Progress in Nonlinear Dynamics and Chaos
Vol. 4, No. 1, 2016, 23-33
ISSN: 2321 – 9238 *(online)*
Published on 22 June 2016
www.researchmathsci.org

Measuring Risk of Diabetic: A Fuzzy Logic Approach

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Received 25 February 2016; accepted 3 March 2016

Abstract. Mortality and Morbidity of the policyholders, within the period of assurance is assessed on the basis of present risk factors or diseases. It is assumed that the most critical problems in underwriting of life insurance applicants, is measured risk for diabetes mellitus when it is occurred. In this case, prognosis of morbidity and mortality using life table is not always significant. In this paper, risks associated to diabetic person have been measured by using fuzzy logic system. Fuzzy logic system is able to adapt with imprecise risk factors which are considered as linguistic variables, and the system aggregates the responses of all risk factors by using max-min composition. The proposed system requires six inputs to measure risk and it is observed that the extreme cases are found the risk from 7.52% to 85%. The fuzzy inference system presented in this paper for measuring risks, contributes to the application field of insurance underwriting, rate making and insurance economics.

Keywords: Fuzzy logic, insurance underwriting, risk measure, fuzzy inference system

1. Introduction

Since the inception of fuzzy set theory in 1965 by its founder Zadeh [30], applications of fuzzy set theory have expanded. Applications have appeared in information science, decision analysis, medical science and engineering, economics, finance and many other disciplines. Inthe field of actuarial science there are many scopes to expand the application of fuzzy mathematics. The fuzzy mathematics in finance investigates the study of mathematical financial when the monetary inputs are assumed to be fuzzy numbers. Buckley (1987) [1] studied fuzzy analogues of the compound interest problems in the mathematics of finance. Buckley *et al.* (2002) [2] studied regular annuities taking interest rate, investment amount are fuzzy numbers. Shahjalal, M., *et al.* (2013) [25] transform various annuities to the fuzzy form taking risk discount is a fuzzy number. The study was performed in the context of usual mathematics of actuarial science. Fuzzy mathematics such as fuzzy logic is an extension of classical multivalued logic that is able to handle imprecise data. It is found that fuzzy logic system is applied as a decision making system under the uncertain and complex event. Shahjalal, M., *et al.* (2012, 2013)

[24, 25] were implemented fuzzy rules in stock data to make investment decision. Measuring risk is very important study for insurance underwriter for making a new product and insurance contract. De Wit, G. Willem (1982) [7] introduced the application of fuzzy mathematics to insurance. They made an attempt to analyse intuitive risks for underwriting in insurance. Since then application range of fuzzy mathematics are found to be used in Actuarial Science. Lemaire (1990) [21] applied fuzzy set theory in insurance framework. He applied fuzzy logic to define preferred policyholder in life insurance, decision making procedures for reinsurance application; finally insurance premiums are calculated by using fuzzy numbers. A computer based fuzzy underwriting system was proposed by Horgby, et al. (1997) in [13] for underwriting diabetes mellitus in life insurance. The system relies on medical knowledge concerning the etiology of diabetes mellitus and underwriting principles in insurance. They reported that fuzzy inference system can cope with complexity of prognostic decision making. Shapiro (2004) [26] studied fuzzy set theory and overviewed the application area in insurance aspects. He overviewed fuzzy set theory, fuzzy arithmetic, fuzzy inference systems,fuzzy clustering, fuzzy programming, fuzzy regression and the same in many insurance areas including classification, underwriting, projected liabilities, fuzzy future and present values, pricing, asset allocation, cash flows, and investments. Simple examples were stated in that study. Horgby (1998) [14] applied fuzzy logic to classify risk by defining risk factors as fuzzy numbers. Here he showed that an insurer can utilize the multiple prognostic factors that are imprecise and vague. The classified risk then applied to adjust the premiums. Kumar and Jain (2012) [20] presented a model, which was based on fuzzy expert system for insurance companies to find out the mortality of insurer in the existence of diabetes for life insurance underwriting. In this study they measure risk for a diabetic person using medical diagnosis. Trapezoidal membership functions were used in their study.

