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"Assessing Credit Risks from the point of view of Commercial Banks"

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Abstract:

Assessing credit risks is one of the most important problems in banking. The credit risk rating is a method of measuring the credit worthiness of enterprises and banks by analyzing their historical data. Most Egyptian commercial banks are unable to determine and predict credit risk rating and so far, there is no accurate model in Egypt for determining and predicting for credit risk rating of these commercial banks. In this paper, the researchers propose a fuzzy logic-based model that can be used to assist in determining and predicting bank credit risk rating. Taking the rating scale of Moody's as an output for the proposed model. The proposed model is based on financial ratios used in Egyptian commercial banks i.e., profitability, debt-paying ability, operation ability, and liquidity to determine their credit risk rating. This model was implemented using fuzzy logic in MATLAB and applied to CIB Egyptian commercial bank. This model could help the decision-makers in the Egyptian commercial banks to determine accurately the credit risk rating of these banks.

Keywords: Credit Risk Assessment, Business Intelligence, Financial Indicators.

1- Introduction

The credit risk rating is one of the most important problems in finance. A credit risk rating is an evaluation of the credit worthiness of a debtor. Credit ratings are issued by credit rating agencies (CRA). Companies like Standard & Poor's, Moody's, and Fitch are considered the most important ones. They assign ratings for several issuers (e.g., firms, nations, local governments, and banks) of specific types of debt. In this paper, the focus is on commercial banks [1, 2].

Commercial Banks (CBs) are profit-making organizations acting as intermediaries between borrowers and lenders. CBs play a critical role in emergent economies like Egypt. Bank lending is very critical for financing agricultural, industrial, and commercial activities of the country. Well-functioning CBs accelerate economic growth [3].

Credit rating agencies often classify the credit rating of certain Egyptian banks such as the National Bank of Egypt (NBE), Banque Misr (BM), and Commercial International Bank (CIB), and do not give a classification of all commercial banks in Egypt. Additionally, there is no accurate model in Egypt for determining and predicting for credit risk rating of these commercial banks.

Furthermore, the application of machine learning techniques has been very limited in the context of economics and studies of finance. This paper highlights the importance of incorporating machine learning techniques in the assessment of the credit risk rating of commercial banks.

In this paper, the researcher proposes a fuzzy logic-based model that can be used to assist in determining and predicting bank credit risk rating. Taking the rating scale of Moody's as an output for the proposed model. This paper focuses on commercial banks in Egypt that have suffered from few models for credit risk rating in recent years which led to loss of finance in these banks. This model could help the decision makers to the right decisions to determine the credit risk rating of these banks.

The paper is organized as follows: Section 2 shows a background overview of credit risk rating and fuzzy logic approach. Section 3 summarizes the most important studies in this research field. Section 4 presents the proposed model for credit risk rating. Section 5 introduces an algorithm of the proposed model. Section 6 presents the implementation of the proposed model. The last section concludes the paper with final remarks.

2- Background Overview

This section provides an overview of the main concepts related to the research topic. It consists of two parts. In the first part, a set of financial ratios that are used in the assessment of bank credit risk rating is presented. In the second part, the basic concept of fuzzy logic is discussed.

2-1 Financial Indicators for Credit Risk Rating

Credit risk rating consists of two parts, namely quantitative and qualitative indicators. Our proposed model for credit risk rating focuses on quantitative factors. The summary of financial indicators that were incorporated in the proposed model is shown in Table 1 [4, 5].

TABLE 1. THE SUMMARY OF FINANCIAL INDICATORS FOR CREDIT RISK RATING

Ratio Name	Indicator Name	Abbreviation
Profitability	Rate of return on capital	ROC
	Net profit margin on sales	NPM
Debt-paying Ability	Current ratio	CTR
	Quick ratio	QKR
	Currency ratio	CYR
	Debt asset ratio	DTR
Operation Ability	Total assets turnover	TAT
Liquidity	Securities to Assets	SA
	Deposits to Assets	DA
	Loans to Deposits	LD

These indicators are classified into four categories as follows:

- Profitability: the ability of banks to earn a profit under normal operation situations reflects the degree of risk.
- Debt-paying ability: the ability of banks to repay the due short-term and long-term debts, which is helpful to forecast the banks' potential earnings and reduces the risk of banks.
- Operation ability: the ability of banks to use various assets to gain profits.
- Liquidity: the bank's ability to pay off its short-term debts obligations.

