Conceptual Fuzzy Temporal Relational Model (FTRM) for Patient Data

AQIL BURNEY, NADEEM MAHMOOD, TAHSEEN JILANI, HUSSAIN SALEEM
Department of Computer Science (UBIT)
University of Karachi
University Road, Karachi-75270
PAKISTAN
burney@uok.edu.pk, nmahmood@uok.edu.pk, tahseenjilani@uok.edu.pk, hussainsaleem@uok.edu.pk

Abstract: - Classical relational model offer very little built-in support for managing time varying data. Relational model mainly deal with crisp data and not with imprecise data. Managing temporal data in the relational environment keeping the imprecise and fuzzy nature of the data requires the extension of the relational model. Small numbers of extended models at conceptual level are proposed and there is no significant implementation of such model exists. Importance of developing ontological framework for imprecise data and temporal data is required in many applications such as health and patient databases. In this paper we propose a temporal fuzzy ontology for patient data in a hospital environment. On the basis of the ontology defined we propose a conceptual fuzzy temporal relational model (FTRM) for handling time varying attributes and fuzzy attributes in the relational database environment. The proposed model is easy to define, manage and incorporates the important and relevant features in the target fuzzy temporal relational model.

Key-Words: - relational model, time varying data, fuzzy data, ontology, fuzzy attributes, fuzzy temporal model.

1 Introduction

The relational model [1] is based on a brand of mathematics called relational algebra. Codd used that concept to manage huge amounts of data very effectively. Codd and others have extended the notion to apply to database design. The relational model is the still the most widely used and well accepted model for database management.
The relational data model only support functionality to access a single state of the real world, called a snapshot. The transition from one database state to another (updates) thereby giving up the old state. This restriction is due to the atomicity or the first normal form (FNF) assumption. There exist, however, many application domains, such as health databases [2], which need to have access not only to the most recent state, but also to past and even future states, and the notion of data consistency must be extended to cover all of these database states.
Efforts to incorporate the temporal domain into database management system (reference) have been ongoing for three decades and dozens of temporal models have been proposed [3][4] and a few of them have been implemented [5].
Many application domains may also have imprecise data apart from the crisp data. Efforts have been made to extend the relational model to incorporate the imprecise data values [6][7][8][9] but very few successful implementations are there [10][11][12]. Imprecision is incorporated in databases in many dimensions [8] which includes the natural language processing as far as imprecise query is concerned, inserting imprecise information into the database at the relation level or the development of fuzzy query language [12] as an extension to the standard SQL.
Realistically speaking most of the application domains involving temporal semantics (crisp data) also involves the imprecise nature of data (non crisp data or fuzzy data). Very little work is done in integrating the temporal and fuzzy dimensions in the context of relational model [13][14][15]. There is both way around temporal data have a fuzzy dimension and vice versa. This idea gave rise to the relatively new concept i.e. fuzzy-temporal relational model. Our proposal includes the capacity of identifying and representing fuzzy temporal data in a relational model. This includes the conceptual fuzzy temporal extended entity relationship model (FT-EERM).
Designing effective, secure and useful healthcare information systems [2] which handle temporal data [16] along with the fuzzy data [17] is a great challenge for software engineers. In this paper we investigate the patient data both with respect to the time and fuzzy nature of data and propose a conceptual fuzzy temporal relational model.
This paper is organized as follows:
This paper is organized as follows: section 2 contains discussion on various aspects of conceptual temporal relational models. Section 3 deals with the

ontology and a proposed requirement analysis: work flow for patient data management through a schematic diagram. Section 4 contains review on fuzzy set theory and temporal fuzzy ontology. Finally, in the last section, the proposed Fuzzy-temporal Extended Entity Relationship Model (FT-EERM) is presented.

2 Discussion

Many data models are introduced so far to capture the semantics of temporal data keeping the traditional entity relationship model (ERM) approach [18]. Traditional ERM is not capable for capturing the whole temporal aspects. Many extensions [5][19] been proposed to extend the ERM to capture time varying information in one way or the other. Similarly extensions have been proposed to ERM capturing the fuzzy data, however very few extensions of ERM are their which integrates both temporal and fuzzy concepts [14].
On the other hand there is a need to identify fuzzy concepts and terms associated with database development. There is no inbuilt mechanism exist for designing database applications dealing with fuzzy and temporal data at the same time.
Since most of the work in the research area of temporal databases [5][20] has been done with respect to the relational data model because of its strong structure. Temporal data models can be categorized as tuple time stamped or attribute time stamped, FNF or NFNF, valid time or transaction time [21].
For a conceptual development an ontology which covers medical and hospital information is required for patient data management (PDM) system [22]. Development of PDM-Requirement analysis work flow model [3] in a hospital/clinical system includes the integration ontological knowledge base with the existing information system. This requires the creation of ontological categories based on the information in patient databases in a hospital.