2. Factors considered measuring addition risk

To develop a life insurance policy many factors are required to study, such as benefit, premiums, health status, mortality and morbidity index of a person etc. Measuring mortality and morbidity rate of a person is an important index to calculate premiums for a policy. In the case of Diabetic person, mortality and morbidity table may not represent the expected measure of survival duration of life. Medical underwriter depends on the Physician's advice to measure the risk of a Diabetic person. Physicians depend on some pathological diagnosis, food habit, family history etc. to state the present health status of Diabetic person. In this condition, by using word, a Physician states the health status like bad, normal, good, etc. Numerical rating system, for measuring risk for the case of diabetic persons is not well accepted [13].

The capability of fuzzy sets to express gradual transitions from membership to non-membership and vice versa has a broad utility. It provides a meaningful and powerful representation of measurement of vague concept expressed in natural language. A fuzzy set can be defined mathematically by assigning a value to each possible individual in the referential set, representing its grade of membership in fuzzy set.

A difficult task for the insurance underwriter is to measure the additional risk of a diabetic person. Fuzzy logic system analyses some risk factors associated to a diabetic person. It generates a decision whether the measured risk is very low, low, normal, high or very high as percentage basis. Finally some examples have been reported in this section. To develop this application [8,13,14,20,26,27,29] have been studied. In this study, the prognosis in diabetes mellitus is found [13,20,26] and [27] on the basis of three primary factors listed as:

1. Adjustment factor (therapy)
   (a) Blood Sugar Level
   (b) Haemoglobin A1c (HbA1c test) glycated haemoglobin test
2. Complication factor
   (a) Blood Pressure (systolic)
   (b) Body Mass Index (BMI)
   (c) Tobacco consumption
3. Time factor
   (a) Duration of diabetes (years)

3. Diabetes and associated risks

Diabetes is a disease that affects how a body uses glucose. Glucose is the main source of energy for the body's cells. Glucose level in the blood is controlled by a hormone, or special chemical in the body, called insulin. Insulin is made by the pancreas, and helps glucose enter the cells. There are two types of diabetes: type-1 and type-2. In type-1 diabetes, the pancreas doesn't make enough insulin. In type-2 diabetes, the body can't respond normally to the insulin that is made. Both types cause glucose levels in the blood to rise, leading to symptoms like increased urination, extreme thirst, and unexplained weight loss.

About causes and risk factors of diabetes are revised [12, 16, 18]. Mortality and Morbidity used in stochastic model can be found in [6]. Risk factors reported for diabetes personal for insurance policy can be found [19, 28], risk for obesity [15], risk for high blood pressure and duration of diabetes [22] are discussed in the references given in the parenthesis.

Risk is the uncertainty about a situation's outcome which is an unpredictable event that leads to unwanted loss or damage.

Cardiovascular disease risk factors: There are many risk factors associated with coronary heart disease and stroke [9]. Some risk factors such as family history, ethnicity and age, cannot be changed. Other risk factors that can be treated or changed include tobacco exposure, high blood pressure (hypertension), high cholesterol, obesity, physical inactivity, diabetes, unhealthy diets, and harmful use of alcohol [9] .

Blood sugar level ranges: Blood glucose level ranges is important to both diabetes diagnosis and diabetes self-management. The NICE recommended target blood glucose levels for adults with type-1 diabetes, type-2 diabetes and children with type 1 diabetes are discussed in ref [4]. The (IDF) International Diabetes Federation's target ranges for people without diabetes are stated in refs [3,5,23]. Blood sugar level ranges are shown in table 3.1. [4].

The Haemoglobin A1c (HbA1c) test for Diabetes: Haemoglobin is found in red blood cells [17], which carry oxygen throughout the body. When diabetes is not controlled (meaning that blood sugar is too high), sugar builds up in a blood and combines with haemoglobin, becoming glycated." The average amount of sugar in a blood can be found by measuring haemoglobin A1c level. If glucose levels have been high over recent weeks, haemoglobin A1c test will be higher. Haemoglobin A1c test ranges are given in Table (3.1) [17].

