A Proposed Fuzzy Model for Reducing the Risk of Insolvent Loans in the Credit Sector as Applied in Egypt

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Abstract

Non-financial analysis is one of the varied crucial directive tools of credit study that is used for judging whether the client has a genuine desire to pay the assigned amounts of the loan at its maturity dates. Fuzzy logic can help to solve the problem of dealing with factors of non-financial analysis by converting the linguistic variables to numerical variables to calculate their accuracy. This study proposes a fuzzy model that contains a complete database of non-financial factors used by the decision-maker using a fuzzy logic technique, which helps in building the fuzzy rules with great accuracy and helps in predicting the actual situation of the client. In addition, it provides constant following-up of the uses of the granted loan to guarantee that all terms set by the bank are met so that the bank can avoid future defaulting of the client. The proposed model is applied in the credit department of a private Egyptian bank (QNB), with random samples of previous real clients. Some real standards are set to calculate non-financial factors that are related to the client, management, economic situation, and project activity. The results of the proposed model revealed that the correlation factor is 95.3% between real successful payment clients and successful model clients. To guarantee the accuracy of the knowledge base quality and validation, the knowledge model was presented to the credit manager of the bank under study (expert), who provided a full evaluation of the results of the proposed model compared to the actual situation of clients.

Keywords: Credit risk, Non-performing loans, Fuzzy information systems, Knowledge base, Decision making

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1. Introduction

In the Egyptian banking sector, insolvent loans are the most significant risk that banks encounter. The ratio of non-performing loans and facilities to total loans was 9.1% at the end of June 2018 [1].

Egyptian banks use traditional models that contain generally accepted statistical rules and methods while specifically examining the case of the client who wants to obtain a loan. Other banks have suffered from large losses during the retrieval of these loans due to the failure of these models to accurately predict the actual situation of the client's repayment, which led to their failure to repay the loan installments on time.

The problem of complexity of the nature of non-financial and credit behavior makes it hard

to predict the rate of credit inflation accurately [1]. In its report issued on August 28, 2018 [2], Moody's had changed expectations about Egypt's long-term export ratings from stable to positive and had affirmed the B3 issuer ratings.

Consequently, it has been the best score since 2011, when Egypt received a ?Ba2? ranking, reflecting that Egypt is able to repay liabilities and the banks are somewhat successful in controlling the problem of loan default [2].

Loans become non-performing when they cannot be recovered within a certain stipulated time, which is governed by bank's respective laws. Decision-making is relevant to how to deal with these loans for maximum possible repayment of loans but becomes a difficult and discretionary process.

Fuzzy logic is a technique of artificial intelligence that simulates a decision-making method in humans. It involves all the median possibilities between numerical values. It is a good technique to deal with linguistic variables and convert them to numerical variables to reach the most accurate result.

The researchers used the fuzzy logic technique because it is built by depending on an expert's opinion and on historical data, and also for its ability to deal with factors of non-financial analysis by converting the linguistic variables to numerical variables to calculate them accurately. Thus, the researchers prefer the fuzzy logic technique to the deep learning technique.

Fuzzy knowledge can help to determine the borrower who will be late or default on the monthly installments and enable the lender to take the right steps to prevent financial losses [3].

2. Literature Review

In [4], a fuzzy logic model is presented, which is used to assist in determining and predicting bank credit risk rating. For Egyptian banks, it depends on the financial ratios used to assign their credit risk rating. The model presented a good effectiveness in predicting the credit risk rating in banks with a reasonable accuracy. It also presented a set of financial indicators that can be used in the assessment of the bank credit risk rating. Results revealed that the fuzzy logic technique is more scalable, reliable, stable, and different from classical methods.

In [5], the researcher applied the fuzzy logic model as a supporting tool for evaluation of the client's situation, with a major goal to develop a new expert decision-making regarding corporate clients in a bank under. Experts reviewed the types of soft variables used for credit risk assessment of corporate clients and provided the inputs for generating membership functions of these. The results presented a new approach for corporate

clients' soft data usage/assessment in commercial banking with an aim of finally being incorporated into a new and superior soft-hard data fusion model.