The proposed model for credit risk rating is based on the system of rating that was originated by John Moody in 1909. The purpose of Moody's ratings is to provide investors with a simple system of gradation. Gradations of creditworthiness are indicated by nine group rating symbols as shown in Table 2. Additionally, Moody's rating system appends numerical modifiers 1, 2, and 3 to each generic rating classification from Aa through Caa [6].

2-2 Fuzzy Logic

Fuzzy logic was introduced by Lotfi Zadeh in 1965. The term fuzzy logic in a broader sense can be defined as a set of mathematical principles for knowledge representation based on degrees of membership rather than on crisp membership of classical binary logic. As such, it is a multi-valued logic [7]. Following are some fuzzy basic concepts:

TABLE 2 THE RATING CLASSES FROM MOODY'S RATING AGENCY

Symbol	Definition
Aaa	Obligations rated Aaa are judged to be of the highest quality, subject to the lowest level of credit risk
Aa	Obligations rated Aa are judged to be of high quality and are subject to very low credit risk.
A	Obligations rated A are judged to be upper-medium grade and are subject to low credit risk.
Baa	Obligations rated Baa are judged to be medium-grade and subject to moderate credit risk and as such may possess certain speculative characteristics.
Ba	Obligations rated Ba are judged to be speculative and are subject to substantial credit risk
B	Obligations rated B are considered speculative and are subject to high credit risk.
Caa	Obligations rated Caa are judged to be speculative of poor standing and are subject to very high credit risk.
Ca	Obligations rated Ca are highly speculative and are likely in, or very near, default, with some prospect of recovery of principal and interest.
C	Obligations rated C are the lowest rated and are typically in default, with little prospect for recovery of principal or interest.

Fuzzy Sets: A fuzzy set is a class of objects with a continuum of grades of membership [8]. Let X be a space of points (objects) and its elements be denoted as x. A fuzzy set A of X is defined by function $f_A(x)$called the membership function of set A:

$$f_A(x): X \to [0,1] \qquad (1)$$

Membership function: A membership function $f_A(x)$ associates with each point in X a real number in the interval [0, 1], with the value of $f_A(x)$ at x representing the "grade of membership" of x in A.

Basic operations of fuzzy sets: There are four basic fuzzy set operations:

Complement: The complement of a fuzzy set A is denoted by A' and can be found as follows:

$$f_{A'} = 1 - f_A \qquad (2)$$

Containment: A is contained in B if and only if $f_A \le f_B$. In symbols:

$$A \subset B \Leftrightarrow f_A \le f_B \qquad (3)$$

Union: The union of two fuzzy sets A and B with respective membership functions $f_A(x)$ and $f_A(x)$ is a fuzzy set C, written as $C = A \cup B$, whose membership function is related to those of A and B by:

$$f_C(x) = Max[f_A(x), f_B(x)] \qquad x \in X \qquad (4)$$

Intersection: The intersection of two fuzzy sets A and B with respective membership functions $f_A(x)$ and $f_A(x)$ is a fuzzy set C, written as $C = A \cap B$, whose membership function is related to those of A and B by:

$$f_C(x) = Min[f_A(x), f_B(x)] \qquad x \in X \qquad (5)$$

Fuzzy rules: A fuzzy rule is a conditional statement of the form IF A THEN B, where A and B are terms with a fuzzy meaning [9].

3- Related Work

In general, several approaches have been proposed in order to establish a model that is capable of determining and predicting for credit risk rating. For example:

- L. Yijun, C. Qiuru, L. Ye and Q. Jin [10] proposed a neural network model to make an effective analysis for corporation credit rating.
- H. A. Abdou [11] conducted a study to investigate the ability of genetic programming (GP) in the analysis of credit scoring models in Egyptian public sector banks.
- W. Hongxia, L. Xueqin and L. Yanhui [12] proposed a model based on fuzzy clustering and decision tree for assessing enterprise credit rating.
- C. Tsai and M. Chen [13] investigated credit rating by hybrid machine learning techniques to help to decide whether to grant credit to consumers before issuing loans.
- Y. Wei, S. Xu and F. Meng [14] proposed a company's credit rating model based on logistic regression and non-financial factors.
- P. Hájek [15] conducted a study to classify US municipalities (located in the State of Connecticut) into rating classes by neural networks.
- V. H. Duc and N. D. Thien [16] proposed a new model to determine credit ratings for Vietnamese companies by using fuzzy logic.
- F. M. Rafiei, S. M. Manzari and M. Khashei [17] used Multilayer Perceptrons (MLPs) and multiple statistics methods to carry out multi-class credit rating of listed corporations in Tehran Stock Exchange (TSE).
- M. R. Gholamian, S. Jahanpour and S. M. Sadatrasoul [18] presented a new method to analyze customer credit worthiness.
- R. H. Abiyev [19] introduced credit rating model using type-2 fuzzy neural networks (FNN).

