A Multi-objective Approach for the Prediction of Loan Defaults

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ABSTRACT

Credit institutions are seldom faced with problems dealing with single objectives. Often, decisions involving optimizing two or more competing goals simultaneously need to be made, and conventional optimization routines and models are incapable of handling the problems. This study applies Fuzzy dominance based Simplex Genetic Algorithm (a multi-objective evolutionary optimization algorithm) in generating decision rules for predicting loan default in a typical credit institution.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods and Search – *graph and tree search strategies, heuristic methods.*

General Terms

Algorithms, Theory.

Keywords

Multi-objective optimization, Fuzzy Inference, Loan default, Prediction.

1. INTRODUCTION

The World Agricultural Supply and Demand Estimates (*WASDE estimates are published by United States Department of Agriculture (USDA))* [24] for the year 2004 indicate that net farm income in the United States (U.S.) is predicted to fall by $7.3 billion from the 2003 level to $47.6 billion. Net cash income is also projected to be $55.9 billion, about $7.1 billion lower than 2003 figure. The United States (U.S.) banking sector is reported to hold over $82 billion in farm debt [10]. This growing farm debt has been projected by USDA [24] to increase by about 3.5 percent in 2005 over the farm debt expansion rate of 4 percent in 2004. Also, four farm banks failed within the last five years; one of which occurred in 2004.

According to the United States Department of Agriculture [24], total farm debt has increased over the past 11 years. Total outstanding farm debt at the end of 2002 was 45.2 percent larger (increase of $62.8 billion) than the 1989 figure and 4.2 percent ($8.1 billion in nominal terms) higher than the 1984 all time high record. As such, farm financial performance and loan issues are important.

Several studies in the finance and agricultural economics literature have examined loan default and credit risk. A number of these studies developed models that predict the probability of loan default ([1],[5],[7],[11],[12]). For instance, a previous study [5] built on existing credit scoring models and proposed a method for estimating portfolio credit risk. The authors [5] used a bivariate probit model to estimate default probabilities and examined the effects of default-risk-based acceptance rule changes on a bank's portfolio. Another study [7] used the distance-to-default approach to determine the Value at Risk (VaR) for a sample of farmers' loan portfolios.

Most agricultural finance analyses are based on farm business financial ratios (liquidity, leverage, profitability ratios, return on assets, repayment capacity, etc.) using rules of thumb, informed by experience. However, while human experts could be biased and subjective, human capital investment in training and development of these experts is large and time consuming. Expert systems are argued to offer cheaper, non-biased and more cost efficient alternatives for identifying bad credit before such turns into loss.

In recent years, machine-learning techniques are increasingly being used in loan analyses. This is based on the fact that some of the factors considered in high-volume loan analyses are subjective, while others are vague or imprecise, making modeling with traditional (probability based) methods quite difficult and restrictive. An example of such an approach is using recurrent neural networks in forecasting exchange rates [9]. Within the past decade, banks and other financial institutions have continued to invest considerable amounts of resources in developing internal risk models. Bank regulators have encouraged this effort [11]. For instance, the 1997 Market Risk Amendment (MRA) to the Basel Capital Accords [2] has formally incorporated banks' internal market risk models into regulatory capital computation. With this, the regulatory capital requirements for a bank's credit risk exposure (*The latest version of the Basel Capital Accords expected to go into operation in 2006 encourages credit institutions to manage credit risk based on internally developed models in a value-at-risk approach to determine economic capital adequacy*) are a function of the bank's own value-at-risk (VaR) estimates, subject to some supervision. The rationale for this is to permit banks to measure the credit quality of their portfolio and appropriately measure the quality of prospective applicants (or

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investment opportunities). This makes it attractive for a bank to develop or buy its own risk-assessment model, enhancing more accurate and efficient management of a bank's assets. This also enables them to appropriately price risk.

With more reliable prediction of the probability of loan loss, creditors attempt to minimize and/or price credit risk (*exposure in this context refers to the overall credit risk arising from loans already extended*) by devoting special attention to the performance rating and approval procedures for any prospective credit application. Rather than use the conventional credit scoring approach, rating of applications for large transactions, usually above \$5 million, are physically examined and rated directly by bank officials, with the degree of scrutiny increasing with credit volume. This has been shown to be expensive relative to the more quantitative credit scoring approach [1]. Because of the cost, statistical models are often used for scoring most small volume loans, in spite of the fact that judgmental rating systems are generally believed to offer greater accuracy, confidence, and flexibility [23].

