Business intelligence: fuzzy logic in the risk client analysis

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Abstract: The following paper focuses on achieving accurate results through rough data. Using an inference model based on fuzzy logic, human reasoning was proactively stimulated, under certain conditions, in order to deal with the possibility of client-loss due to service quality. The experimentation is carried out by information related of complaint receipts from a period of two years (70,000 registers). For that effect, a prototypical program is set in C++ language, which receives as input the crisp values that result from the failure resolution for each relevant service. The proposed model is intended to classify clients according to the risk they may have in the contractual relationship with the company.

Keywords: business intelligence; fuzzy logic; soft computing; decision.

1 Introduction

Generally, the day-to-day decisions made in a business have an implicit degree of imprecision, due to characteristics of the data involved. Subsequently, these decisions are evaluated in terms of their consequences in application. That is notwithstanding the fact that in order to take a particular decision, an exhaustive study and approximation of its consequence must be done, including a determination of the associated risk, which would be based on the relevant data.

However, companies exist in a dynamic and changing environment; there are variables which can be neither managed nor controlled. Such environmental factors can even affect the result, for instance, when they apply to a decision that may not have the desired effect. That is to say, the decision has to have a certain degree of ambiguity, in terms of the description of its nature or origin that could be associated with the precise instant where the decision was taken: the surrounding, the context, interpretation, verbal or written way of expressing it, data characteristics, or even the emphasis in how it is described. For example, it is not a good enough reason to let a client go, when they are unsatisfied by the service they have received and are determined to terminate the contract.

Nowadays, there is no accurate information about the client's dissatisfaction, which were the reasons or variables that influence to make the decision, certainly it is more than the dissatisfaction for the contracted services.

When we have determined the reasons involved in or variables influencing the decision, we have reached an adequate level of precision: We leave ambiguity behind. Furthermore, new procedures or processes can be re-evaluated and redesigned, reassessing them as many times as necessary, in order to improve the service quality and to gain customer loyalty for a long time.

This paper addresses one of the main problems faced by businesses, since service quality is one of the most common causes of the termination of contracts by clients. This paper is focused on how to manage business, from the point of view of associated risk, using fuzzy logic in the context of business intelligence.

Therefore, the need arises to determine the moment when the client is at risk. Hence, the company can act proactively, defining a strategy focused on lowering the risk and improving the customer loyalty in the long term.

2 Business intelligence and fuzzy logic

The term ‘business intelligence’ entered the market in the 1990s, via the Gartner Company in Technological Research of Information. ‘Business Intelligence’ is defined as the process, used by businesses in their diverse operations, of transforming rough data into knowledge emerged from their analysis (Quinm, 2003; Wang, 2016). In addition, business intelligence is recognised as the process of generating information, based on real or rough data, for a strategic decision-making process (Grigori et al., 2004). Furthermore, some researchers define it as “the system that provides the necessary information for the process control, destined to the decision taking by the business users” (Fernández, 2008). It is worth noticing that Wieder and Ossimitz (2015) proposes a definition that can project current trends in Business Intelligence, such as “an analytic and technological process that gathers and transforms fragmented data from companies and markets into information or knowledge about objectives, opportunities, and positions of an organization”.

Currently, business intelligence has become a major area of investment in information technology (hereafter IT) in all the organisations. This has been characterised as the highest technological priority by CIOs from around the world, during many years (Arnott et al., 2017).

The application of the fuzzy logic to business intelligence proposes to aid the decision-making process, specifically by mitigating the uncertainty related with making decisions. That is to say, it proposes to minimise company risk, with the aim of improving the system-value from a systematic viewpoint (Dash et al., 2014). It is also important to highlight that Nazemi et al. (2017) claim that the combination of decisions in the fuzzy logic can be applied as a combined output of basic models with the characteristic that, when these are combined, clear limits are avoided. Hence, more efficiency is generated in order to manage uncertainty. The idea is to train a base of fuzzy rules that dynamically ponder the involved models in the used data base.

In this work, a model based on fuzzy rules is used, proposed by Mamdani (Rodríguez, 2005). Aguirre et al. (2008) specifies that, regarding the Mamdani model, “these were the first systems to be approved in a practical way as universal approximators of their functions”. Indeed, it can be established that a relation between the variables of input and output can be approximate through a fuzzy system built in linguistic terms with a great degree of accurateness. That is to say, according to González et al. (2017), once the inputs and outputs have faded away, these have to be connected.

