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Abstract - Expert technologies have obdurately changed the landscape of financial granting. This has been manifested through the numbers of research breakthroughs that are published and adopted by financial institution around the globe. However, in the Philippines, it has been a challenge for most granting institutions to find out and predict credit risk intelligently due to lack of accurate models to be adopted specifically for granting loans to small and micro enterprises (SMEs). To address this problem, the researchers developed a risk analysis and recommendation system using a rule-based fuzzy logic model that is build up as a utility application. With the system at hand, DOST SET-UP being a government financial granting organization will be able to create more sound decisions in approving loans through the use of an expert system.

Keywords - Fuzzy logic model, credit risk analysis, recommendation system, credit score, expert system

I. INTRODUCTION

The effect of globalization has been manifested in different economic settings around the world. This shift has brought more advantages to big market players and lesser opportunity to the small ones. With such lenient competition, survival has been a challenge especially for small and micro enterprises (SMEs) in third world countries, particularly in the Philippines. This is where the government gives intervention to help SMEs survive in the trade through capacity building and financial granting projects. These monetary grants are given in a form of a loan. This means that the SME beneficiary is responsible for paying back as stipulated in a written contract of agreement.

However, the real challenge in credit granting is related to relentless information predicament related to moral peril and detrimental selection. This made the risk of borrowers hard to appraise and their performance is hard to track. This is why the government funding projects must be able to mitigate this problem to safeguard government from delinquency and to make sure that the funds be allocated well [1]. This difficulty has called for the adoption of more innovated tools and models to help financial granting companies in their selection and approval decisions.

Presently, one of the recognized tools that have been widely used to measure creditworthiness is risk analysis and recommendation system since it uses computer technology and conceptualization of new statistical and risk models to process credit granting [2]. In view of this, this research highlights the incorporation of the expert system since it has a very limited utilization in the field of finance, specifically, in credit risk analysis and recommendation.

In paper presents a fuzzy logic based model that could help in the determining and predicting for the government financial granting program risk scoring. This gives much importance of including an expert system solution in the assessment and recommendation process of the approval of financial grants through a knowledge-based application.

Furthermore, this paper utilizes the results from the first phase of this research entitled, “Variable Selection for Credit Risk Scoring on Loan Performance Using Regression Analysis” for the adoption of the selected variables in the scoring process for the development of the fuzzy logic model.

II. BACKGROUND OF THE STUDY

Expert systems are an application that aims to imitate the analytic of humans as it attempts to deal with complicated, poorly structured problems through intelligent solutions. This is characterized by two components which are knowledge-based and an inference engine [3]. The knowledge is represented by numbers, dates, facts, and rules using “fuzzy” expert experience. This is often drawn as production rules or “if/then rules”.

On the other hand, the inference engine combines the production rules to be able to create conclusions that could answer specific problems. In a credit risk analysis situation, first financial indicators for risk scoring must be identified.

A. Financial Indicators for Risk Scoring

Risk analysis rating in financial granting is made up of qualitative and quantitative indicators. The proposed fuzzy logic model for risk analysis and recommendation system focuses on quantitative aspects. This is through the construction of a credit risk rating that is articulated into a simple system of gradation for creditworthiness and is represented by numerical modifiers.
These are represented by financial four indicators that such as net profit margin, return on investment, debt-to-asset ratio, and liquidity ratio.

**B. Rule-based Fuzzy Logic Concept**

The fuzzy logic was developed by Lofti Zadeh when he published his paper on “Fussy sets” in 1965. He defined this as a group of statistical principles for knowledge exhibition based on degrees of membership in place of on crisp membership of classical binary logic. Because of this, it offers with the tiers of membership and degrees of truth [4]. This can be understood through the presence of a number of basic concepts such as fuzzy sets, membership functions, fundamental processes of fuzzy sets and fuzzy rules.

- A fuzzy set is defined as a group of entities with a range of grade of membership [5]. Let \( X \) stands as the space of points in the objects and its components stand for \( x \). Thus, a fuzzy set \( A \) of \( X \) is construed by function \( f_A \) \( x \) called the membership function of set \( A \): \( X \rightarrow [0, 1] \).

- A membership function \( f_A \) \( x \) correlates with every point in \( X \) using a real digit in the interval \([0, 1]\). With this, the value of \( f_A \) \( x \) at \( x \) signifying the “grade of membership” of \( x \) in \( A \).