3 The Proposed Model

Our proposed model of development is represented in the Fig. 1. The hospital environment needs special attention because it involves complex information which is characterized as temporal, non-temporal, partially temporal and as well as fuzzy, non-fuzzy and fuzzy temporal. Ontology of the patient data is divided into three categories, temporal ontology, fuzzy ontology and fuzzy temporal ontology [23]. Once the ontology is defined then work flow model can be developed which becomes the basis for developing temporal EER [4] schema and later transform it into fuzzy temporal EER schema. Consequently temporal and fuzzy temporal relational schema can be generated.

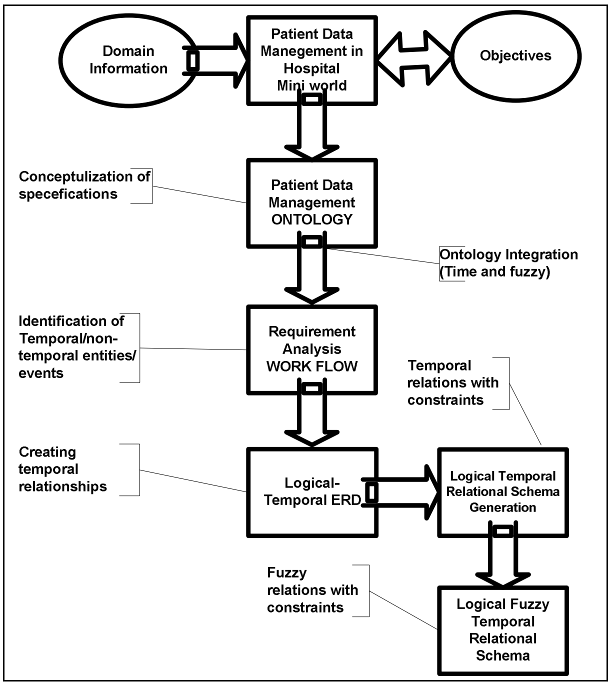


Fig. 1 The schematic diagram of generating fuzzy temporal relational schema

4. Requirement Analysis: Work Flow Model for PDM.

4.1 Ontology

Ontology provides a guide to identify relationship between different concepts, such as entities, abstractions and events in a given domain.
The basic idea is to model a situation see Fig. 2 where we can distinguish temporal and non-temporal, temporal fuzzy, fuzzy and non fuzzy and temporal fuzzy concepts.

4.1.1 Temporal Ontology

Temporal aspect is significantly important in various fields and it can be very helpful in analyzing understanding domain performance. We have proposed a requirement analysis work flow model for patient data management in a hospital. The purpose of this model is to analyze the importance of patient's data to improve healthcare organizations service. Fig. 3 gives a work flow model of patient data management by highlighting and categorizing the important and useful patient information. Treatment data is represented with a clock in the