Diagnosis	**Haemoglobin A1c Level**
Normal	below 5.6 percent
Pre-diabetes	5.7 to 6.4 percent
Diabetes	6.5 percent or above

Table 3.1: HbA1c test ranges

Blood Pressure: Hypertension (HTN) or high blood pressure, sometimes called arterial hypertension, is a chronic medical condition in which the blood pressure in the arteries is elevated. Blood pressure is summarised by two measurements, systolic and diastolic, which depend on whether the heart muscle is contracting (systole) or relaxed between beats (diastole). This equals the maximum and minimum pressure, respectively. There are different definitions of the normal range of blood pressure. Normal blood pressure at rest is within the range of 100-140mmHg systolic (top reading) and 60-90mmHg diastolic (bottom reading). High blood pressure is said to be present if it is often at or above 140/90 mmHg. Hypertension is classified as either primary (essential) hypertension or secondary hypertension; about 90-95% of cases are categorized as primary hypertension" which means high blood pressure with no obvious underlying medical cause. The remaining 5-10% of cases (secondary hypertension) is caused by other conditions that affect the kidneys, arteries, heart or endocrine system. Hypertension puts strain on the heart, leading to hypertensive heart disease and coronary artery disease if not treated. Hypertension is also a major risk factor for stroke, aneurysms of the arteries (e.g. aortic aneurysm), and peripheral arterial disease and is a cause of chronic kidney disease. A moderately high arterial blood pressure is associated with a shortened life expectancy while mild elevation is not. Dietary and lifestyle changes can improve blood pressure control and decrease the risk of health complications, although drug treatment is still often necessary in people for whom lifestyle changes are not enough or not effective. Different Blood Pressure status has been shown in Table 3.2.

Blood Pressure Status	**Systolic/Diastolic**
Low	90/60 or Less
Ideal More	90/60 to less 120/80
Normal More	120/80 to less 140/90
High	140/90 or higher

Table 3.2: Blood pressure status

Body Mass Index: BMI is an important index to measure obesity of a person health it takes on height and weight. Table 3.3 shows the different obesity and BMI index.

Health status	**BMI**

Underweight	Less than 18.5
Healthy weight	Between 18.5 to 24.9
Overweight	Between 25 to 29.9
Obese	30 or higher

Table 3.3: BMI Index and health status

Tobacco Consumption: Tobacco use leads most commonly to diseases affecting the heart, liver and lungs, etc. The added risk from smoking is greater than the people without diabetes. Tobacco consumption is a factor to measure risk for a diabetic person.

4. Fuzzy rule based inference system

In the case of ambiguous situation Boolean two valued logic does not meet the real world problems of engineering, economics and finance. Fuzzy logic is able to handle these problems with a degree of satisfaction. Fuzzy set theory and Fuzzy logic was introduced by L. A. Zadeh [30]. Boolean logic assumes that every fact is either entirely true or false. The term fuzzy logic refers to the logic of approximation and allows for varying grades of truth. [10, 11].

Fuzzy logic base system or rule based inference system is the process of obtaining a conclusion for a given input that was possible never encountered before. The basic rule (law) for a fuzzy logic based system is the compositional rule of inference.

Definition 4.1. Let X and Y be classical sets. Then the fuzzy set $R: X \times Y \to I$ is called a fuzzy relation from X to Y, where $I = [0,1]$. Set of all fuzzy relation from X to Y, is denoted by $I^{X \times Y}$.

Definition 4.2. A **Fuzzy rule** of "If *x* is *A* then *y* is *B*" is defined by a fuzzy relation as $R(x, y) = A(x) \wedge B(x)$.