- N. Shovgun [20] suggested a new method based on fuzzy neural networks for evaluating the creditworthiness of the borrowers.
- F. Abdulrahman, J. K. Panford and J. Hayfron [21] proposed a fuzzy logic approach to credit scoring for Micro Finance.

4- The Proposed Approach Architecture

The main objective of the proposed model is to predict credit risk rating for Egyptian commercial banks in advance with a reasonable accuracy. The proposed model is a method of measuring the creditworthiness for commercial banks that shows whether commercial banks have a history of financial stability. This model is based on the quantitative financial indicators that are presented in Table 1. As shown in Fig.1, the proposed model consists of the following seven components:

1. Member function base
2. Fuzzy rule base
3. Fuzzy inference engine
4. Database Management System (DBMS)
5. Database (DB).
6. User interface
7. Defuzzification process

The main components of the proposed model are discussed briefly in the following subsections.

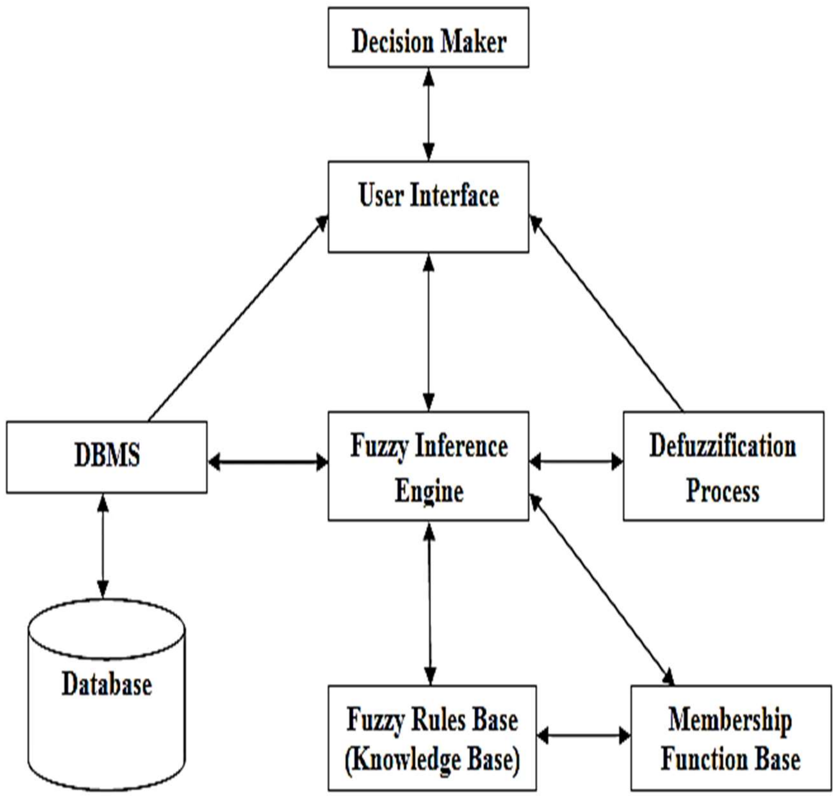

Figure1. The Proposed Model Architecture

4-1 Membership Function Base

Membership function base is a mechanism that presents the membership functions of linguistic variables terms. This section presents membership functions for each financial indicator of the bank performance.

1. Profitability ratio: Fuzzy logic techniques use linguistic variables in profitability evaluation to represent ROC indicator and NPM indicator. In this case, each indicator value is assigned a degree of membership in relation to the linguistic

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descriptors “high”, “medium”, and “low” as presented in Tables 3, 4 and Fig.2, 3.

a. *Membership functions for ROC indicator:*

TABLE 3. FUZZY VALUES FOR ROC

Linguistic	Notation	Numerical range
Low	L	[0 , 2.63]
Medium	M	[0.78 , 3.95]
High	H	[2.64 , 5.26]