- There are four basic fuzzy set operations such as complement where a fuzzy set \( A \) is denoted by \( A \). Containment where \( A \) is contained in \( B \) if and only if \( f_A \leq f_B \). The union where two fuzzy sets \( A \) and \( B \) with respective membership functions \( f_A \) \( x \) and \( f_B \) \( x \) is a fuzzy set \( C \), written as \( C = A \cup B \), and the membership function is transmitted to those of \( A \) and \( B \). Lastly is the intersection where two sets \( A \) and \( B \) with particular membership functions \( f_A \) \( x \) and \( f_B \) \( x \) is a fuzzy set \( C \), printed as \( C = A \cap B \), and its membership function is associated to those of \( A \) and \( B \).

- A fuzzy rule can be defined as a conditional if statement with terminologies and meanings [6].

**III. RELATED WORKS**

In credit granting a few methodologies has been adopted to quantify and assess risk. The existing number of writings on financial grant assessment chance appraisal and default forecast gives models assembling for the most part in a quantitative way [7]. In this note, an ongoing advancement that expands the set of market-based pointers utilized in the credit chance appraisal of money related counterparties is exhibited. These pointers supplement existing major quantitative and subjective credit chance investigation by giving an opportune perusing of business sectors’ impression of the credit nature of monetary counterparties [8]. However, all examiners concur that the biggest risk and concern to administration today is neglecting to adjust information technology to genuine business needs, and an inability to convey and value to the business. Since information technology can have such a sensational impact on business execution and aggressiveness, an inability to oversee information technology successfully can have an intense effect on the business totality [9].

With this, computer applications for credit risk assessment have been prioritized by financial granting institutions. This advancement is incorporated into the business through the use of a hybrid algorithm. An example of which is the use of neural networks as it patterns and consummates a credit assessor’s appraisal and decision procedure to control loss and guide business development. Specifically, the neural system screens applications to control loss and to discover headings where business volume can increment with a base increment in loss [10].

Another model uses a statistical approach that introduced ways to appraise classification algorithms for credit risk through the creation of a scoring system that could measure the performance classification algorithms and creates criteria for decision-making models showing linear logistic, Bayesian Network, and ensemble methods that ranked as the best three classifiers [11]. However, Shovgun presents an innovative way using fuzzy logic for assessing the financial soundness of the creditors has been introduced by [12, 13]. This algorithm presents dynamic features to analyze the risk.
Thus, the fuzzy logic approach, being a dynamic algorithm, presents the best characteristic to be adopted in the study. In the development of a system, computer architecture puts emphasis on the set of principles and strategies that depict the usefulness, association, and usage of a computer framework, and this is done best when system parameters from significant data are logically identified and are incorporated in an algorithm that best solves the problem [14].

IV. PROPOSED SYSTEM MODEL ARCHITECTURE

The key purpose of the proposed system is to predict credit risk rating for the Department of Science and Technology VII Small & Medium Enterprise Technology Upgrading Program (DOST VII-SETUP). This is patterned on the financial indicators that are shown in table I.

The proposed model is illustrated in figure 1 below.

![Figure 1: The proposed System Model Architecture for Risk Analysis and Recommendation System](image)

In the system architecture, a number of processes have been identified to perform the risk analysis and recommendation.

Process 1 (P1) indicates the selected variables to be used in credit scoring. This was performed during phase 1 of the research where the 9-year data of the project has been processed using data mining techniques to get the selected variables that could be used for the system. These are the form of financial indicators shown in Table 1. This will be incorporated in process 2 or P2 and be presented using a membership function base.