Definition 4.3. A single fuzzy relation is barely enough to make an informed decision. By fuzzy rule base we mean a finite collection of fuzzy rules.
A fuzzy rule base of"If *x* is A_i then *y*is $B_i, i = 1, \ldots, n$" is defined by the fuzzy relation as

$$R(x, y) = \vee_{i=1}^{n} \left(A_i(x) \wedge B_i(y) \right);$$

Definition 4.4. Let $A \in I^X, B \in I^Y$ two fuzzy sets and $R \in I^{X \times Y}$ be a fuzzy relation. A fuzzy logic system or fuzzy rule based system or fuzzy compositional rule of inference is a function $f: A \to B$ determine through a composition

$$B' = A' \otimes R \text{, with } \otimes: f(X) \times f(X \times Y) \to f(Y) \text{ .}$$

Fuzzy logic system on the composition $\otimes$ is defined by

$$B(y) = A(x) \otimes R(x, y) = \vee_{x \in X} \left(A(x) \wedge R(x, y) \right)$$

Theorem 4.1. *Continuity property of the membership function of the conclusion Q in the fuzzy compositional rule of inference is independent of the observation P.*

[10] Let *R* be a continuous fuzzy relation, and let *T* be a continuous *t*-norm, then *Q* is continuous

$$\omega_Q(\delta) \le \omega_T(\omega_R(\delta)), \text{ for each } \delta \ge 0$$

Theorem 4.2. *Stability property of the conclusion Q with respect to small changes in the membership function of the observation P in the compositional rule of inference scheme is independent of fuzzy relation R.*

[10] Let and *T* be a continuous *t*-norm, and let P, P' be fuzzy numbers. If $d_H(P, P') \le \delta$ then

$$\bigvee_{y \in \mathbb{R}} \left|\mu_Q(y) - \mu_{Q'}(y)\right| \le \omega_T\left(\vee\left\{\omega_P(\delta), \omega_{P'}(\delta)\right\}\right)$$

where $\omega_P(\delta)$ and $\omega_{P'}(\delta)$ denotes the modulus of continuity of P and P' at δ.

Theorem 4.3. *Continuity property of Conclusion Q holds for small changes in fuzzy relations* W_i.

[10] Let W_i be fuzzy relations, $i = 1, \dots, m$ and let *T* be a continuous *t*-norm, then *Q* is continuous and

$$\omega_Q(\delta) \le \omega_T(\omega_R(\delta)), \text{ for each } \delta \ge 0$$

where $\omega(\delta) \le \vee\left\{\omega_{w_i}(\delta), \dots, \omega_{w_m}(\delta)\right\}$

Theorem 4.4: *Stability property holds for small changes of observations P, $P^{/}$.*

[10] Let and *T* be a continuous *t*-norm, and let P, P' be fuzzy numbers. If $d_H(P, P') \le \delta$ then

$$\bigvee_{u \in I^{v \times u}} \left|\mu_Q(u) - \mu_{Q'}(u)\right| \le \omega_T\left(\vee\left\{\omega_P(\delta), \omega_{P'}(\delta)\right\}\right)$$

where $\omega_P(\delta)$ and $\omega_{P'}(\delta)$ denotes the modulus of continuity of P and P' at δ.

5. System structure of fuzzy logic based system to measure risk

Generally a fuzzy logic based inference system or decision making system involves some modules. Figure 5.1 illustrates the modules of a fuzzy rule based system. In the fuzzy logic based system six inputs have been taken. The system statistics of variables, rules and functions are given in table 5.2. The complete system structure and flow chart is shown in Figure 5.3. The abbreviated variables name, units and their input domains are presented in table 5.3.

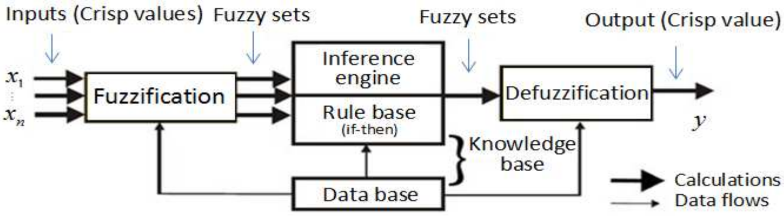


Figure 5.1: Modules of a fuzzy rule based system

Input variables	6
Output variable	1
Rule blocks	4
Rules	9,18,3,27
Membership function	21