In [6], the researcher proposed a hybrid system that used neural networks to build a model based on learning abilities and put it into a fuzzy inference module for loan risk evaluation. It is based on an accuracy of forecasting loan risks and measures of average absolute deviation. The results indicated that the hybrid decision support system would decrease the risk often associated with granting loans to clients as well as providing an objective evaluation source for banks.

In [7], a fuzzy logic was introduced to evaluate retail loans that can be used to describe imprecise data or human subjective judgment using linguistic terms. It was based on information inputs used by banks to evaluate a retail loan. The fuzzy inputs were the loan applicant's income level, credit history, character, collateral, and employment with linguistic terms such as "low," "medium," "high," and so on. The model's knowledge base consisted of a rule base of "IF...Then" rules. The output of the model was credit standing, which was also a fuzzy variable with linguistic terms.

After reviewing a number of previous studies in the same field, the researchers suggest that fuzzy logic techniques have been used in a small specific part related to the type of credit provided by banks. This can be attained only by using the financial indicators that are always clearly presented in the client's financial statements. This study presents all types of loans that the bank offers to clients, especially medium- and long-term loans, which are always the cause of a client's financial failure due to the length of the period of repayment of the loan. Some non-financial rules for obtaining the loan, which are difficult to measure with regular equations, such as staff experience, client behavior, marketing skills, product type, and so on, are used.

All of these factors are collected and a knowledge base of "IF...Then" rules is created to help the decision maker select the right financial and loan decision. Most tasks requiring intelligent behavior have some degree of uncertainty associated with them. This type of uncertainty that can occur in knowledge-based systems may be caused by problems with data, for example data may be missing or unavailable, or representation of the data may be imprecise or inconsistent.

The researchers use the fuzzy knowledge base with certainty factors as a method of handling uncertainty of the rules. A certainty factor is a method of dealing with uncertainty and was originally developed for the MYCIN system [8].

2.1 Reasoning Under Uncertainty

The theory of probability states that:

$$P(H) + P(H') = 1,$$

and so

$$P(H) = 1 - P(H').$$

In MYCIN, the certainty factor (CF) was originally defined as the difference between belief and disbelief.

$$CF(H, E) = MB(H, E) - MD(H, E). \quad (1)$$

where, CF is the certainty factor in the hypothesis H due to evidence E; MB is the measure of increased belief in H due to E; and MD is the measure of increased disbelief in H due to E.

CFs for the rules have many conditions items [9]:

For the Unified Rules:

IF < Evidence E1 >
 AND < Evidence E2 >
 AND < Evidence E3 >
 AND < Evidence En >
 THEN < Hypothesis H > { cf }

$$CF(H, E1 \cap E2 \cap E3 \cap \dots \cap En) \\ = \text{Min}[cf(E1), cf(E2), cf(E3), \dots, cf(En)] \times CF.$$

The CF for each rule is calculated according to the value that is determined by the (QNB) bank's expert, and the linguistic variables table using CF for unified rules.

2.2 Defuzzification Subsystem

Defuzzification is the process of obtaining a single number from the output of the aggregated fuzzy set. It is used to transfer fuzzy inference results into a crisp output (Figure 1).

Defuzzification is realized by a decision-making algorithm that selects the best crisp value based on a fuzzy set. There are several forms of defuzzification including center of gravity (CoG), mean of maximum (MOM), and center average methods.

Several methods exist in the literature to perform defuzzification, the most popular of which is the CoG method, which derives a single crisp numeric value to best represents the inferred fuzzy values of the linguistic output variable. For discrete triangular linear functions, the CoG method is obtained by the

Figure 1. Structure of a fuzzy logic system.

moments of area as defined by:

$$C^{\wedge} = \frac{\sum C_i(\mu c)}{\sum \mu c(C_i)}, \quad (2)$$

where $C_i(\mu c)$ is membership value in the membership function and μc is center of membership function [10].

3. Proposed Fuzzy Expert Model Domain

This study focuses on the activities involved in the credit risk management departments in the Egyptian business banks that are working under the supervision of the Central Bank of Egypt and following the Egyptian financial laws issued in 1958 and updates.

3.1 Proposed Model Architecture

The proposed expert model is designed as a fuzzy expert system that consists of the following components shown in Figure 2.