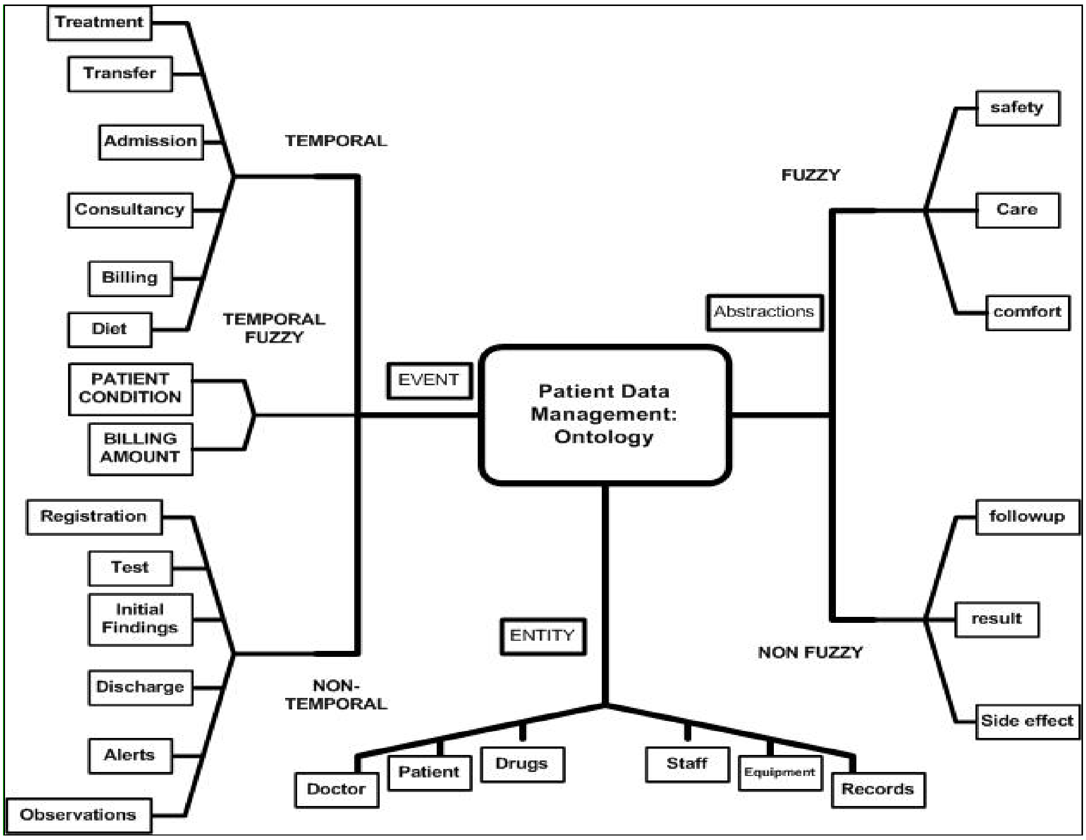


Fig. 2 Fuzzy Temporal Ontology for Patient Data Management

model, highlighting the fact that the treatment data is temporal in nature. Treatment may change with the passage of time and we must have to manage and retrieve that data when required, because time is one of the most important features while we want to improve health care process.
Similarly the data regarding the doctors who are looking after the patient and the para-medical staff who is performing duties in the wards has to be kept in the database. These relationships are represented with the dotted line and with the clock symbol. These relationships are called as temporal relationships [21]. The model depicts the information flow in a hospital and also represents the important work stations and information flow to the patient database and servers, with the objective to incorporate those features which best suit to patient database model.

4.1.2 Fuzzy Ontology

other possibilities exist in the relation between an element and a set emerging in various practical processes [26][27][28]. Fuzzy theory holds that many things in life are matter of degree [29][30][31]. Thus the association of each element in a universe of discourse is a matter of degree, which is a number between 0 and 1 and represented

A fuzzy ontology [23] can be defined as consisting of fuzzy concepts, such as fuzzy attributes which may have crisp or imprecise values. Let's consider an attribute patient_bp which may be defined as "low", "high", or "very high". These values are defined through fuzzy sets, after assessment of membership function defined.

The fuzzy ontology [24][25] is based around the concept that each index term or object is related to every other item (or object) in the ontology, with a degree of membership assigned to that relationship based on fuzzy logic [26].

4.2 Fuzzy Sets With Some Properties

Fuzzy sets [27] are a natural outgrowth and generalization of crisp sets. Fuzzy set theory offers us a new angle to observe and investigate the relationship between sets and their elements other than traditional "Black and White" way. It tells us besides "belongs to" and "not belongs to" way,

4.2.1 α -cut and strong α -cut

One of the most important concepts of fuzzy sets is the concept of an α -cut and its variant strong α - cut. Given a fuzzy set A defined on X and **any** number $\alpha \in [0,1]$, the $\alpha-$cut , $({}^{\alpha}A)$ and the strong