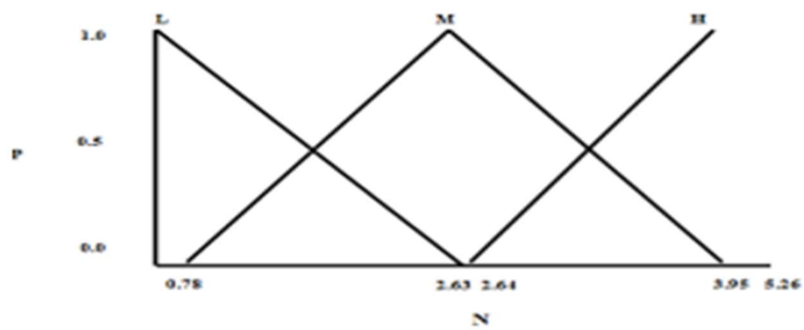

Figure 2. Membership functions for ROC

b. *Membership functions for NPM indicator:*

TABLE 4. FUZZY VALUES FOR NPM

Linguistic	Notation	Numerical range
Low	L	[0 , 43.08]
Medium	M	[12.92 , 64.62]
High	H	[43.09 , 86.16]

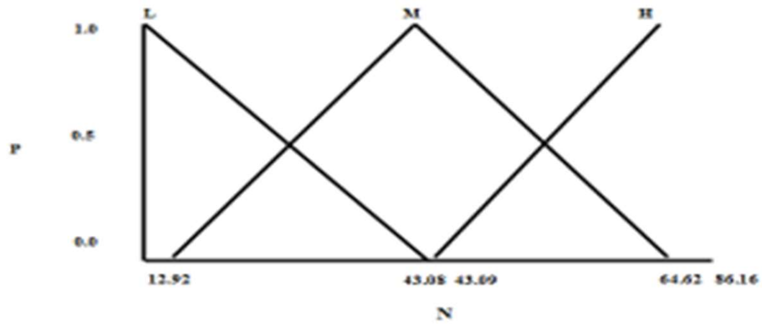

Figure 3. Membership Functions for NPM

2. Debt-paying ability ratio: Fuzzy logic techniques use linguistic variables in debt-paying ability evaluation to represent CTR indicator, QKR indicator, CYR indicator, and DTR indicator. In this case, each indicator value is assigned a degree of membership in relation to the linguistic descriptors “high”, “medium”, and “low” as presented in Tables 5, 6, 7, 8 and Fig. 4, 5, 6, 7.

    a. *Membership functions for CTR indicator:*

TABLE 5. Fuzzy values for CTR

Linguistic	Notation	Numerical range
Low	L	[0 , 102.28]
Medium	M	[51.14 , 153.42]
High	H	[102.29 , 204.56]

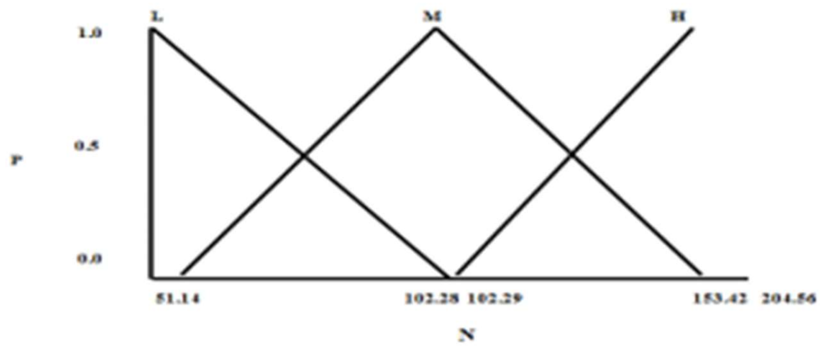

Figure 4. Membership Functions for CTR

b. *Membership functions for QKR indicator:*

TABLE 6. FUZZY VALUES FOR QKR

Linguistic	Notation	Numerical range
Low	L	[0 , 106.75]
Medium	M	[53.38 , 160.13]
High	H	[106.76 , 213.52]

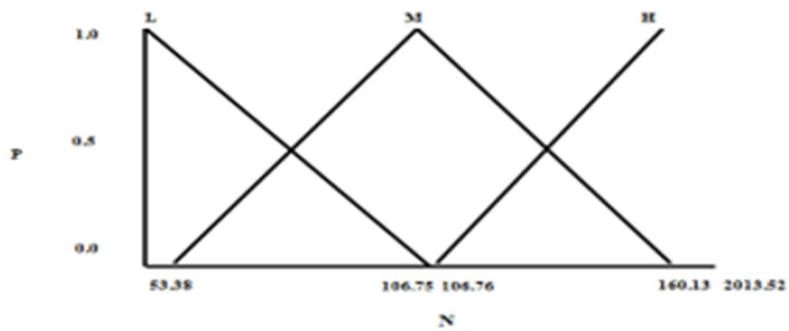

Figure 5. Membership Functions for QKR

c. Membership functions for CYR indicator:

TABLE 7. FUZZY VALUES FOR CYR

Linguistic	Notation	Numerical range
Low	L	[0 , 68.69]
Medium	M	[34.35 , 103.04]
High	H	[68.70 , 137.38]

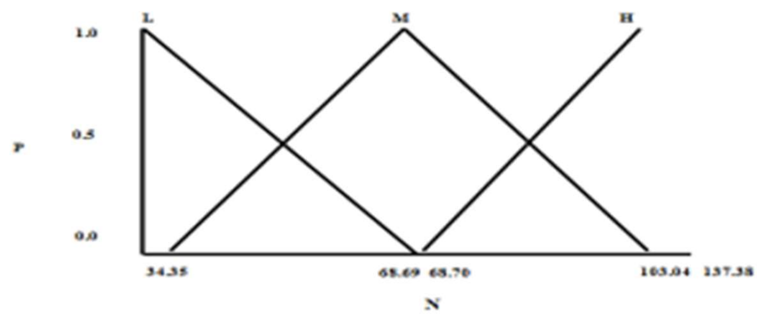

Figure 6. Membership Functions for CYR

d. Membership functions for DTR indicator:

TABLE 8. FUZZY VALUES FOR DTR

Linguistic	Notation	Numerical range
Low	L	[0 , 94.58]
Medium	M	[47.29 , 141.87]
High	H	[94.59 , 189.16]

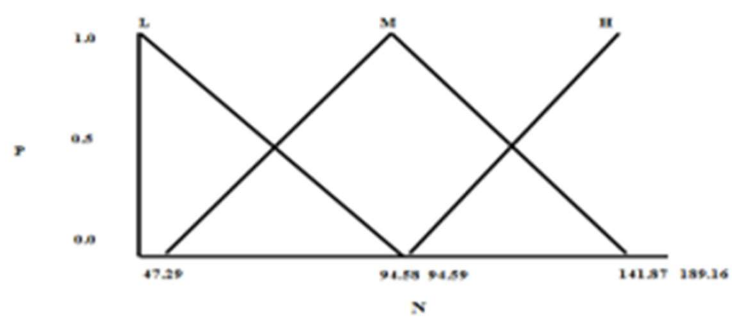

Fig. 7. Membership Functions for DTR

3. Operation ability ratio: Fuzzy logic techniques use linguistic variables in operation ability evaluation to represent TAT indicator. In this case, each indicator value is assigned a degree of membership in relation to the linguistic descriptors “high”, “medium”, and “low” as presented in Table 9 and Fig. 8.

TABLE 9. FUZZY VALUES FOR TAT

Linguistic	Notation	Numerical range
Low	L	[0 , 2.18]
Medium	M	[1.09 , 3.27]
High	H	[2.19 , 4.36]

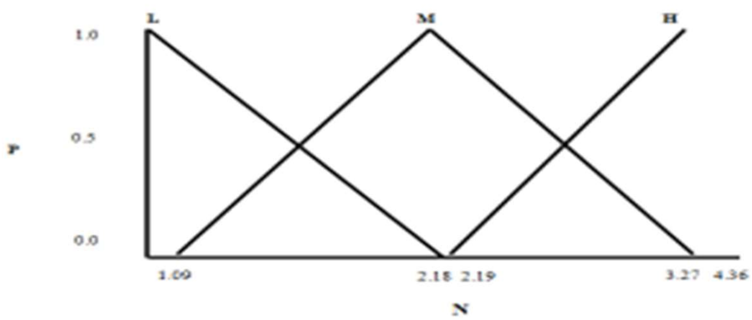

Figure 8. Membership Functions for TAT indicator

4. Liquidity ability ratio: Fuzzy logic techniques use linguistic variables in liquidity evaluation to represent SA indicator, DA indicator, and LD indicator. In this case, each indicator value is assigned a degree of membership in relation to the linguistic descriptors “high”, “medium”, and “low” as presented in Tables 10, 11, 12, and Fig. 9, 10, 11.

a. *Membership functions for SA indicator:*

TABLE 10. FUZZY VALUES FOR SA

Linguistic	Notation	Numerical range
Low	L	[0 , 21.2]
Medium	M	[4.26 , 38.34]
High	H	[21.3 , 42.7]