2.1 Related research

There is a great variety of research using the fuzzy logic with inference motors, oriented to determine certain relations with the clients of a company. This is the case for Cabrera et al. (2007), who formulated a fuzzy system for the calculation of the customer loyalty to touristic destinations. Also, Díscoli et al. (2006) proposes a quality model, making use of a valuation system of basic urban services of infrastructure, which applies fuzzy logic. Furthermore, Llano et al. (2007) research the fuzzy inference system, in order to identify events in terms of failure in real time, using registers of sequences of operational events (SOE); Karmarkar and Gilke (2018) propose a fuzzy model in the decision making area, that allows the agent to help a client to select a family vehicle, with the necessary accessories for their satisfaction based on a rage of them. Dehghani et al. (2018) design and evaluate the model based on rules of reasoning and a fuzzy logic classifier, in order to predict the Triage level in emergency situations and patient seriousness. Prabakaran et al. (2018) present a fuzzy inference system to reduce the fertiliser consumption and improvement in the crop productivity, having as a final aim to support taking decisions, so that crops achieve the proposed objectives.

Moreover, Hung and Khanh (2018) formulate a method for constructing fuzzy linguistic logics, based on axioms and an algorithm made of a group of operations, which is focused on annulling or reducing risk. Over a linguistic domain, it represents and reasons with human knowledge.

Another group of researchers (Ming-Kuen and Shih-Ching, 2010) has focused its effort on reducing the business risk in service companies, developing hybrid models, owing to market globalisation. Therein, the main component is the model of fuzzy logic, whose objective is to propose a wider framework with business elements that allow to precise the support to business intelligence to take better decisions.

An alternative approach concerns the verbal decisions made by the user. In the majority of support systems to take decisions, behaviour relations in terms of mathematical functions are used for knowledge formulation. Users are practically not accustomed to using them, so verbal descriptions are transformed in relations with fuzzy groups, i.e., fuzzy business rules (Harald, 1988).

Garavelli et al. (1999) specified that "companies must face lots of processes when taking decisions, so that their impact in the global performance can be really strong. As a consequence, the role of the decision support system (henceforth DSS) inside an organisation is essential. The capacity to manage uncertainty becomes a crucial issue for a DSS. Particularly, the design of a DSS requires a formulation of the preferences of experts, which is usually affected by uncertainty". In this case, they indicate that the robustness of the system is an effective way to evaluate its capacity to manage uncertainty. Under these circumstances, the fuzzy logic is proposed as a technique for Systems that allow to support the 'decision-making process'.

It is worth noticing that Nazemi et al. (2017) make an important contribution in developing, for the first time, models of fuzzy decision combination that can be applied to the LGD model of corporate bonuses in order to manage the risk in terms of the expected loss in financial institutions.

2.2 Business rules

The generic term 'business rules' has been used extensively in different contexts, models and domains. Its purpose is to capture what is necessary, rather than what is simply permitted, in a business (Savvion, 2004). Every business can be seen as a group of rules that represent their own activities.

Zur et al. (2007) specifies that a business rule is a declaration that attempts to influence or guide the behaviour and the information in an organisation. On the other hand, the procedures and the policies are methods whose objective is to gather and make business rules known. These are essential in all type of business, such as business to business (B2B), business to customer (B2C) and business to employee (B2E).

Today, the concession regarding Business Rules is based on their independence principles under the 'business rules manifesto'. This manifesto comprises ten articles, contributed by the business rules group around 2003. Currently, it has been used in a diverse range of applications, for example, in the predictive monitoring of companies' processes (Márquez-Chamorro et al., 2017).

3 Model of business intelligence

3.1 Definition of the problem

While some decisions can be made using traditional logic by making calculations and other operations, there are other cases where no such operations can be applied. This is either because there is no known or related calculation or mathematical model that can describe the behaviour of the system, or because relevant experience or expertise is required on the topic. At the same time, on some occasions, the decision variables are not the same in a finite group.

Due to their nature, some of the variables that business intelligence manages have some fuzzy characteristics. This implies that in business rules, the antecedent variables, just like the consequences, are fuzzy, since the operation must adapt to the degree of accomplishment of the respective antecedent.

The application of fuzzy logic in business intelligence with business rules proposes to support the making decision process.