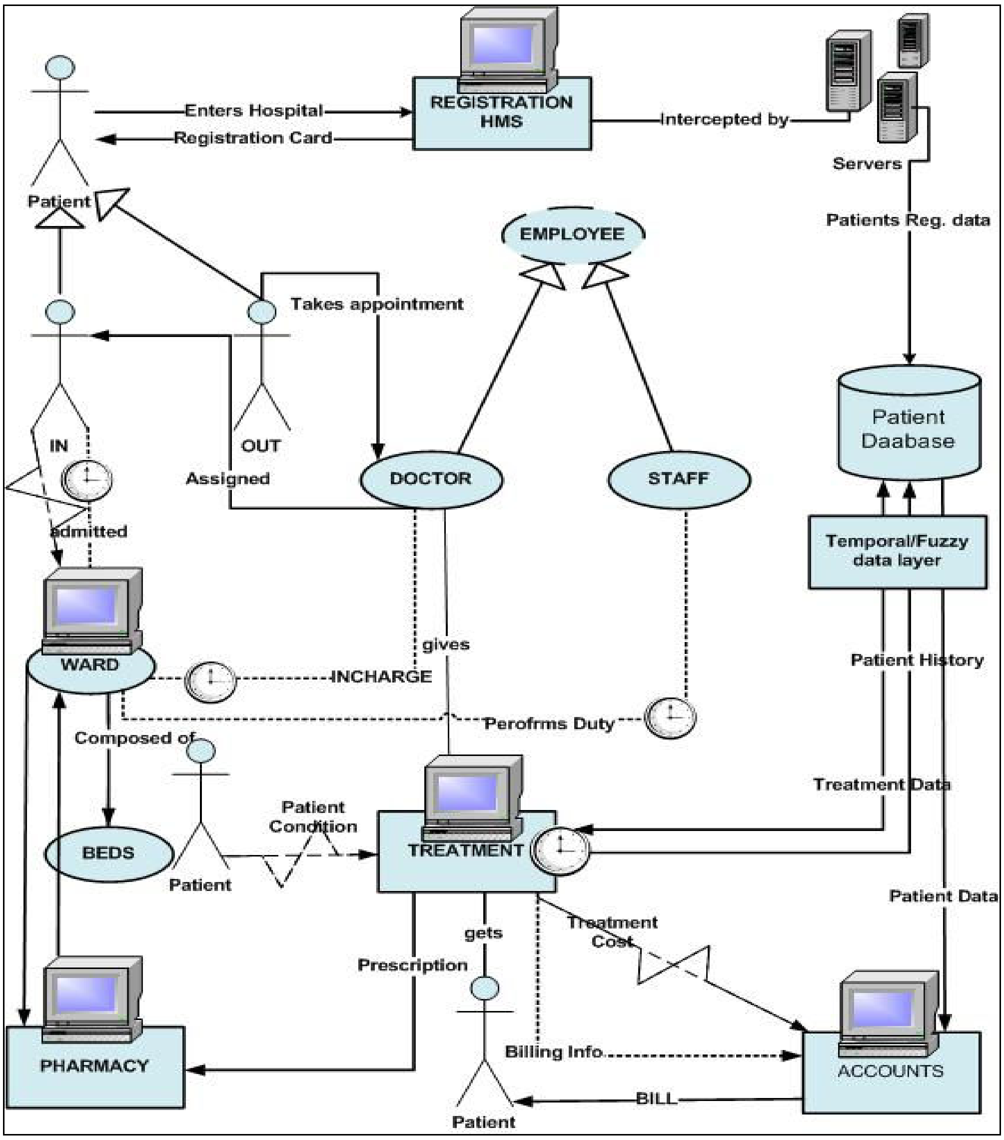


Fig. 3 Requirement analysis: Work flow model for PDM

α-cut, ${}^{\alpha+}A$ are crisp sets given by

$$
\begin{aligned}
{}^{\alpha}A &= \{x \mid A(x) \geq \alpha\} \\
{}^{\alpha+}A &= \{x \mid A(x) > \alpha\}
\end{aligned} \tag{1}
$$

4.2.2 Support of a Fuzzy Set

The support of a fuzzy set A denoted by supp(A), within a universe of discourse X is the crisp set that contains all the elements of X that have nonzero membership grades in A. Clearly, support of A is exactly the same as the strong α-cut of A for α=0. Support of a fuzzy set A may also be represented as ${}^{0+}A$.

$$\text{Support}\,(A) = \{x \mid \mu_A(x) > 0\} \tag{2}$$

4.2.3 Membership Functions/ Formulation

A membership function provides a gradual transition from regions completely outside a set to regions completely inside the set. Although mathematically based on fuzzy sets, it has far greater expressive power than classical mathematics based on crisp sets. Its usefulness depends critically on our capability to construct appropriate membership functions for various given concepts in various contexts. A membership function can be designed in three ways,

Triangular membership functions:

$$f(x;a,b,c) = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right) \tag{3}$$

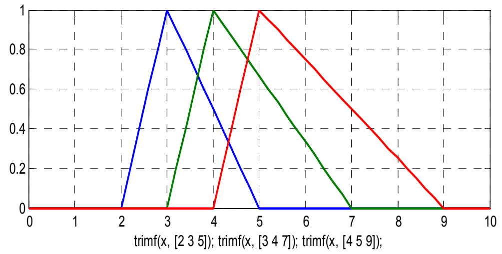
Trapezoidal membership function:

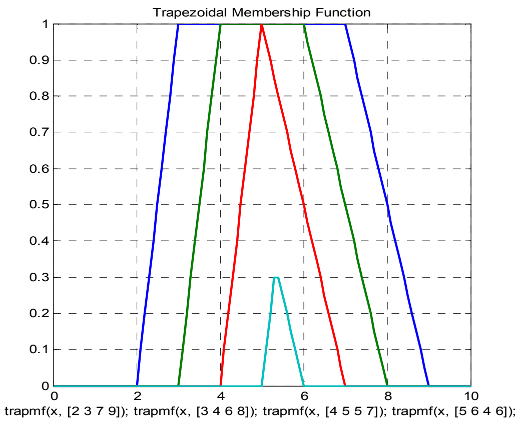
$$f(x;a,b,c,d) = \max\left(\min\left(\frac{x-a}{b-a},1,\frac{d-x}{d-c}\right),0\right) \quad (4)$$