For process 2 (P2), the fuzzy logic technique uses linguistic variables in the assessment to represent Net Profit Margin (NPM), Return on Investment (ROI), Liability Ratio (LR) and Debt-to-Asset Ratio (DAR) indicators. Each of these indicators has a value with a degree of membership assignment of “low”, “marginal”, and “high” as presented in Table III. In this process, the risk analysis process started to take place through evaluation of creditworthiness using a fuzzy logic system. The if/then rules in the knowledge base model the links between input values and the output value and represents the output using Matlab software of an if/then rule shown in Table 8. The fuzzy inference engine is responsible for the computer-based evaluation of the if/then rules in the knowledge base. The resulting output by the fuzzy inference engine is an overall assessment based on a linguistic variable. At this point, degrees of membership are still used, meaning that the resulting statement is still expressed in fuzzy terms. The result from the inference engine is therefore transformed into a clear and distinct credit rating in the process of defuzzification. Further, this will execute through the rule-based fuzzy system, the center of gravity is now identified. Using the COG, the system may now analyze the degree of risk of the creditworthiness of a
proposed project. COG is computed using the formula by Negnevitsky [4]:

$$\text{COG} = \frac{\int_{a}^{b} \mu_{A}(x) x \, dx}{\int_{a}^{b} \mu_{A}(x) \, dx}$$

The result of defuzzification, the crisp output will be the center of gravity. It means, for instance, that the risk involved in the ‘fuzzy’ project is based on the value of the COG. So, based on the COG the risk rating will be given.

Process 3 (P3) execute the recommendation. After risk rating is given, the recommendation will be generated using if/then condition in the rule-based fuzzy logic. Thus, the output of the recommendation will only be based on a written condition in the system.

Once the project is recommended for approval, the project may now commence. However, if not, the recommendation may be addressed so that the project proposal will be approved by the system. The recommendation is executed by the system after risk analysis has been done. The recommendation falls under three conditions using the project proposal approval in the terms of: Approved, Conditional with Suggested Revisions and Rejected.

In the history of DOST SET-UP project, the guidelines and policy have already been revised for about two to three times. That is why, to make the system dynamic, process 6 takes place. This process is executed once a revision is done on the existing policy and guidelines of the project. After determining new requirements from the revised policy, the said data will then be normalized. After normalization, process 1 on data convergence, process 2 on risk analysis using fuzzy logic and process 3 on the recommendation will take place accordingly.

For actual implementation of the system, a new proposal may be subjected for evaluation as it is feed to process 4 where data are being processed through the use of the rule-based fuzzy logic algorithm defined by the system. After the risk analysis, the risk rating on process 2 will then be automatically generated by the system. And from that rating, comes its recommendation as stipulated in process 3. In the case that the project is rejected for the aid tranche, a revised proposal may be subjected for another round of risk analysis and recommendation for the following tranche.

A. Benchmarks on Financial Ratio

For the study, the researcher adopted a structures business tool to identify the different financial ratios that measure the performance of each of the variables used in the algorithm simulation. This has indicated the different numerical benchmarks that are measured as how marginal and high. With the measurement at hand, the risk impact on each benchmark has also been stipulated as it is implemented during the simulation [15]. This is presented in table III.

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Benchmark</th>
<th>Risk Impact</th>
</tr>
</thead>
<tbody>
<tr>
<td>Net Profit Margin</td>
<td>≥ 25%</td>
<td>Higher margin then lesser risk</td>
</tr>
<tr>
<td>Return on Investment</td>
<td>≥ 1.50</td>
<td>Higher ratio than less risk</td>
</tr>
<tr>
<td>Liquidity Ratio</td>
<td>≥ 30%</td>
<td>Higher than less risk</td>
</tr>
<tr>
<td>Debt to Asset Ratio</td>
<td>≤ 30%</td>
<td>Higher than less risk</td>
</tr>
</tbody>
</table>

The table shows the different financial indicators and different benchmarks. For net profit margin (NPM) it shows that the higher the margin then the lesser the risk there will be. For return on investment (ROI) the higher the ratio than the lesser the risk. For liquidity ratio (LR), the higher the ratio then the lesser the risk and lastly for the debt-to-asset ratio (DAR) the higher the ratio then the more risk there will be.

B. Fuzzy Logic Simulation Results and Discussion

This section presents the different variable simulations which identify the center of gravity to each of the financial indicators. The data are run using Matlab software. The results are as follows:

<table>
<thead>
<tr>
<th>Linguistic</th>
<th>Notation</th>
<th>Numerical Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>1</td>
<td>[15 20.34 25.9 35.9]</td>
</tr>
<tr>
<td>Marginal</td>
<td>2</td>
<td>[5.13 10 15 19.9]</td>
</tr>
<tr>
<td>High</td>
<td>3</td>
<td>[-11.3 -1.25 4.993 10]</td>
</tr>
</tbody>
</table>

Table IV shows that for NPM, it is found out that the risk is low if the numerical range is 15 20.34 25.9 35.9, marginal if it is from 5.13 10 15 19.9 and high if it is -11.3 -1.25 4.993 10 percent. This means that the higher the net profit margin there will be the lesser the credit risk.