The knowledge-base used is generated from complaints made by clients to a business that provides technological services, considering around 70,000 registrations in a period of two years for this study (see Table 1). It is worth noting that, from the total quantity of available services, a pre-selection was made. This included the most important and basic services for any other type of service. Within this group, three services were chosen, which will be evaluated in their respective models, considering the time taken to solve the failure as a criterion of selection: the service with the highest value, the service with the median value, and finally, the lowest value service.

These types of companies usually provide a variety of services, such as access, hosting, internet, landline, among others. Each service has specific processes along with their correspondent drivers (indicators), defined following their management, modification, transportation, and finally, their withdrawal.

Table 1 Data structure

Creation_Date	*Solution_Date*	*Id_incidence*	*Num_incidence*	*Incidence_description*	*sector_description*	*Id_customer*
31/12/2007 10:55	31/12/2007 10:55	489	2248540	Band change was made	Customer service	6651887
31/12/2007 11:26	31/12/2007 11:26	426	2249946	Sinister block request is generated	Customer service	73999435
31/12/2007 13:26	31/12/2007 13:26	489	2256205	Band change was made	Massive SVA deputy management	11518559
31/12/2007 10:11	31/12/2007 10:11	192	2246310	Provisioning service is	Activated customer service	6474884
31/12/2007 10:36	31/12/2007 10:36	51	2247545	2424 portal configuration	Customer service	4665529

On more than one occasion these services can present failures, resulting in customer complaints. These complaints are made via telephone calls, which are received in a call centre. These complaints are comprised in a 'complaints register' and thereby form the knowledge-base.

On other occasions, the method for restoring the relevant service is analysed, considering the time taken to resolve the failure (shorter resolution times minimise the adverse impact on the operations of the customer company) and the quality of the resolution. These aspects are important for maintaining customer satisfaction, thus lowering the associated and generated cost incurred by the resolution of the failed system. Furthermore, the services are defined in terms of technological concepts, implying a strategic plan in IT. Interacting with businesses and their focus at the level of processes, which are the processes of support, it delivers, in terms of their operational aspects, the relevant service in the shortest possible time.

3.2 Problems in the quality of services

One of the main problems faced by businesses is the loss of contracts by its customers. Service quality is among the main, probable causes of this problem. Chen and Yang (2015) define service quality as "the difference between the customer expectations and the service performance". Therefore, it is presented the necessity to determine when the company is in risk of losing a client. It is also essential to act proactively to define a strategy oriented to lower the risk and keep the customer loyalty for a longer time.

The relation between company and client becomes salient when the latter hires the services given by the company. When the customer surpasses a minimum number of hired services, they are variously defined as a captive customer, Premium customer, VIP, among others. Those concepts identify to some extent that loyalty has, to some degree, been gained with the customer.

It is also necessary to highlight, in terms of the services given by a company that these might at some point provoke one or many failures, whose causes are related with external variables of the service. For example, when the user tries to configure or modify parameters of services, having no knowledge about the scope and consequences or simply, due to the degradation of service performance, caused by variations in the physical structure, such as antiquity, temperature, among others. In any of the above mentioned situations, the service objective must be completely restored, depending on the complexity of the failure and the time required to resolve it.

As companies focus their service on the customer, they measure the service quality by the time used to solve a failure and by totally restoring service. Therefore, if the service quality is minimal, the customer is more likely to consider moving to a competitor company with the desired service quality.

3.2.1 Experiment

One of the previous steps in dealing with the problem presented in this paper is to clarify the ideal amount of time in which to solve a specific service failure. For every case, a first, minimum time range is defined, greater than zero (value of x) and its corresponding SLA, where SLA is identified as service level agreement, that is, the required time for an ideal resolution. The SLA will also depend on the type of service. The SLA is defined by each company in particular, considering the resources available and the technologies used (Ziyarazavi and Magnusson, 2013).