Gaussian membership function:
A Gauss membership function is specified by two parameters $\{c,\sigma^2\}$

$$\text{gaussian}(x;c,\sigma^2) = \exp\left(\frac{-1}{2}\left(\frac{x-c}{\sigma^2}\right)^2\right) \quad (5)$$

Fuzzy membership function graphs are represented in fig. 4.





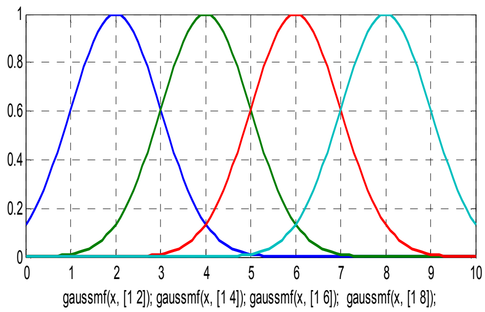


Fig. 4 fuzzy membership function graphs

4.2.4 Fuzzy t-norm and fuzzy t-conorm
The intersection of two fuzzy sets A and B is specified in general by a function $T:[0,1]\times[0,1]\rightarrow[0,1]$. If membership values of A and B are $\mu_A(x)$ and $\mu_B(x)$ then fuzzy conjunction is given by

$$(A\cap B)(x) = T[A(x),B(x)] \text{ for all } x\in X \quad (6)$$

where T represents a binary operation for the fuzzy intersection.
Like fuzzy intersection, fuzzy union operator is defined by a function $S:[0,1]\times[0,1]\rightarrow[0,1]$.

$$(A\cup B)(x) = S[A(x),B(x)] \text{ for all } x\in X \quad (7)$$

where S represents a binary operation for the fuzzy union. T-norm and t-conorm operator satisfies the fuzzy arithmetic axioms like boundary condition, monotonicity, commutativity, associativity, continuity and etc.

4.2.5 Fuzzy Similarity
A similarity relation [31] is a mapping, $S_j : D_j \, X \, D_j \rightarrow [0,1]$ such that for $x, y, z \in D_j$,

(i) $S_j(x, x) = 1$ (reflexivity)
(ii) $S_j(x, y) = S_j(y, X)$ (symmetry)
(iii) $S_j(x, Z) \geq \max\{\min[s_j(x, y), s_j(y, z)]\}$ (max-min transitivity).

A proximity relation [27] is a mapping,
$S_j : D_j \, X \, D_j \rightarrow [0,1]$, such that for $x, y \in D_j$,
(i) $S_j(x, x) = 1$ (reflexivity)
(ii) $S_j(x, y) = S_j(y, X)$ (symmetry)

A convenient representation of temporal fuzzy similarity using membership function is possible using Sagittal diagram, where $r_{xy}=R(x,y)$. Each of the sets X, Y is represented by a set of nodes in the diagram; nodes corresponding to one set are clearly distinguishable from nodes representing the other set (bipartite graph) [30][33]. An example of the sagittal diagram of a temporal binary fuzzy relation R(X,Y) together with the corresponding membership matrix is shown in Fig. 5.
Assume A and B are two fuzzy sets, the similarity of fuzzy sets A and B being developed as

$$S_{AB} = \frac{|A\cap B|}{|A|+|B|-|A\cap B|} \quad (8)$$

where $\cap$ and $\cup$ denote fuzzy intersection and union of fuzzy sets A and B, respectively. $|.|$ denotes the size of a fuzzy set. The computation of fuzzy similarity is easy in case of triangular and trapezoidal functions. For Gaussian membership function, trapezoidal function is used to approximate the long tails of bell shaped curve. Further similarity functions can be formed in [34].