- Knowledge base: Extracted through the knowledge acquisition process from the bank periodicals and experts in the domain are then transferred into the knowledge base.
- Inference Engine: Matches the facts with the rules' condition to determine which rules to apply and the most appropriate rule for its operation and then performs the associated procedure.
- Working Memory: Client and non-financial databases and facts used with the application.
- User Interface: Facilitates the method of interaction between the person and model, which is used to input the client's data, credit risk management, employees' inquiries or other financial data, and receiving the output.

Figure 2. Proposed fuzzy model.

- Explanation Facilities: Inquiries procedures in the model to help the user ask questions or inquire about the knowledge base, justify the decision-making process, and follow it.
- Fuzzifier: Accepts the numerical data (Crisp Input) and converts it to a linguistic variable.
- Defuzzification: Converts the result from the inference engine into fuzzy crisp output.

3.2 The Model Functions according to the Following Steps

- Step 1.** The credit officer who runs the model will enter the client's main data and the project data in the specific forms in the user interface.
- Step 2.** They will then complete the loan request from the client to identify all information about the requested loan and the facilities that are suitable to the client and the bank.
- Step 3.** After finishing, the decision maker will complete collecting the non-financial factors of the client to study the actual situation of the client and project.
- Step 4.** . The queries department will collect the information about the client and project them to determine if the company's activity is profitable and the extra client dealing with banks are good.

Step 5. Depending on the rules of identification algorithm, results lead the non-financial algorithm to be activated using the inference engine to search through the involved fuzzy rules database to find the suitable decision that covers the client case while taking the queries department report into consideration.

Step 6. If the client request is refused, the process is finished. If it is accepted, the algorithm successfully finds the suitable decision with suitable facilities. The model is stopped, and the result is displayed.

4. Fuzzy Expert System Development

The Fuzzy Logic Toolbox is a set of functions built in the MATLAB digital computing environment. It provides the tools needed to create and edit the fuzzy inference system with the MATLAB framework or integrate the fuzzy system into simulation with reality.

4.1 The Model Input Data

4.1.1 Data collection

The researchers collected various data related to the system in credit departments in the Egyptian banks according to the rules of the central Egyptian bank from different resources such as professional experts in banks, banking and credit risk management textbooks, and monthly periodicals of the Central Bank of Egypt [11].

4.1.2 Database structure

The researchers created a relational database consisting of many tables including client data, loan data, non-financial rules, and all tables that include the extracted data concerning previous clients' cases, which were clarified by the professional experts in credit departments.

The researchers created a fuzzy rule database using the MATLAB application that can accept the linguistic variables of non-financial factors: Official Experience, Project Funding, Company's Activity, and Client Personality (Tables 1 and 2). The results were exported to the relational database to be interchanged to numerical variables and produce the final report to the decision maker as shown in Figure 3. The researchers used the relational data base for the following reasons:

- (i) There are many relations between tables that ought to be connected.

Table 1. Examples of management rules

No. of rule	Rule
1	IF Official Experience is High (0.9)
	AND Project Funding is Adequate (0.8)
	AND Project Stuff is Large (0.85)
	THEN Management Efficient is High [cf 0.9]
	$CF(H, E1 \cap E2 \cap E3) = \min[0.9, 0.8, 0.85] * 0.9 = 0.8 * 0.9 = 0.72$
2	IF Official Experience is High (0.9)
	AND Project Funding is Marginal (0.5)
	AND Project Stuff is Average (0.55)
	THEN Management Efficient is High [cf 0.9]
	$CF(H, E1 \cap E2 \cap E3) = \min[0.9, 0.5, 0.55] * 0.9 = 0.5 * 0.9 = 0.42$
3	IF Official Experience is High (0.6)
	AND Project Funding is Adequate (0.8)
	AND Project Stuff is Average (0.55)
	THEN Management Efficient is High [cf 0.9]
	$CF(H, E1 \cap E2 \cap E3) = \min[0.6, 0.8, 0.55] * 0.9 = 0.55 * 0.9 = 0.495$
4	IF Official Experience is High (0.9)
	AND Project Funding is Marginal (0.5)
	AND Project Stuff is Large (0.85)
	THEN Management Efficient is High [cf 0.9]
	$CF(H, E1 \cap E2 \cap E3) = \min[0.9, 0.5, 0.85] * 0.9 = 0.5 * 0.9 = 0.45$

- (ii) The convenience of creating new tables of non-financial factors with the difference of client's nature and surrounding conditions.