Considering the definition of ideal minimum time, a second time range is defined. This is calculated between the SLA, already defined, and a predetermined value (value of y), which slightly surpasses SLA. Subsequently, a third time range is determined, superior to the second (value between z and k), previously defined, time range. These time ranges are defined and/or associated with the service quality as: Excellent, Satisfactory, and Poor. For a better appreciation they are defined as: (See Ec. 3.1).

$$
\begin{aligned}
&\forall x, y, z, k, SLA \in R \\
&\quad \textit{First range} \quad \textit{Excellent} = [x, SLA], \text{ where } z > 0 \text{ and } SLA > x \\
&\quad \textit{Second range} \quad \textit{Satisfactory} = [SLA, y], \text{ where } y > SLA \\
&\quad \textit{Third range} \quad \textit{Poor} = [z, k], \text{ where } z > y \text{ and } k > z
\end{aligned}
\tag{3.1}
$$

Furthermore, if a service suffers repeated failures in a short period of time, or these failures have an intermittent character, the following conditions emerge:

- If the client is loyal (the amount of contracts surpasses the minimum normal amount, determined by the company), they can finish their commercial relation. Therefore, the company must know this situation in order to generate remedial policies.
- If the client does not count on enough contracts, under the minimum normal amount, this implies that, for them, there are no relevant differences between companies, and that they are focused only on whether the hired service has enough quality and can put an end to the services in any moment. However, the company could generate, apart from remedial policies, certain strategies directed especially to such customers, with the aim of achieving their fidelity.
- When a customer is loyal and the performance of the service is satisfactory, the customer will keep the company and will probably increase the hired services, if required.

In the situations described above, the client can be classified under the following conditions: 'high risk' in the first case, 'medium risk' in the second case, and lastly, 'no risk' for the third case. This is shown in Table 2.

Table 2 Risk classification

Risk level	*Contract number*	*Failure number*
High risk	>3	>0
Medium risk	<3	>0
No risk	>3	0

One way to simulate this situation is through the business rules, where the result of the rule will increase or decrease the risk.

3.2.2 Model

The generic model presenting the defined situation in terms of business rules, in relation to the service quality and the hired contracts, would be as follows:

If *Type_Service_is* $= A_i$ ***and***

Time_of_Resol_Fail_is $= B_i$ ***and***

NumberofContract_is $= C_i$

Then

RiskVariation_is D

Another necessary business rule for the process is focused on determining whether there are failures in a determined period, so that the client risk can decrease. The generic model of the rule associated with the Risk variation would have the following structure:

If *Type_Service_is* $= A_i$ ***and***

$(Date\_process - Date\_LastFail) > 1$

Then

RiskVariation_is D

In the proposed model (see Figure 2), the linguistic variables, defined as follows, are related with the characteristics of the resolution of the associated failure with the hired services by the clients, which are provision of basic services, internet and access to platforms, among others and to the number of services hired by each of them. Linguistic variables are defined as the following input variables: services (excellent, satisfactory, poor), contracts (indifferent, normal, committed); output variables: associated risk (High risk, medium risk, no risk) being a dependent variable, risk variation (considerably increased, slightly increases) being a dependent variable.

Belonging-functions are defined for each, previously mentioned variable. Sub-intervals are established, which correspond to the categories defined for each variable involved. Alongside these, a belonging function base, which is standard for all the Services, and individual belonging functions for contracts, associated risk, and risk variation, are generated. The standard base function of Services is defined in Figure 1. Each input parameter is defined under the hour unit, as follows:

Figure 1 Standard function of the services (see online version for colours)

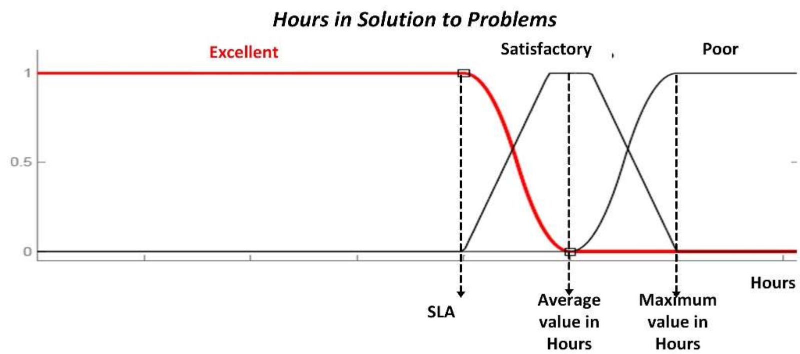
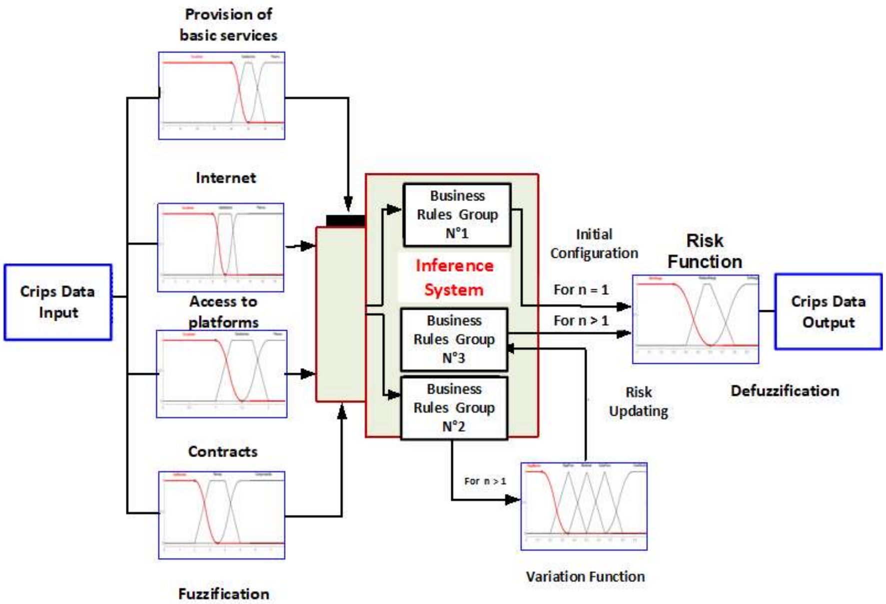