For ROI, it is stated that the risk is low if the numerical range is from 5% to 10%, marginal if it is from 1% to 5% and high if it is less than 1%. This goes to show that the higher the return on investment there will be the lesser the credit risk. This is demonstrated using table V.

<table>
<thead>
<tr>
<th>Linguistic</th>
<th>Notation</th>
<th>Numerical Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>1</td>
<td>[2.48 4.76 5.26 7.26]</td>
</tr>
<tr>
<td>Marginal</td>
<td>2</td>
<td>[0.985 2.25 2.75 3.975]</td>
</tr>
<tr>
<td>High</td>
<td>3</td>
<td>[-2.25 -0.25 0.25 2.52]</td>
</tr>
</tbody>
</table>

For table V on ROI, it is stated that the risk is low if the numerical range is 2.48 4.76 5.26 7.26, marginal if it is from 0.985 2.25 2.75 3.975 and high if it is -2.25 -0.25 0.25 2.52 percent. This goes to show that the higher the return on investment there will be the lesser the credit risk there is.
For LR, it is stated that the risk is low if the numerical range is from less than 1%, marginal if it is from 1% to 1.5% and high if it is equal to 1.5% to 5%. This means that the higher the liquidity ratio the lower the credit risk. See illustration in table VI.

<table>
<thead>
<tr>
<th>Linguistic</th>
<th>Notation</th>
<th>Numerical Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>1</td>
<td>[-2.18 -0.184 0.9854 2.48]</td>
</tr>
<tr>
<td>Marginal</td>
<td>2</td>
<td>[0.0331 2.23 2.758 5.02]</td>
</tr>
<tr>
<td>High</td>
<td>3</td>
<td>[2.53 4.001 5.26 7.26]</td>
</tr>
</tbody>
</table>

Table VI shows that for LR, it is stated that the risk is low if the numerical range is from -2.18 -0.184 0.9854 2.48, marginal if it is from 0.0331 2.23 2.758 5.02 and high if it is 2.53 4.001 5.26 7.26 percent. This means that the higher the liquidity ratio the lower the credit risk.

For DAR, it is stated that the risk is low if the numerical range is from less than 30%, marginal if it is from 30% to 55% and high if it is greater than 55%. This means that the higher the debt-to-asset ratio the more credit risk there will be. See illustration in table VII.

<table>
<thead>
<tr>
<th>Linguistic</th>
<th>Notation</th>
<th>Numerical Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>1</td>
<td>[-24.8 -2.75 2.75 30.19]</td>
</tr>
<tr>
<td>Marginal</td>
<td>2</td>
<td>[4.73 24.8 30.19 49.8]</td>
</tr>
<tr>
<td>High</td>
<td>3</td>
<td>[30.25 52.25 57.75 79.75]</td>
</tr>
</tbody>
</table>

Table VII shows that for DAR, it is stated that the risk is low if the numerical range is from -24.8 -2.75 2.75 30.19, marginal if it is 4.73 24.8 30.19 49.8 and high if it is 30.25 52.25 57.75 79.75 percent. This means that the higher the debt-to-asset ratio the more credit risk there will be.

For the fuzzy logic output, CREDIT RISK uses the classical set for credit scoring [17, 18], see figure 2.

![Figure 2. Classical Set for Credit Score](image)

This figure shows that each of the set belongs to a membership function that decides for the degree of truth that an element fit into the set. For credit risk, it is stated that the risk is low if the numerical range is from less than 1, marginal if it is from 1 to 3 and high if it is from 3 to 5. This means that the higher the credit risk score the higher the risk too and the lower the score the lower the risk. See the illustration in figure 3:

![Figure 3. Membership functions for Credit Risk](image)

Figure 3 shows that the credit risk is low if the numerical range is from 0 0.5, 1, marginal if it is from 1, 2, 3 and high if it is from 3, 4, 5. This means that the higher the credit risk score the higher the risk too and the lower the score the lower the risk.