Table 5.2: Variable statistics

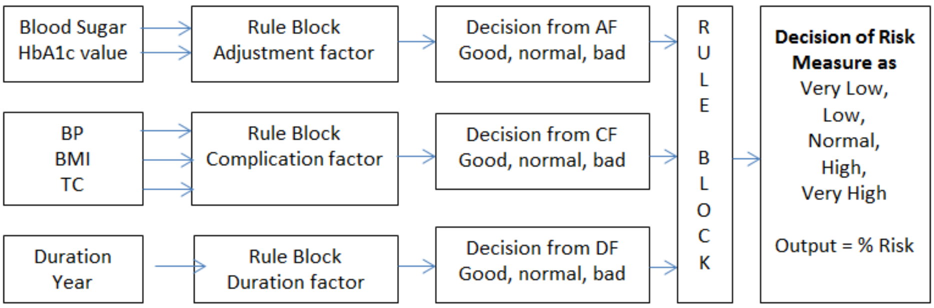


Figure 5.3: System structure and flow chart

Variable name	Abbreviation	Unit SI	Input Domain
Blood Sugar Level	BSL	Mg/dL (milligrams per decilitre) Or Mmol/L (millimoles per litre)	[40,220]
HbA1c test (Measures haemoglobin in the blood)	HbA1c	Mmol/mol (millimoles HbA1c per mole) of toatal haemoglobin	[3,13]
Blood Pressure (Systolic)	Bp	mmHg(millimetres of mercury)	[70, 190]
Body Mass Index	BMI	Kg/m^2	[17, 40]
Tobacco Consumption status	TC	no=0, yes=1	0,1
Duration of diabetes	DuD	year	[0,10]

Table 5.4: Domain of input variables

5.1. Implementation of the system to measure risk

In this section risk has been measured for diabetes persons. Different inputs such as Blood sugar level, Haemoglobin, Blood Pressure, Body Mass Index, Tobacco consumption status and duration of diabetes have been taken to know the risk level as Low, Normal and High. Input variables name, unit and domain are shown in table 5.4.

5.2. Parameter setting for linguistic variables

The most difficult task for a fuzzy rule based inference system is to set the parameters value for corresponding linguistic variables. The prognoses of diabetes mellitus have been reviewed in section 3. The table 5.5 illustrates the parameter values of used linguistic variables. Parameters for final decision variable called risk are shown in table 5.6.

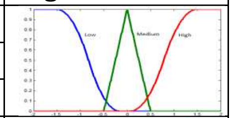
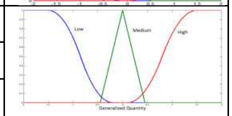
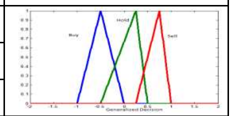
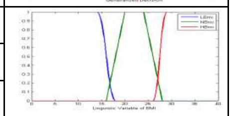
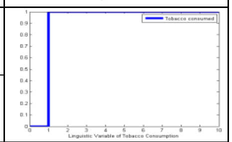
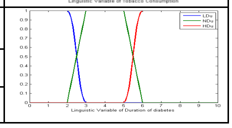
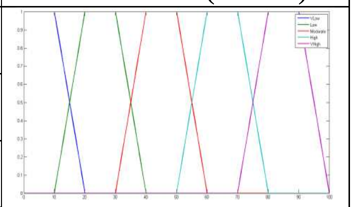
Name of Linguistic	**Fuzzy Numbers**	**Parameter**	**Fig.**
Bsl=Blood Sugar Level (LBsl, NBsl, HBsl)	Z-Shaped for	Z (40,80)	
	Trapezium for	Trap	
	S-Shaped for	S (180, 240)	
Hemoglobin A1c HbA1c (LHbA1c, NHbA1c, HHbA1c)	Z-Shaped for	Z (3,6)	
	Trapezium for	Trap (3,6,9,11)	
	S-Shaped for HHbA1c	S (9,13)	
Blood Pressure=BP (LBp,NBp,HBp)	Z-Shaped for	Z (70, 90)	
	Trapezium for	Trap (80, 90, 120,	
	S-Shaped for	S (120,140)	
BMI=Body Mass Index (LBmi,NBmi,Hmi)	Z-Shaped for	Z (14, 18)	
	Trapezium for	Trap (16, 20, 24,	
	S-Shaped for	S (26, 29)	
Tc=Tobacco Consumption (LTc, HTc)	LTc for 0 Consumed	LTc=0	
	HTc for 1 or more	HTc=1	
DuD=Duration of Diabetes (LDu, NDu, HDu)	Z-Shaped for	Z (2, 3)	
	Trapezium for	Trap (2, 3, 5, 6)	
	S-Shaped for	S (5, 6)	