The proposed model can be applied in the bank's branches by implementing the distributed databases, which are a set of networked computer databases at different sites. It can be managed by the main branch of the bank while appearing to the user as a single database.

4.2 Fuzzy set of the Proposed Model

Based on the knowledge of the experts in this field, the input and output variables selected for this research were explained by 24 linguistic variables. Table 3 presents a sample of the extent of the fuzzy value of each linguistic variable. During this process, the linguistic variables are evaluated using the triple membership function and accompanied by an associated membership degree ranging from 0 to 1 as shown in Figure 4.

The model provides the fuzzy rules to measure the non-financial aspects such as education and experience level, project activity, and economic and market conditions, which the bank

Table 2. Examples of management rules

No. of rule	Rule
1	IF Product\Service Kind is Popular (0.95)
	AND Production Operation is Active (0.9)
	AND Marketing Method is Modern (0.85)
	AND Pay Method is Cash (0.9)
	THEN Active Nature is Ongoing [cf 0.95] $CF(H, E1 \cap E2 \cap E3 \cap E4) = \min[0.95, 0.9, 0.85, 0.9] * 0.95 = 0.85 * 0.95 = 0.81$
2	IF Product\Service Kind is Popular (0.95)
	AND Production Operation is Active (0.9)
	AND Marketing Method is Modern (0.85)
	AND Pay Method is Premium (0.6)
	THEN Active Nature is Ongoing [cf 0.95] $CF(H, E1 \cap E2 \cap E3 \cap E4) = \min[0.95, 0.9, 0.85, 0.6] * 0.95 = 0.6 * 0.95 = 0.57$
3	IF Product\Service Kind is Popular (0.95)
	AND Production Operation is Active (0.9)
	AND Marketing Method is Normal (0.7)
	AND Pay Method is Cash (0.9)
	THEN Active Nature is Ongoing [cf 0.95] $CF(H, E1 \cap E2 \cap E3 \cap E4) = \min[0.95, 0.9, 0.7, 0.9] * 0.95 = 0.7 * 0.95 = 0.67$
4	IF Product\Service Kind is Popular (0.95)
	AND Production Operation is Active (0.9)
	AND Marketing Method is Normal (0.7)
	AND Pay Method is Premium (0.9)
	THEN Active Nature is Ongoing [cf 0.95] $CF(H, E1 \cap E2 \cap E3 \cap E4) = \min[0.95, 0.9, 0.7, 0.6] * 0.95 = 0.6 * 0.95 = 0.57$
5	IF Product\Service Kind is Popular (0.95)
	AND Production Operation is Active (0.9)
	AND Marketing Method is Old (0.45)
	AND Pay Method is Cash (0.9)
	THEN Active Nature is Ongoing [cf 0.95] $CF(H, E1 \cap E2 \cap E3 \cap E4) = \min[0.95, 0.9, 0.45, 0.9] * 0.95 = 0.45 * 0.95 = 0.43$

use to judge the client (always updated) as shown in Figure 5 [9].

4.3 Fuzzy Production Rules of the Proposed System

There are 84 variables as system input parameters. These were used to create 241 fuzzy production rules. Rules in the model

The Credit Risk Management Dept. Date: 24/4/2019
Time: 10:30 AM

The committee Report

Case ID : 124KGM Customer Name: Ali Heda for Trading
Address: 24 Al Oroba St., Port Fouad
Loan value : 150,000 LE

Check list criteria

Condition risk analysis	25 %	Estimated : Low
The Active Nature is	47 %	Estimated : Accepted
Management Efficiency	50 %	Estimated : Accepted
Risk for Customer Analysis	24 %	Estimated : Low

The Customer Request is:

Committee Suggestion

Not Accepted

Signature of committee members

Figure 3. Snapshot credit risk management department report.