### C. Fuzzy Rules Based

Fuzzy logic rules contain the master information of pointers relations and the arrangement of an aggregate judgment as though then standards. All the fuzzy principles together form the purported “information base”. The model takes into account including or refreshing theories govern if there should be an occurrence of expanding the logic rules. Fuzzy rules are utilized to ascertain financial ratios. These ratios are calculated based on the following statistical formulas:

\[
NPM = \frac{Net\ Profit}{Total\ Revenue}
\]

\[
ROI = \frac{Net\ Profit}{Total\ Investment} \times 100
\]

\[
LR = \frac{Current\ Asset}{Current\ Liability}
\]

\[
DAR = \frac{Total\ Asset}{Total\ Debt}
\]

Table VIII shows an example of the credit risk scoring rules that will be applied by the fuzzy inference engine for the DOST SET-UP Risk Analysis and Recommendation System.
TABLE VIII. CREDIT RISK RULES SAMPLES

<table>
<thead>
<tr>
<th>Rule #</th>
<th>Fuzzy Rules</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>If (DAR is high) and (NPM is low) and (LR is low) and (ROI is low) then (CREDIT_RISK is high)</td>
</tr>
<tr>
<td>2</td>
<td>If (DAR is marginal) and (NPM is marginal) and (LR is marginal) and (ROI is marginal) then (CREDIT_RISK is marginal)</td>
</tr>
<tr>
<td>3</td>
<td>If (DAR is low) and (NPM is high) and (LR is high) and (ROI is high) then (CREDIT_RISK is low)</td>
</tr>
<tr>
<td>4</td>
<td>If (DAR is high) and (NPM is marginal) and (LR is marginal) and (ROI is marginal) then (CREDIT_RISK is marginal)</td>
</tr>
</tbody>
</table>

After creating the rules, MATLAB implements it as illustrated in figure 4.

Figure 4 shows the roadmap of the whole fuzzy inference process. The four plots across the top of the figures represent the antecedent and one plot for the output. This may be known as the center of gravity of the four inputs. These are as follows:

a) debt-to-asset- ratio (DAR) center of gravity is 27.5,
b) net profit margin (NPM) center of gravity is 12.5,
c) liquidity ratio (LR) center of gravity is 2.5; and
d) return on investment (ROI) center of gravity is 2.5.

With the rules on hand, the numerical values are then incorporated into the rules. Using Matlab, these rules can be illustrated using the surface viewer as shown in figure 5 and 6.

The figures illustrate a three-dimensional representation of mapping the from debt-to-asset-ratio and return on investment to credit risk and net profit margin and liquidity ratio to credit score. Since this representation shows four input- one output case, the mapping is divided into two plots.

As a result, the calculation of the proposed system is as follows:

a) credit risk is low when the score is (0.5),
b) credit risk is marginal when a score is (2.0); and
c) credit risk is high when the score is (4.0).

D. Testing of the Proposed Model

The algorithm for the proposed system has been tested using Matlab software. However, since this is a research-in-progress the proposed model must be tested for accuracy by
comparing this system generated a result and the actual evaluation result of the Department of Science and Technology loan experts. It is then recommended that validation is made once the proposed model will be fully developed and implemented to ensure system efficiency and effectiveness.

V. CONCLUSION

The proposed fuzzy logic model for risk analysis and recommendation system for Department of Science and Technology’s Small Enterprise Technology Upgrading Program (DOST-SETUP) is developed to aid the approval process of SET-UP projects beneficiaries in the Philippines. This system evaluates whether submitted project proposals for SET-UP funding could pass the requirements using identified variables as extracted from the DOST Administrative Order No. 002 on Revised Small Enterprises Technology (SET-UP) Guidelines through a utility software that incorporates text analysis. Specifically, the study considers selected variables such as net profit margin, return on investment, liquidity ratio and debt-to-asset ratio that are considered important financial indicators to be considered in putting up small and micro enterprises (SME’s).

The proposed system seeks to help can help DOST SET-UP implements its project to create sound decisions on approving project grant to intensify success rate and eliminate project failures. Thus, ensures that government funds are allocated on project proposal with better feasibility. Furthermore, this research can be made further by considering more factors for evaluating the credit risk for SMEs. Also, this system could also be reflected in other organization that grants loans through project proposals such as cooperatives and other financial institutions.

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REFERENCES


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