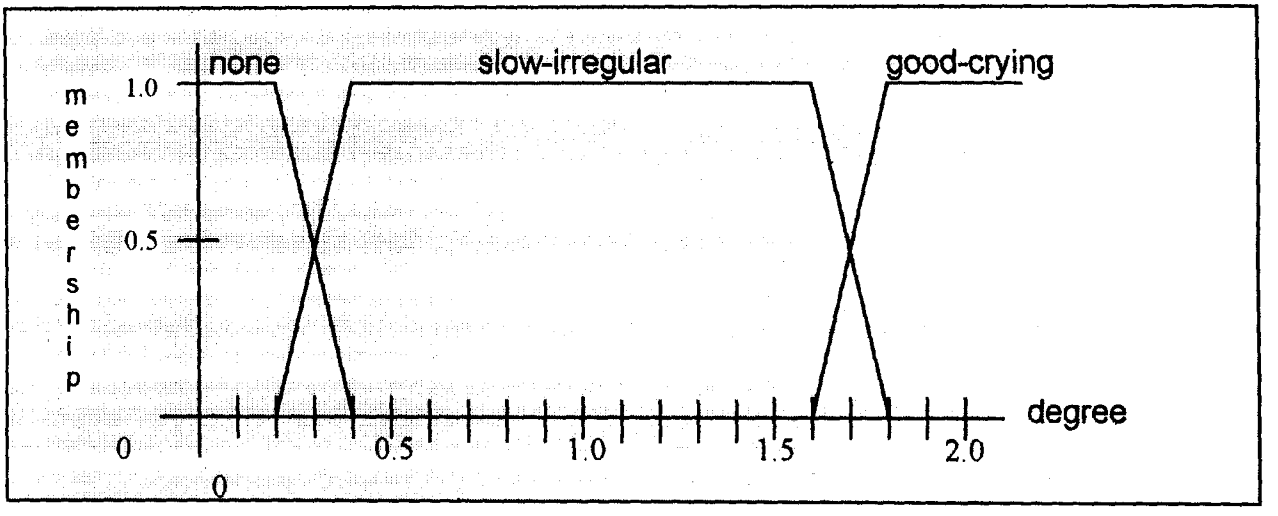

Fig.9.7. Respiratory effort

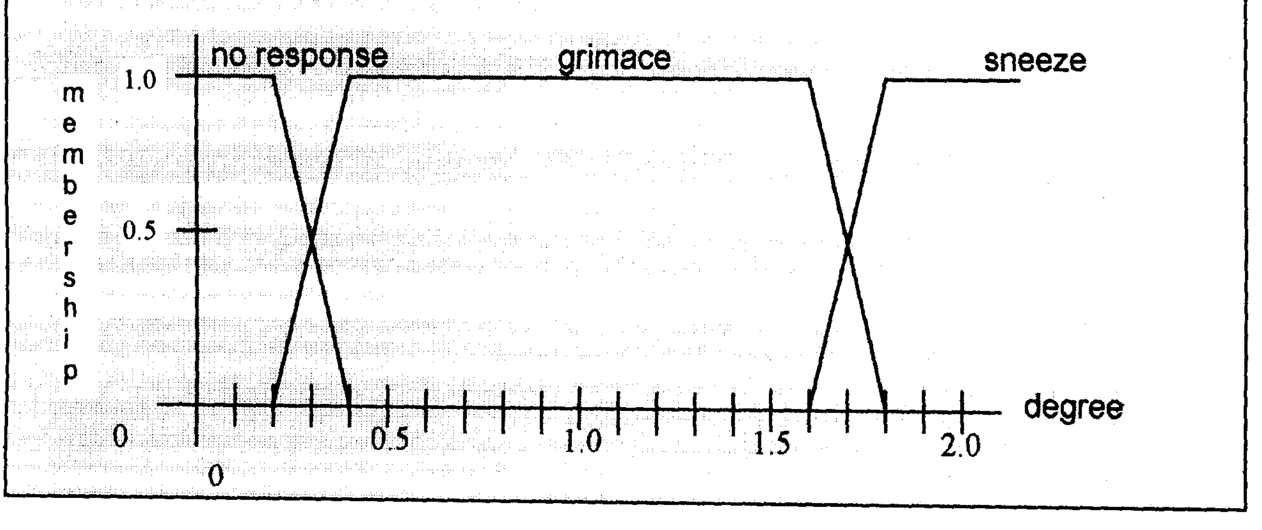

Fig.9.8. Reflex stimulation

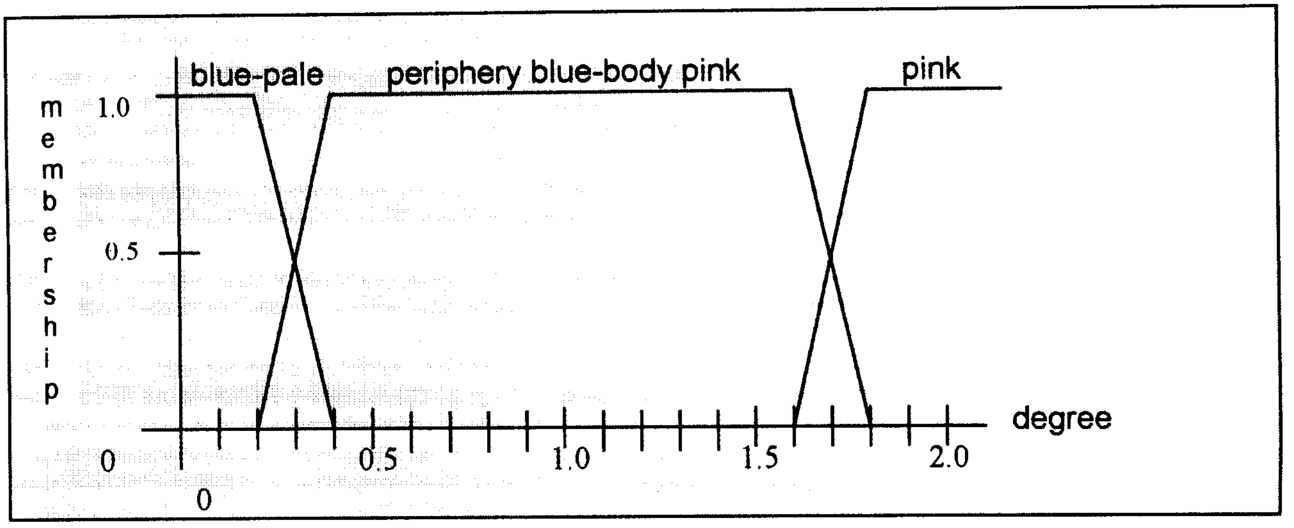

Fig. 9.9. Colour

9.5.3. **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. 9.10.

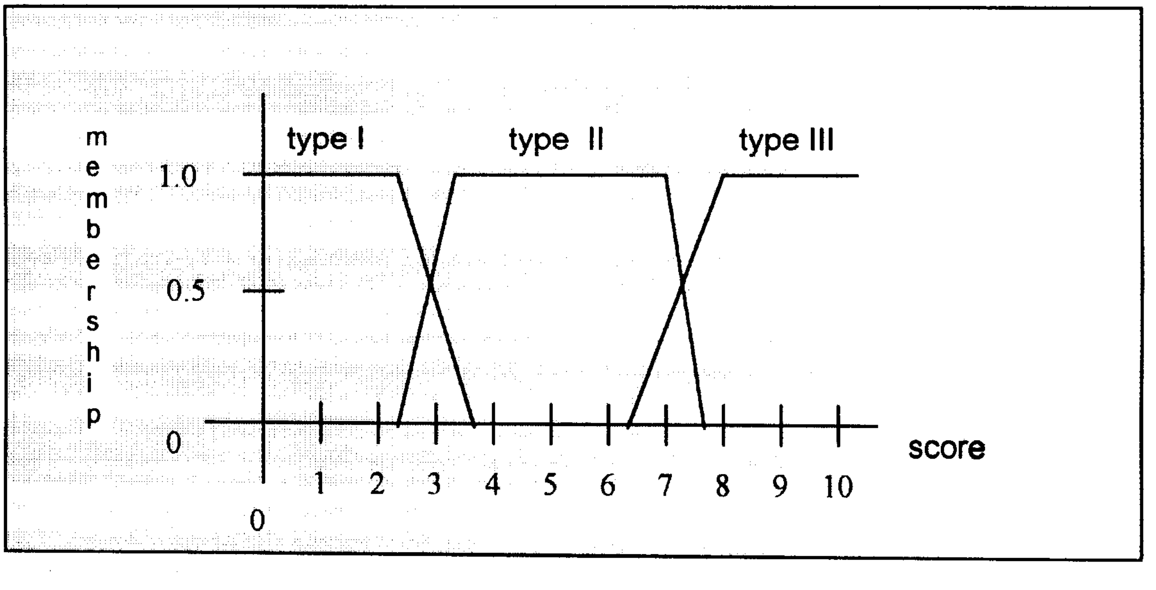

Fig. 9.10. Fuzzification of system output variable : resuscitation

9.5.4. 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 [11,16]. 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 propositions 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 a 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. 9.4.