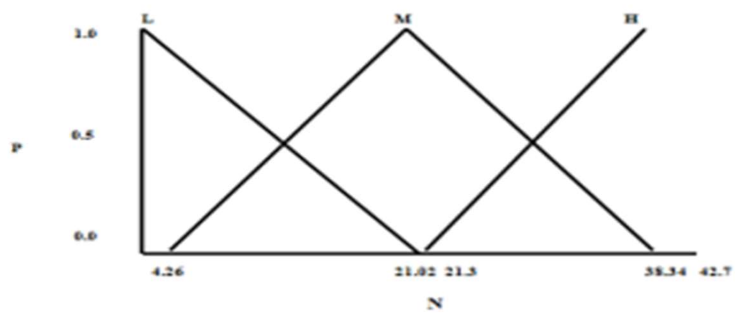

Figure 9. Membership Functions for SA

b. *Membership functions for DA indicator:*

TABLE 11. FUZZY VALUES FOR DA

Linguistic	Notation	Numerical range
Low	L	[0 , 70.6]
Medium	M	[14.5 , 127.8]
High	H	[70.8 , 141.6]

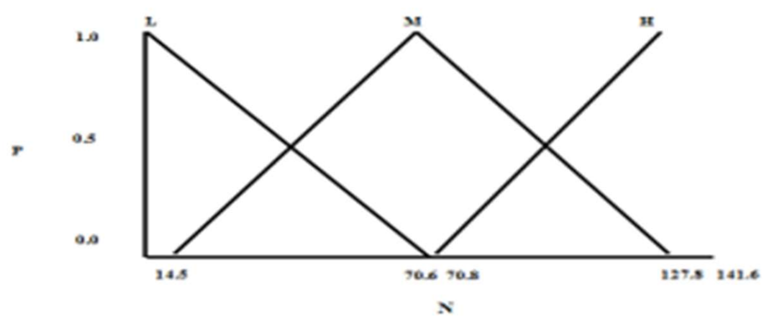

Figure 10. Membership Functions for DA

c. *Membership functions for LD indicator:*

TABLE 12. FUZZY VALUES FOR LD

Linguistic	Notation	Numerical range
Low	L	[0 , 49.9]
Medium	M	[13.3 , 90.3]
High	H	[50 , 100]

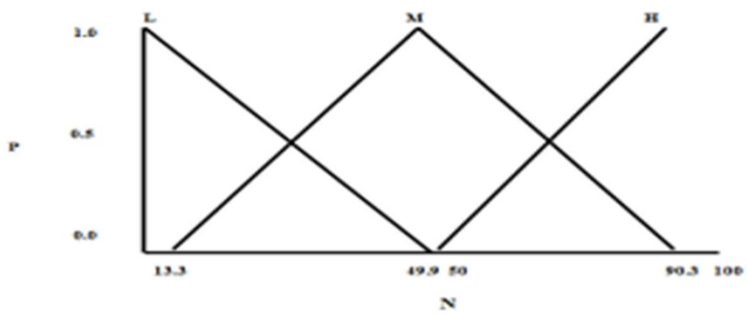

Figure 11. Membership Functions for LD

4-2 Fuzzy Rules Base

Fuzzy rules base contains the expert knowledge of indicators relations and the formation of a total judgment as if-then rules. All the fuzzy rules together compose the so called "knowledge base". The model allows for adding or updating these rules in case of extending the rules base. Fuzzy rules are used to calculate financial ratios including profitability, debt-paying ability, operation ability, and liquidity.

1. Profitability ratio: As shown in Table 13, this section presents samples of the profitability ratio rules that are applied by the fuzzy inference engine. Profitability ratio is based on calculating the following two indicators:
   - ROC = (Net income - Dividends) / (Debt + Equity)
   - NPM = Net Profit/Total Revenue

TABLE 13. PROFITABILITY RATIO RULES SAMPLES

Rule #	Fuzzy Rule	
1	IF	ROC is low
	AND	NPM is low
	THEN	Profitability is low
2	IF	ROC is low
	AND	NPM is high
	THEN	Profitability is medium
3	IF	ROC is high
	AND	NPM is medium
	THEN	Profitability is high

2. Debt-paying ability ratio: As shown in Table 14, this section presents samples of the dept-paying ability ratio rules that are applied by the fuzzy inference engine. Dept-paying ability ratio is based on calculating the following four indicators:
   - CTR = Current Assets / Current Liabilities
   - QKR = (Current Asset – Inventories) / Current Liabilities
   - CYR = Current Assets / Current Liabilities
   - DTR = Total Debit / Total Assets

TABLE 14. DEPT-PAYING ABILITY RATIO RULES SAMPLES

Rule #	Fuzzy Rule
1	IF CTR is low AND QKR is low AND QKR is low AND DTR is low THEN Dept-Paying Ability is low
2	IF CTR is low AND QKR is medium AND QKR is medium AND DTR is high THEN Dept-Paying Ability is medium
3	IF CTR is low AND QKR is medium AND QKR is high AND DTR is low THEN Dept-Paying Ability is medium