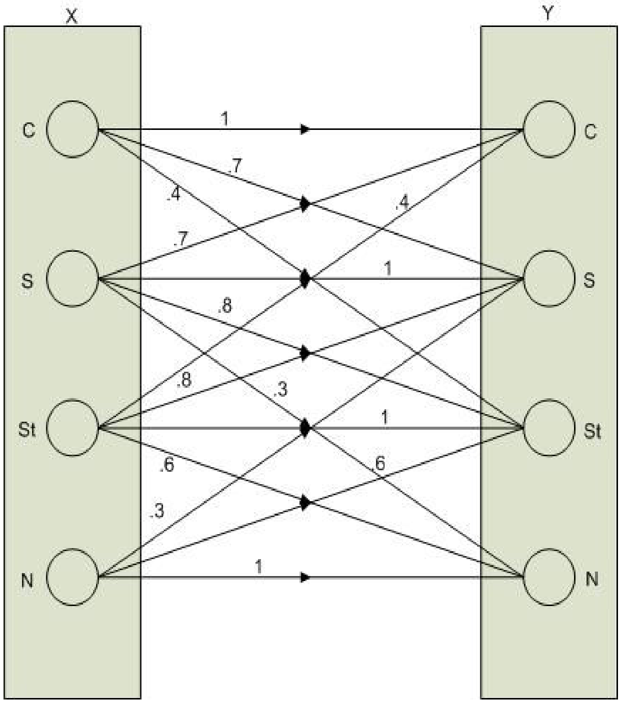


Fig. 5: Sagittal diagram for Temporal Fuzzy Relationship for time stamps X and Y each with four states{C,S,St,N}={critical, Severe, Stable, Normal

5. Fuzzy Temporal Extended Entity Relationship Model (FT-EERM).

By now the relational model is the most effective method for organizing huge amounts of data and still the widely accepted technology amongst vendors and enterprises all around the world. ERM approach is considered to be the best as far as the conceptual model is concerned. Once we have the ER schema then it can easily mapped into the database at the physical level. Temporal data has its own semantics and organization of such data

requires some modifications in the relational model. Attributes in a relation can be time varying or non-time varying attributes. Treatment relation is a temporal relation, because treatment changes with time and forms a treatment history, contrary doctor relation is a non temporal relation because it deals with the attribute which are non time varying. The fuzzy nature of the data such as patient condition and treatment cost is represented as break line in the model.

Fuzzy Temporal Relational Model (FTRM)

FRTM extends the relational model by modeling time and imprecision (fuzziness) in data. There are different kinds of imprecision as far as FTRM is concerned, the imprecision in the degree of membership of an entity itself, imprecision in the supertype entity and its subtype entities, imprecision in the tuple in a relation, imprecision at the attribute level and imprecision at the value associated with the attribute type.

5.1 Structure of Time

We will take the Structure of the set Time to be < T,< >, where T is some countable set and < is a linear order on T, i.e. for any two times t1 and t2, either t1 = t2, t1 ≤ t2, or t2 ≤ t1. In our model we treat time as discrete and isomorphic to the natural numbers because any practical domain that we might define for time attributes in our proposed model would have at most an infinite countable set of names for time moments or time intervals.

Tuple time-stamping [21] approach has been adopted to define a temporal model. The reason for this is the simplicity and to keep the 1NF assumption and the essence of the relational model.

5.2 Temporal and Fuzzy Terms and Representation of Entities, Relationships and Attributes.

The proposed logical temporal data model Fig. 7 comprises of three main constructs namely, the entity (temporal or no temporal), attributes (time-varying, non-time-varying and partial time varying attributes) and fuzzy attributes, thirdly the relationship type amongst the entities .

Following are some constraints to ensure the consistency of the conceptual schema:

- We have introduced a new term as activation_start and activation_end rather than valid time because validity itself is of many types and it creates complexity while defining an entity.
- It represents temporal facts both at time points and as well as on intervals.
- It represents fuzzy concepts (attributes) with a break symbol.(fig)
- Update time is introduced instead of transaction time. An update refers to change in data (tuple) of any sort (insert, delete or change).
- Activation time can be represented with different time granularities [35] such as year, month, week, day, hour, minute and second and even beyond that. Conversion from one time

granularity [35] to another is accomplished by the conversion functions.

- Entity is categorized as a temporal and non-temporal entity
- Temporal entity may hold a fuzzy attribute.
- Fuzzy attribute value also depends on the temporal attribute value.
- Fuzzy temporal relationship is also represented with a dotted line with a break line symbol Fig 6.
- Temporal entity type must have a combinational primary key composed of time-varying and non-time-varying attributes. The activation start time is the part of the key.
- The n-ary relationship determines whether it is temporal, non-temporal or fuzzy temporal relationship.