Figure 2 Proposed model (see online version for colours)



3.2.3 Rules of fuzzy interference

Business rules are defined in relation with a pursued objective. In such cases, three groups of business rules are defined, as follows:

Group 1 These will be used initially to configure the process, that is to say, to initiate the associated risk variable. Some examples of them are:

- if (service 1 is excellent) and (service 2 is excellent) and (service 3 is poor) and (contract is indifferent) then (risk is without risk)
- if (service 1 is poor) and (service 2 is poor) and (service 3 is satisfactory) and (contract is committed) then (risk is high risk).

Group 2 These are used to determine the risk variability after the process has been initiated, (nth time), that is to say, to initiate the risk variation variable, such as:

- if (service 1 is excellent) and (service 2 is excellent) and (service 3 is excellent) and (contract is indifferent) then (risk variation is kept)
- If (service 1 is satisfactory) and (service 2 is poor) and (service 3 is excellent) and (contract is committed) then (risk variation is slightly high).

Group 3 These are used to determine the current associated risk, given the variability presented through the risk variation variable, which will be defined, for example, as:

- if (risk variations is really decrease) then (Risk is without risk)
- if (risk variations is really increase) then (risk is high risk).

4 Experimentation and result analysis

4.1 Experimentation

The experimentation is carried out by examining the database, which contains the information related with complaint receipts from a period of two years, with around 70,000 registers.

Figure 3 Fuzzification crisp data input (see online version for colours)