3. Operation ability ratio: As shown in Table 15, this section presents samples of the operation ability ratio rules that are applied by the fuzzy inference engine. Operation ability ratio is based on calculating the following indicator:
    - TAT = Sales or Revenues / Total Assets

TABLE 15. OPERATION ABILITY RATIO RULES SAMPLES

Rule #	Fuzzy Rule
1	IF TAT is low THEN Operation Ability is low
2	IF TAT is medium THEN Operation Ability is medium
3	IF TAT is high THEN Operation Ability is high

4. Liquidity ratio: As shown in Table 16, this section presents samples of the liquidity ratio rules that are applied by the fuzzy inference engine. Liquidity ratio is based on calculating the following three indicators:
   - SA = Securities / Assets
   - DA = Deposits / Assets
   - LD = Loans / Deposits

TABLE 16. LIQUIDITY RATIO RULES SAMPLES

Rule #	Fuzzy Rule
1	IF SA is low AND DA is high AND LD is low THEN Liquidity is medium
2	IF SA is medium AND DA is low AND DA is low THEN Liquidity is low
3	IF SA is high AND DA is low AND MBGR is low THEN Liquidity is medium

4-3 Other Components

1. Fuzzy Inference engine: The most important two types of fuzzy inference method are Mamdani and Sugeno fuzzy inference methods [22]. This model is based on Mamdani inference method as the core of the reasoning process. The Mamdani-style fuzzy inference process is performed in four steps [23]:
   a. Fuzzification of the input variables
   b. Rule evaluation
   c. Aggregation of the rule outputs
   d. Defuzzification

The inputs of the model include the indicators values for the profitability, debt-paying ability, operation ability and liquidity ratios. The output includes fuzzy values and defuzzified values. The role of fuzzy inference engine is to match the fuzzy rules that are contained in the rules base with the entered values for the indicators data that is stored in the database to identify which rules should be applied and manage the reasoning process.

2. DBMS: The bank’s data is managed by the database management system (DBMS). DBMS is used by the users to perform model's database managing operations including storing, retrieving, adding, deleting and modifying.
3. Database (DB): Database is used to store the entire bank’s data including the financial indicators data. It is managed by the DBMS that allows the users (decision makers) to add, update and delete the bank's data.
4. User Interface (UI): User interface facilitates communication between the user (decision maker) and the implemented system of the model. It is also used to input the bank’s data and show the results.
5. Defuzzification Process: Defuzzification is the process which transforms a fuzzy output of the inference engine to crisp output [24]. The input for the defuzzification process is the aggregate output fuzzy set and the output is a crisp number [25]. There are several defuzzification methods. Each provides a means to choose a single output based on the implied fuzzy sets [26]. Commonly used defuzzifying methods are:
    a. The mean of maximum method.
    b. The maximizing decision.
    c. The center of gravity method. [27]

In this paper, the center of gravity method is used as a defuzzification strategy.

5- The Algorithm of the Proposed Approach

This section presents an algorithm of the proposed model for determining and predicting the credit risk rating for Egyptian commercial banks. Fig.12 shows the flow chart of the proposed model.

1. Login into the system.
2. Input the values of indicators for each financial ratio used in the credit risk rating assessment.
3. Determine the membership function numerical range for each indicator linguistic value.
4. If new bank
   {
   Input indicators values and data of the bank
   }
   Else
   {
   Retrieve indicators values and data of the bank.
   }
5. Determine the bank indicator membership value.
6. Calculate the final value for each financial ratio by applying the appropriate fuzzy rules.
7. Defuzzify the calculated financial ratios values by using the center of gravity method.
8. Compare the output of the defuzzification process with Moody's ratings.
9. Print the class of credit risk rating of the bank.