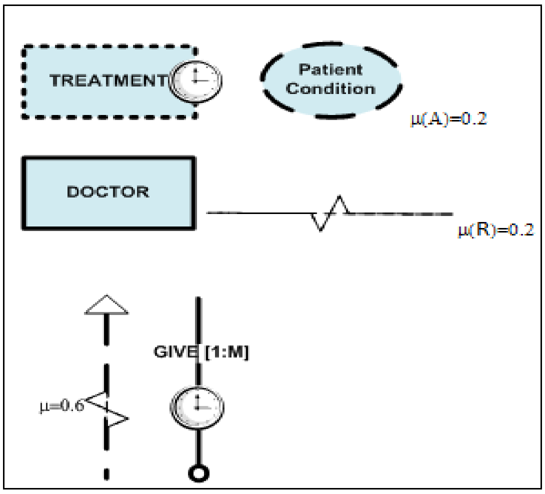


Fig. 6: FT-EER Diagrammatic notation

5.3 Characteristics of FT-EER Model

The ER/EER model is one of the most widely used and well accepted model for building the logical structure of a database. ER model is a semantic model depicts the conceptual aspects of a given mini world. The main focus of the ER model is to conceptualize the schema in terms of database structure and constraints.

Human always deal with chaotic or uncertain data in analyzing and to reach to a conclusion. Uncertainty or fuzziness is found inherent in decision making process. Inherently database systems are not able to manage uncertainty in data. Constructing a database and to identify the data elements in the database schema is also require an identification of uncertain (fuzzy) data. First step is to develop a fuzzy ontology for a database schema to be built. The characterization and classification may help us to develop a conceptual schema based on fuzzy data sets. Remarkable work on the application of fuzzy set theory was laid down by [7]. They introduced the fuzzy sets for entities, attributes and relationships.

The extended ER model incorporating temporal and fuzzy characteristics of the data is required to represent imprecise and vague concepts at the conceptual level.

The concept of a triple M = (E, R, A) introduced by [35] where M → model, E → entities, R → relationships and A → attributes. E, R and A are defined to have fuzzy membership functions. In particular:

R = {Ur (R)/R | where R is a relationship involving entities in (E) and Ur(R) ‥ [0,1]

In this case, Ur( ) is a fuzzy membership function on the relationship between entities in a model.

Table: 1 Fuzzy Data Regarding Patient Condition

PRegNo.	Name	Activation _start	Activation _end	Update _time	Patient Cond	Bill Amt
1002	Bilal	01-12-2009 12:30 pm	03-12-2009 1:00 pm	01-12-2009 1:00 pm	Severe	Medium
1004	Ali	31-11-2009 10:00 am	03-12-2009 2:00 pm	31-11-2009 10:00 am	Stable	High
1101	Sajid	12-12-2009 09:00 am	Current Time	12-12-2009 08:50 am	Critical	Very High
1109	Salman	12-12-2009 10:50 am	Current Time	12-12-2009 09:50 am	Normal	Low
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5.4 Representing the time and fuzzy dimension

The fuzzy temporal relation Table 1 describes the data regarding patient condition, which is a fuzzy attribute which may take a value (severe, critical, stable, normal). Similarly the bill_amount attribute refers to the treatment cost which may take a value (very high, high, medium, low). Both these attributes are fuzzy in nature and the fuzzy membership function determines the values on the basis of fuzzy set theory. Regardless of the fuzzy nature these attributes changes as the time changes so the fuzzy value associated with one attribute may change when the time changes.

The similarity degree S of fuzzy terms of patient condition are calculated and shown in the Table (2).