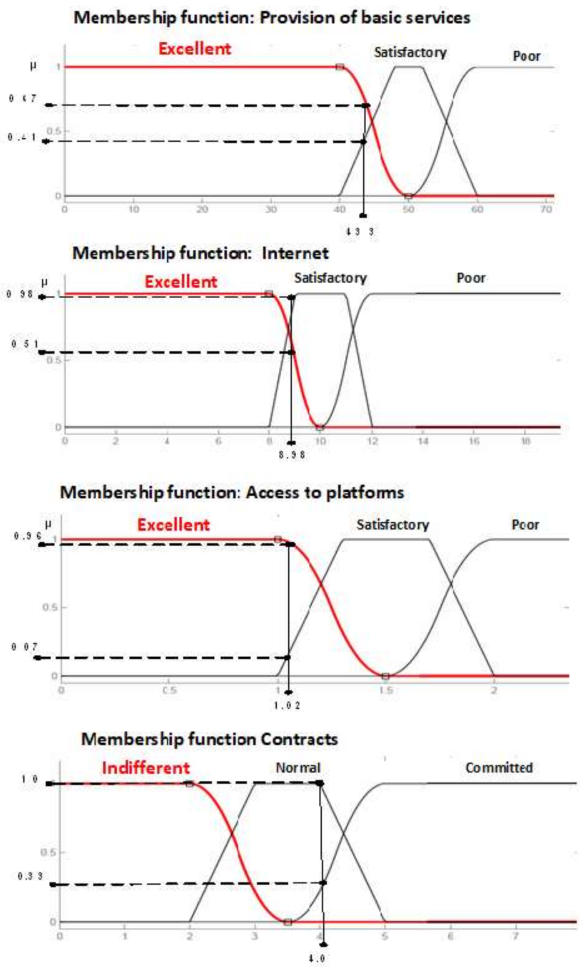
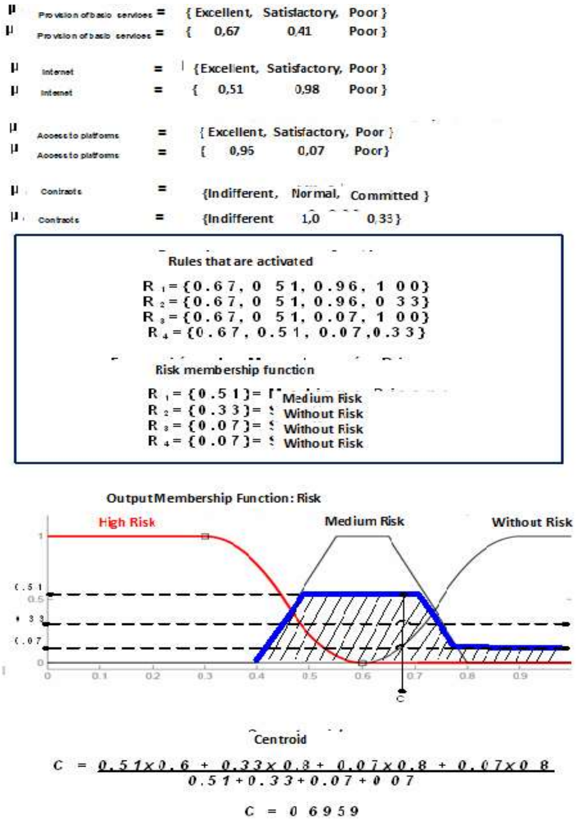


Figure 4 Initial risk (see online version for colours)



Before using the data, they go through a process of normalisation and standardization in order to consider only the services determined for the study. For that effect, a prototypical program is set in C++ language, which receives as input the crisp values that result from the failure resolution for each relevant service. These are taken directly from the database.

The values are fuzzified according to the membership functions previously defined, obtaining the belonging values that correspond to the associated fuzzy group. Subsequently, these serve as inputs for the fuzzy inference system, using the defined rules for the relevant effect that correspond, in terms of structure of the model, to group 1.

When finishing the operation previously described, the aggregation action must proceed for each involved rule, over the output function, in this case, the associated risk variable. The associated risk variable is interpreted as the initial configuration of this variable, and is necessary to measure the grade of variation that the associated risk variable undergoes with respect to a particular customer and that sees itself modified, if there are more failures related with the involved services in the experimentation. Later on, the resultant area is defuzzified, through the centroid method, as seen in Figure 3.

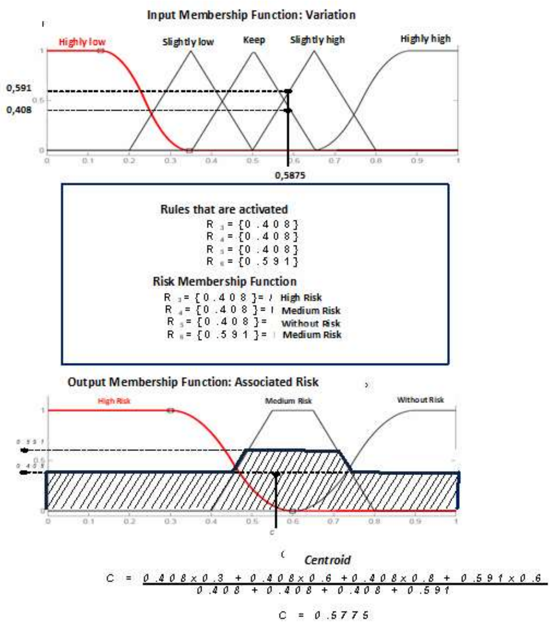
The following step determines the value that will be represented in the variation risk variable, which will subsequently influence the output variable of the associated risk. In that case, new inputs are considered, which contain the database and whose main characteristic is that they are later than those considered in the initial configuration. Furthermore, their time of registration is considered, which makes it possible to deduce the failures they produce in chronological order.