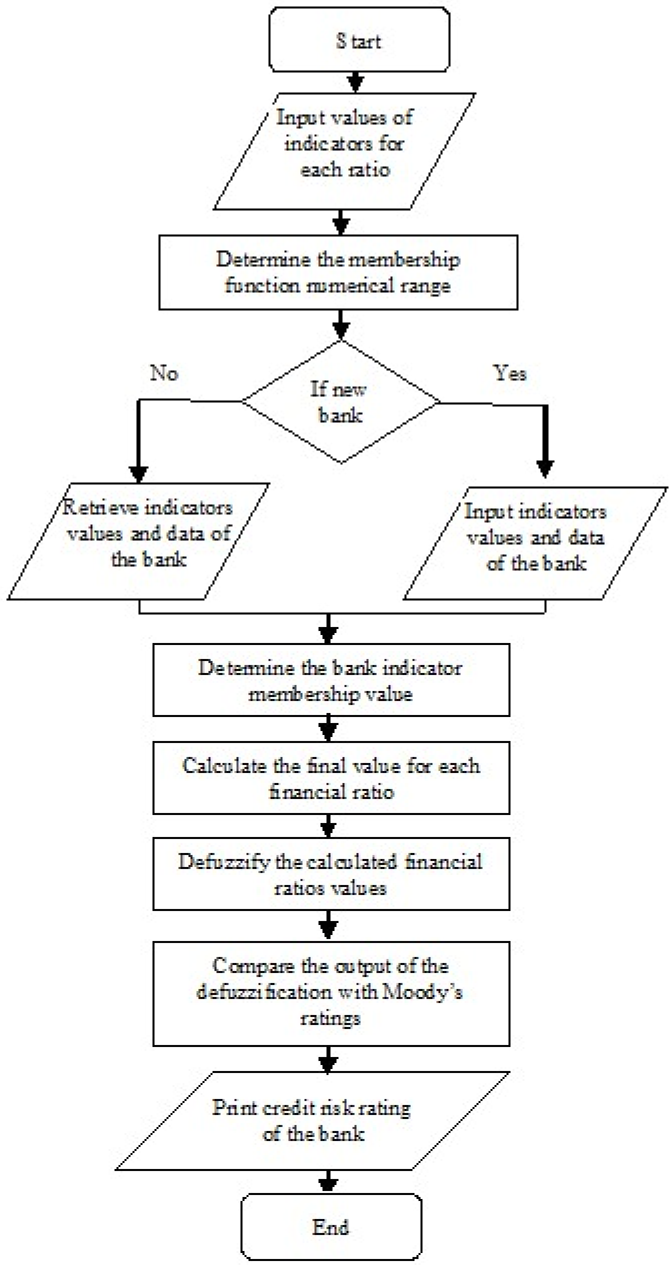

Figure 12 . Flow Chart of the Proposed Model

6- The Implementation of the Proposed Approach

This section presents the major steps used in implementing the proposed model and evaluating its effectiveness. The proposed model was implemented using fuzzy logic in MATLAB since it is the most common tool that is used for fuzzy systems. It can be used for defining the input, output, fuzzy rules, and the shape of membership function for the fuzzy system.

Using MATLAB, financial ratios membership functions were calculated, including profitability membership, debt-paying ability membership, operation ability membership and liquidity membership. The proposed model provides a user interface that allows decision makers to interact with it. The Visual Studio 2013 was used to create the graphical user interface (GUI) that allows decision makers to interact with electronic devices with images rather than text commands. The proposed model was applied on CIB Egyptian commercial bank. The calculated ratios by the model for the CIB bank are as follows:

1. Profitably ratio is low (2.60)
2. Debt-paying ability ratio is low (41.99)
3. Operation ability ratio is medium (9.86)
4. Liquidity ratio is low (25.7)

Calculation of CIB Bank credit rating percentage:

$$f = \frac{(2.60 \times 25) + (41.99 \times 25) + (9.86 \times 50) + (25.7 \times 25)}{2.60 + 41.99 + 9.86 + 25.7}$$

$$f = \frac{65 + 1049.75 + 493 + 642.5}{80.15}$$

$$f = \frac{2250.25}{80.15} = 28.07$$

Percentage of CIB bank credit rating by defuzzification process is (28.07), based on profitably ratio is low (2.60), dept-paying ability ratio is low (41.99), operation ability ratio is medium (9.86) and liquidity ratio is low (25.7). As a result, the proposed model predicted the rating classification of the CIB bank according to Moody's ratings as (Ba3).

7- Conclusion

The proposed model in this paper has proven its effectiveness in predicting the credit risk rating of commercial banks in advance with reasonable accuracy. This paper also provides a set of financial indicators which can be used in the assessment of the bank credit risk rating. These indicators were classified into four categories: profitability, debt-paying ability, operation ability and liquidity. By using the proposed model, decision makers will be able to determine the class of credit risk rating of commercial banks. The results showed that Fuzzy logic is one of the most significant techniques in machine learning that are used to predict credit risk rating of commercial banks. The results also indicated that fuzzy logic technique is more scalable, reliable, stable, and different from classical methods. It is recommended as a future work to integrate other machine learning techniques such as neural networks with the proposed model in order to enhance the accuracy of the model results.

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