Table 3. Linguistic variables [9]

Linguistic value	Numerical range
Very short	[0, 0.3]
Short	[0.1, 0.5]
Medium	[0.4, 0.7]
Long	[0.6, 1]
Very small	[0, 0.35]
Small	[0, 0.40]
Medium	[0.30, 0.70]
Low	[0, 0.6]
Average	[0.4, 0.8]
High	[0.6, 1]
Large	[0.6, 1]
Very large	[0.70, 1]

Figure 4. Fuzzy sets of membership degree.

knowledge base are structural to reflect the nature of human thinking in the field of the domain. Tables 1 and 2 present some examples of rules.

Figure 5. Non-financial fuzzy factors of the client.

4.4 Validation of Proposed Model

To overcome the problems of the knowledge base validation and avoid errors in it, the researchers followed the methodologies listed below:

- Extract the knowledge base of the model from standard documents in the domain. The standard processes that created the model are assumed to have validated the knowledge in the standard. Referring to the textbooks and banking references used for building the knowledge base.
- Create a knowledge model under supervision of an expert (Credit Expert in QNB) and review the model with external experts (individually) and modify or expand the knowledge base according to their responses. Table 4 shows the knowledge base confidence level of the external experts; it is probably a good idea to ask at least four experts to verify each important assumption backing up the knowledge base. When four or more experts agree unanimously, the assumption is reasonably validated. A total of experts agreeing provides a high level of confidence in the assumption.
- Apply the proposed model in the credit department in one of the Egyptian banks to test the model.

4.5 User Interface

GUI tools are used to create, edit, and monitor fuzzy heuristics in the Fuzzy Logic Toolbox. In the proposed model, the interface consists of a set of forms built in Visual Studio .NET 2016

Table 4. Experts' confidence level of model knowledge base

Expert No.	Confidence level (%)
1	80
2	89
3	78
4	90
5	92

Figure 6. Snapshot management analysis.

because it is considered a flexible and a common software. The user can input the raw data needed for a consultation. Once the user completes a form, the data is translated into a format that can be understood by the inference engine. When the inference engine reaches a result, the user interface returns this information in natural language so that it can be understood by the user (Figures 3 and 6). The user may have information regarding a specific result and the interface can provide additional explanations about how the inference engine reached this conclusion.

5. Results

Due to many considerations such as laws, security issues and so on, it was difficult to get any public banks to agree to use the proposed model in a practical setting in the credit load department. The bank's administration allowed the researchers to obtain and study the historical data of the previous year, and only offered a set of available historical client cases (200 banks 603084102 approved clients separated on 8 months). 67 successful payment clients, and 33 defaulted clients. The bank accepted the requested loans on a past period from 1/1/2017 to

Table 5. Client sample

	Month								Total
	1	2	3	4	5	6	7	8	
Bank's approved	20	26	26	30	20	24	22	32	200
Payment success (X)	12	16	18	20	12	14	16	26	134
Defaulted cases	8	10	8	10	8	10	6	6	66
Accepted model result (Y)	11	16	16	17	10	13	14	20	117
Refused model result	9	10	10	13	10	11	8	12	83

Figure 7. Deference between bank cases and model cases.

31/12/2017.

By applying the proposed model on these clients for testing the model, the following results were obtained. Table 5 reports the numbers of classified clients in the sample and Figure 7 illustrates the difference between bank and model clients.

- The model classified 117 clients as accepted is 117 clients.
- The model refused 83 clients (from 200 clients) from the chosen sample and classified them as defaulted.
- The 83 clients that are rejected by the proposed model include 66 actual clients that had been classified as defaulted and were unable to repay the fixed installments on their due dates.

6. Evaluation of Proposed Model

To calculate the success average between the bank's actual clients and the number predicted by the model, the correlation factor method is used. The number of clients that the model classified as defaulted is reported in Table 6. Correlation Factor is defined as "the amount of deviation in a measurement that is accounted for in the calibration process." It is a statistical measure of the interdependence of two or more random variables. Fundamentally, the value indicates how much of a change in one variable is explained by a change in another.