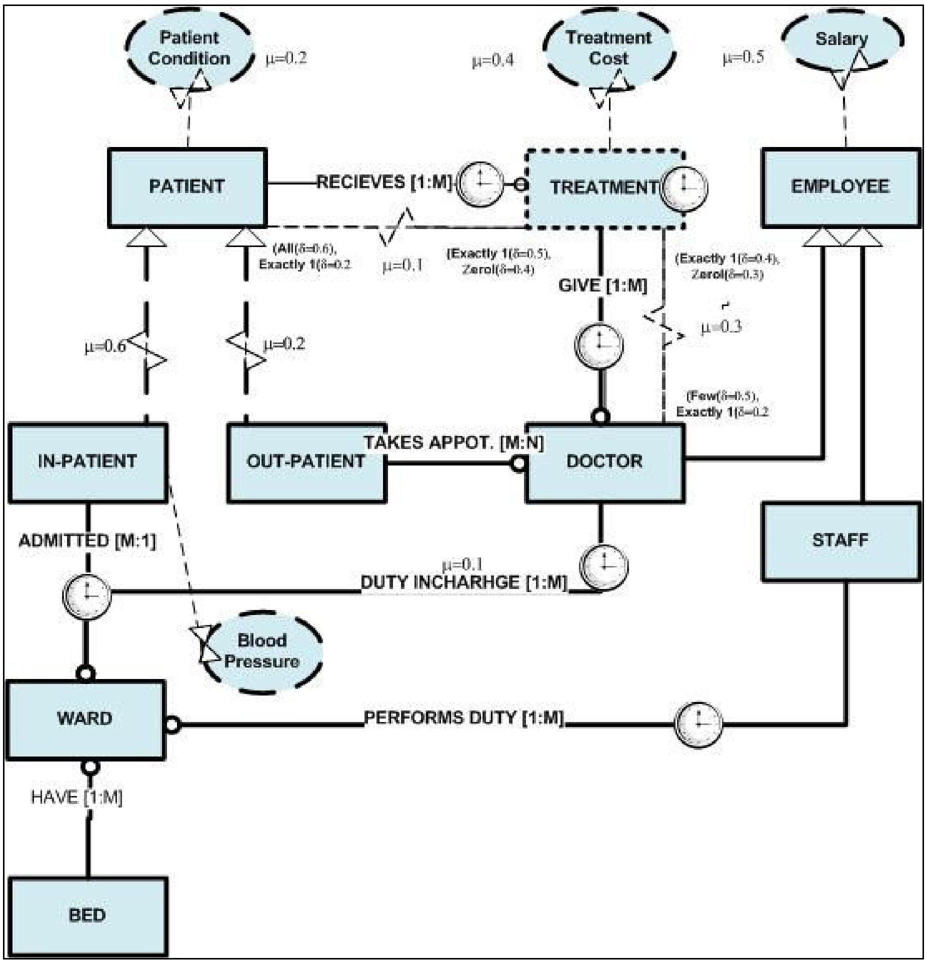
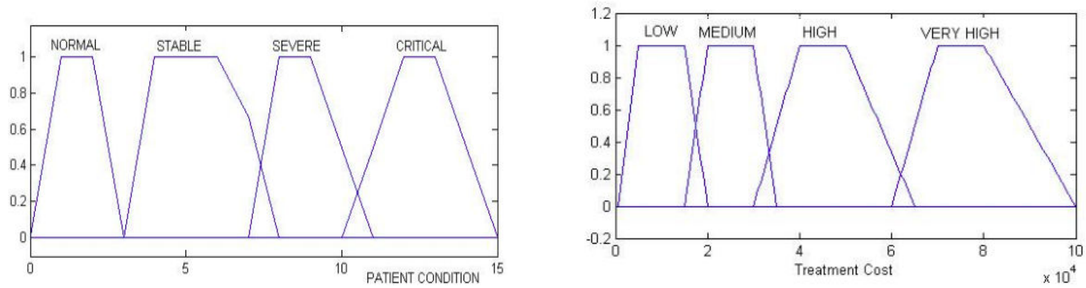


Fig 7: FT-EERM of Patient data



(a) **(b)**

Fig. 8 The membership function graph of fuzzy attributes patient condition and bill amount are represented in fig (8) using a trapezoidal membership function.

Table 2: similarity Degree S of Fuzzy Terms of Patient Condition

	Critical	Severe	Stable	Normal
Critical	1	0.7	0.4	0
Severe		1	0.8	0.3
Stable	--		1	0.6
Normal	--	--	--	1

Temporal fuzzy queries

If the database consists of both temporal and fuzzy terms, we require a query language which can deal with both the aspects. “List of all patients in critical condition from 10-10-2009 to 15-12-2009”, “list of all patients with high bill amount (treatment cost) admitted after 31-01-2009”. Queries can be fuzzy temporal or temporal fuzzy depends upon the nature of the problem. A same value associated with one entity at one point in time is considered high and the same value associated with that entity in next point in time may be considered as medium. The authors aim to provide more detailed discussion on FT-SQL in their next paper as a continuity of our research work.

4 Conclusion

This paper has proposed the requirement analysis work flow model of patient data in a typical hospital environment. The significance of this model is to highlight the temporal and fuzzy concepts during requirement analysis phase. Moreover the ontology of the example patient data is proposed, however this ontology is further extended to a complete domain.

The important contribution of this paper is the extended ERM, which incorporates the fuzzy and temporal aspects considering the ontology and the workflow model. This includes the representation of fuzzy and temporal entities, attributes, relationships and constraints in a simple and effective manner. The concepts discussed and the explorations indicated in the paper could be the way forward towards effective representation of vagueness and fuzziness in temporal data modeling at a conceptual level.

The examples presented in this paper do not represent a complete picture, however this can be revised and scaled to a larger problem domain easily. It decreases development time and highlight the most important features of the target fuzzy temporal relational database schema.

Future Work

In future, we extend our work from temporal fuzzy data modeling to the design of modeling operations on the data. We can develop a prototype where we can implement the necessary program code and triggers to activate the temporal fuzzy constraints described in the model. Design of Temporal fuzzy data sub language (FT-SQL) which allows the effective and efficient management of temporal and imprecise data.

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