The new data is fuzzified using the input variables, characterised by the determined Services; the fuzzified data will be the input for the inference motor, which is then used for the inference process: the group of rules defined as group 2. The inference result will fuzzify under the centroid method and will directly affect the risk variation variable, which is the output variable in this stage. Finally, the crisp result obtained in the previous process will serve as input to the update process in the associated risk (see Figure 4).

The value obtained is fuzzified, using as an input the risk variable, which will be used by the inference motor. This in turn will use the rules of group 3, as defined above.

By generating its corresponding output, the result will be evaluated in the Associated Risk variable, so that it can subsequently be defuzzified, and thereby obtain the real variation produced in the system, as seen in Figure 5.

Figure 5 System variation (see online version for colours)



In Figure 6, some of the partial results are presented in terms of associated risk variation for a particular client.

Figure 6 Partial results of the prototype

Minimum Value Resulting From Variation Rule

Rule	Provision of basic services	Internet	Access to platforms	Contracts	Minimum	Belonging to: Function	Curve	Output S
1	1	1	1	1	0.00	0	0	3
2	1	2	3	2	1.00	4	2	4
3	3	3	3	3	0.33	4	3	5
4	2	2	2	2	0.78	1	2	2
5	1	1	1	3	0.33	4	3	1
6	2	3	1	3	0.33	4	3	4

Variation of Defuzzification: 0.530180

Fuzzy Set : 3 - (** keep **)

Risk value - Variation

Var	Current state	Fuzzy set	Current Variation	Fuzzy set
1	0.6956	** Medium Risk **	0.5887	** Keep **
2	0.5775	** Medium Risk **	0.4295	** Slightdy Low **
3	0.5800	** Medium Risk **	0.4589	** Slightdy Low **
4	0.5761	** Medium Risk **	0.3940	** Slightdy Low **
5	0.5865	** Medium Risk **	0.3940	** Slightdy Low **
6	0.5865	** Medium Risk **	0.5302	** Keep **
7	0.5758	** Medium Risk **	0.5302	** Keep **
8	0.0000	0.0000		
9	0.0000	0.0000		

4.2 Result analysis

Once the prototype is analysed and given a mock test to visualise its behaviour, it is necessary to adjust the model. The reason is that the defined times for the membership functions present a variation that can generate a deviation from the pursued objectives.

In order to proceed with the comparative process, which is done in a period no longer than thirty days, whose objective is the verification of the success of the model, it can be determined that:

- From a universe of 3,000 customers, 1.2% corresponds to 36 clients, classified as ‘high risk’, i.e., those who would abandon the company. That is to say, it would leave the contractual relation with no outcome.

5 Conclusions and future research

The decision-making process is complex, since it involves variables that are directly and indirectly affected by the environment. Among the decisions it generates, it might be the case that the possibilities are successful and some others not that successful on the occasion of implementing them and obtaining results. It is known that only some of them possess a degree of certainty, due to the dynamic environment in which they are taken. It is not enough to know some relevant variables, but rather to consider under what environment they are managed and other associated factor, even more if they involve the most important actor of a company, the client. Given the previous information, the problems about how to make a decision, reaching an effective solution, through a decision, that had generally a reactive nature, could sometimes be totally predictive, where the probability of success can be minimal. Therefore, by using the fuzzy logic, inserted in the context of business intelligence, where the decision is undoubtedly proactive, generates a bigger benefit, both for the company, that, in this case, retains the customer, and also for the latter, since it reflects the quality service given by the company.

The membership functions, by being defined according to the problem, will allow in a better way to treat uncertainty, since variables involved do not admit that they can be stochastic. Besides, by being defined, they demand that they are real data that reflect the behaviour of the involved variables, as close as possible, have to be about the reality across time.

Based on this research and the applied experimentation, it can be determined that the only variation that can be done is the chosen function to represent the behaviour of the problem in an accurate way, through linguistic variables and in the levels of accuracy of the data, in terms of quantity of representative decimals.

On the other hand, it is clear that the fuzzy logic can be used in proactive processes, which are currently necessary and important in a variety of organisations, given their structure, and their existence in a completely dynamic and changing environment, as well as being inserted in the competition of the market.

5.1 Future work

In future work we can find, among others things:

- the implementation of a fuzzy controller in order to control the stages of the obtention of information in the processes of business intelligence
- the precision and effectivity of the decisions under a changing environment, using the fuzzy logic
- the definition of a cleaning process for the data before being used by the model.

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