The researcher applied the following mathematical equation to calculate the result [12]:

$$R = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{n \sum x^2 - (\sum x)^2} \sqrt{n \sum y^2 - (\sum y)^2}}, \quad (3)$$

N = number of months (8),

X = number of successful payment clients (134),

Y = number of clients the model accepted (117).

$$R = \frac{8 * 2062 - (134 * 117)}{\sqrt{8 * 2396 - (134)^2} \sqrt{8 * 1787 - (117)^2}},$$

$$R = \frac{16496 - 1568}{\sqrt{19168 - 17956} \sqrt{14296 - 13689}},$$

$$R = \frac{818}{\sqrt{1212} \sqrt{607}} = \frac{818}{857.7} = 0.953.$$

6.1 Applying the Defuzzification

The researchers used MATLAB membership functions and obtained the following results:

- (i) Risk for condition analysis is Low (0.25)
- (ii) Active Nature is Acceptable (0.47)
- (iii) Management Efficiency is Acceptable (0.50)
- (iv) Risk for client analysis is Low (0.24)

Then, applying the defuzzification using CoG formula (2) as previously mentioned, the result is as shown in Figure 3, which is not acceptable for the model.

7. Discussion of Results

Based on the analysis of the results, this study reaches the following conclusions:

- The bank approved a total of 200 clients. A total of 134 clients were considered successful payment clients (who repaid the total loan to the bank). The model classified

Figure 8. Model dependency.

117 clients as accepted and predicted that they would pay the loan. The model rejected 83 clients from the chosen sample and classified them as defaulted, including 66 actual clients who were unable to pay the fixed installments on their due dates.

- Based on the above findings, the model is found to be 95.3% efficient. The slight accuracy difference between the results of the proposed model and the actual reality as shown in Figure 8 is 4.7% (i.e., 17 clients who were rejected by the model and paid off their loans in full). This means that to be more accurate, the model needs more developing in terms of analysis of non-financial factors.
- When the actual payment position of refused clients was examined, they were found to default and did not pay the due premium to the bank on their due dates.
- According to the experts' views, the result of a classification accuracy rate of 95.3% is a very good result in terms in model evaluation.

8. Comparison between the Proposed Model and Another Models

Soares et al. [13] found that his model was able to give a prediction classification rate with an accuracy of 80%.

Martin et al. [14] implemented a fuzzy model to predict defaulted clients using the expert knowledge that was applied in fuzzy rules with an accuracy rate of 88% in one model. In a hybrid model, which used neuro-fuzzy and genetic algorithms, the accuracy rate was 73.6%, but with extra and different input variables.

Figure 9. Accuracy of different models.

Nuijten et al. [15] developed a fuzzy model with an accuracy rate of 62.2%, which was slightly better than a random system may achieve.

In the proposed model, the accuracy rate is 95.3%, a better rate than the aforementioned models. The model was improved by creating a fuzzy knowledge base that includes all the linguistic rules used by decision makers to judge the clients. These rules did not have any clear ratios to measure them, so the researchers are working on improving this. The result is shown in Figure 9.

9. Conclusion

The duty of credit risk management departments becomes more complicated due to the consideration of financial laws and business banks' articles and procedures. In addition, globalization increases the need for flexibility, and it becomes more challenging. Automation of credit risk management is another challenge in the future for the development of generic diagnostic architectures that can potentially use a variety of analysis and predicting techniques of clients' financial and non-financial position and demand, which can be applied to all the credit risk management departments in all types of banks.

The proposed model has been programmed from human expertise and the documents of the specific domain. Although the application is not large, it is rather complicated, it has a high performance, and has an accuracy rate of 95.3%, which experts considered sufficient. The proposed model is not considered a complete solution. Human expert's intelligence is still the final judgment; however, it is considered as a starting point to help the decision maker in credit departments in banks to make the right decision about approving loans or rejecting client's

request.

The main interest in developing the model is to ensure the accuracy of all its recommendations in difficult as well as simple cases, thereby obtaining a good understanding of the field and an accurate characterization of this understanding in a form that can be maintained. Clear and proven logical programming is used for the purposes of this research. This approach was sufficiently flexible to allow for the application of the model to easily accommodate the ongoing modifications into the initial designs.

Conflict of Interest

No potential conflict of interest relevant to this article was reported.

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