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. 9.11 shows the inferencing and defuzzification process due to multiple rules. The 'maximum' method of defuzzification has been applied in the model [17]. This simply means that from among the fuzzy rules for the input set, the one with the largest

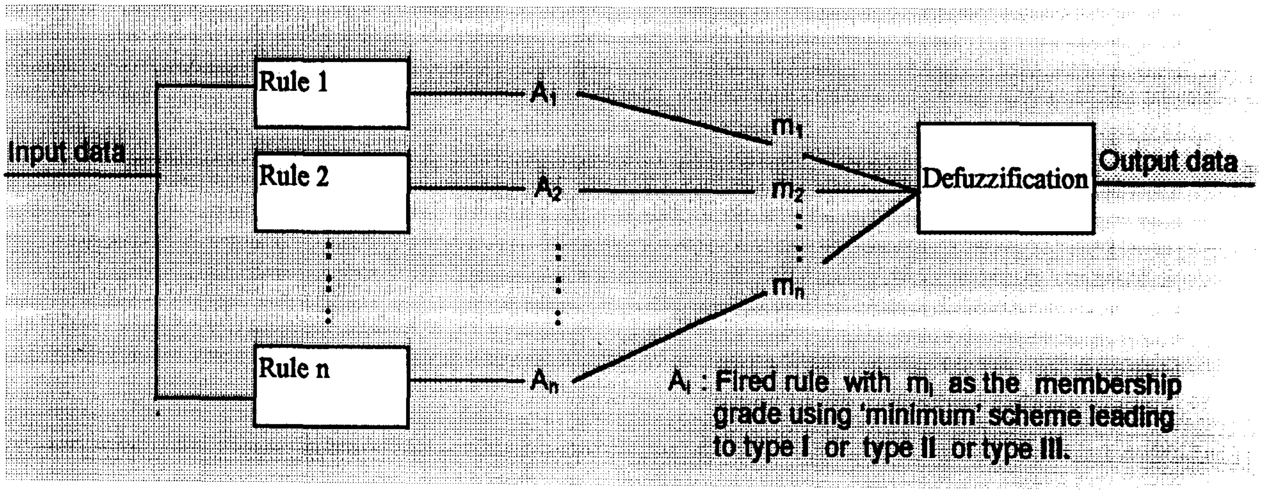

Fig. 9.11. Inferencing and defuzzification

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 Turbo-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 prefer Prolog as one object-oriented language [18]. 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.

9.5.5. **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.

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%**.

9.6. Conclusions

In this chapter, we have presented an outline of fuzzy concepts in paediatric problem domain to show the usefulness and importance of fuzzy logic and fuzzy set theory keeping in mind the importance of experience and judgement that an expert uses when examining a patient. In designing computer-based expert systems, one of the key problems is to manage inexact knowledge of different kinds. One important kind is fuzziness arising from human linguistic articulations. It is argued that fuzzy concepts have to be dealt with properly to offer a rational decision. After a brief introduction to fuzzy logic and fuzzy set theory, we have identified different primary linguistic variables and corresponding term sets which were required during the design of a fuzzy, knowledge based neonatal resuscitation management system. Some potential problems, e.g., the problem of 'adequacy' of a term set, have also been addressed in this context. 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 performance was further evaluated using some practical case studies available from two domain experts engaged in Hospital and / or Nursing homes. We are 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.

Finally, fuzzy logic offers a natural and convenient way of managing inexactness expressed in the form of vagueness. The naturalness of fuzzy logic may certainly assist us in both knowledge acquisition and inferencing procedures. Due to the naturalness of input - such as low, normal, slow-irregular, the programs for inferencing are generally much smaller and faster than conventional programs using binary logic.

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