Table 5.5: Parameter values for different linguistic variable

Decision for risk	Fuzzy numbers	Parameter	L/v. Decision (Risk %)
Risk = (Very Low, Low, Normal, High, Very High) risk	Trapezium for VLR	Trap (0 0 10 20)	
	Trapezium for LR	Trap (10 20 30 40)	
	Trapezium for NR	Trap (30 40 50 60)	
	Trapezium for HR	Trap (50 60 70	

		80)	
	Trapezium for VHR	Trap (70 80 90 100)	

Table 5.6: Parameter for final decision as risk

6. Results and discussion

The paper presents a fuzzy logic based system to measure risk for diabetic person. The system requires six inputs to measure risk of a diabetic person. From some pathological diagnosis the input values can be collected for a diabetic person. The system structure illustrated in figure 5.3 has been implemented by writing some MATLAB program script. As some output we can see from table 6.1 the extreme cases for diabetic person. The table 6.2 shows some observation of diabetes cases where it is seen that 7.52% is minimum and 65% is maximum risks. It is difficult to adjust the linguistic variables to the fuzzy system. The parameters value is not possible to choose accurately. Theorems 4.1-4.3 states for small changes of parameter that is observation, the system decision is stable and continuous.

Observation no.	In put						Out put
	BSI	HbA1c	BP	BMI	TC	DuD	Risk (%)
1	40	4	75	18	0	2	7.52
2	40	4	75	18	1	2	25
3	55	6	95	20	0	4	45
4	55	6	95	20	1	4	65
5	190	12	160	30	0	7	85
6	190	12	160	30	1	7	85

Table 6.1: Risk are measured for some observations extreme cases

Observation no.	In put						Out put
	BSI	HbA1c	BP	BMI	TC	DuD	Risk (%)
1	55	5	80	20	0	3	20.3
2	75	7	85	25	0	5	45
3	95	5	90	25	0	4	45
4	105	9	95	27	0	7	45
5	120	11	100	25	0	8	65
6	135	8	120	23	0	6	45

Table 6.2: Risk are measured for some observations

Horgby, et al. (1997) [13] presented a fuzzy underwriting system is mainly measure the risk of the persons with diabetes mellitus and then apply this risk to calculate premium surcharge. It was shown with limited examples. In this paper, the risk of the different diabetic persons, are measured as a percentage basis. The measured risk or its portion can be used as an additional risk load. Pathak, Dwivedi (2013) presented a model using fuzzy mathematics and expert system to measure the risk of old aged personals. The risk was done by taking social and socio economic (Education, Previous Occupation and Income), self-sufficiency and health indexes. In the present paper, we have measured risk, only for diabetic person for any age, and this risk can be apply to calculate premium.

The fuzzy expert system proposed by Kumar and Jain (2012) [20], is to carry out themortality of insurer in the existence of diabetes for life insurance underwriting. The fuzzy rule based expert system was able to measure risk for the diabetic person. The present work measured the same risk for different inputs and presented the risk of the affected persons.

7. Conclusion

Fuzzy logic has been applied to measure risk of diabetic persons. Risk factors of a diabetic person vary independently and identically. When a diabetic patient is under treatment he might has many factors to be concern but few factors may dominated to fall in a critical situation like heart attack. Besides the risk factors person's activity like physical exercise, proper medication may reduce the impact of risks. By using therapy, complication and time factors, we measure risk (in percentage) for a diabetic person. The risk measured by applying fuzzy logic approach can be applicable in medical underwriting in view of addition risk load to calculate insurance product and premium.

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