Managers and credit officers in credit institutions are not always faced with problems involving single objectives. Rather, they make decisions involving optimizing two or more competing goals simultaneously. In which case, conventional optimization routines designed to handle single objective optimization problems and models are incapable of handling these problems.

Modeling credit rating problems may involve minimizing the estimation error (Sq-err) while ensuring some confidence or risk tolerance level for misclassification. The risk element relates to misclassifying bad credit as good such that any amount granted based therein will be lost. But the profit of the credit institution is closely tied to its ability to make profit from funds loaned to customers, who have to pay back the principal and the interest. Profit cannot be made unless repayments (Principal and interest) are made in a timely fashion. Small errors in credit assessment are not important given the lumpiness of credit pricing which is usually in 25 basis point increments. However, large misclassifications are important as that would often result in the mispricing of risk. Because different institutions price risk differently it is important to allow for more than one risk tolerance in addition to allowing a financial institution to examine the effect of alternative tolerance levels on the optimal decision rules. As such, this results in the competing objectives as shown in Fig 1.

Existing optimization routines (e.g. EV model used in risk modeling) often translate multi-objective problems into a single objective function by using aggregated weight techniques. This requires the problem to be solved several times to obtain all the good solutions that are optimal in all the objectives considered. This approach is inappropriate in solving two or more objective function problems because available options or combinations of different varieties of optimal options are not explored. For instance, the simultaneity and interaction between these alternative combinations are never empirically examined. Based on recent developments in the engineering profession ([3], [6], [8]), this study applies a multi-objective optimization algorithm [8] useful in handling problems like these. Second, the proposed approach also offers the credit analyst the opportunity and flexibility to incorporate some prior knowledge into the estimation process. This allows using the peculiar characteristic of the data to generate linguistic rules that are useful in improving credit assessment decisions.

In this study, an elitist fuzzy dominance based multi-objective hybrid of an elitist multi-objective genetic algorithm and simplex algorithm [8] is used to optimize the fuzzy rules over a range of risk tolerance levels (delta). A credit analyst would therefore be presented with equally optimized decisions rules based on the available data. So, in addition to offering rules that are similar to everyday language, these rules are optimized empirically and the best ones are selected.

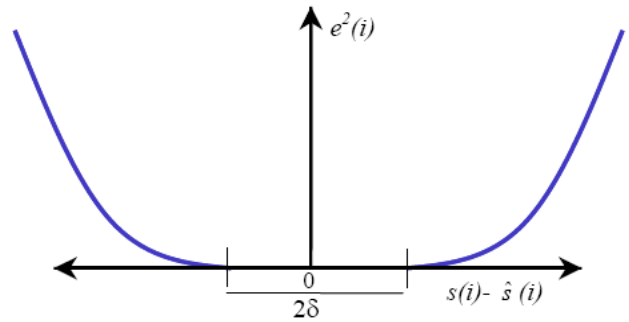

Figure 1. Two-objective optimization

In this study the two objective functions (f_1 and f_2) that are to be minimized are defined as:

$$f_1 = \frac{\sum_{i=1}^{n} e^2(i)}{n}, \quad where$$

$$e(i) = \begin{cases} \left|s(i) - \hat{s}(i)\right| - \delta, & if \left|s(i) - \hat{s}(i)\right| \geq \delta \\ 0, & otherwise \end{cases} \quad (1)$$

$$f_2 = \delta, \; where \; 0 \leq \delta < 0.3 \quad (2)$$

where equation (1) minimizes the average error in prediction of $\hat{s}(i)$ as a function of error tolerance and equation (2) minimizes the error tolerance while restricting it to a pre-specified range. The error tolerance is the absolute difference between the model output and the original target output, less than a specified tolerance value (chosen to be 0.3). The tolerance (delta) shows the credit risk margin within which the misclassification error is acceptable and hence, no penalty will be denoted. Values lower than delta (0.3 in the initial case) is set to zero, as shown in Figure 1. This particular objective function ensures that solutions with error less than the pre-specified value are equally preferred while those greater than this specified values are penalized.

2. PROBLEM STATEMENT

The objective of a *typical* credit institution is to minimize portfolio loss, which is often expressed as:

$$EL = PD * LGD * EAD \quad (3)$$

where EL is the expected loss, PD is the Probability of default, LGD is the loss given default and EAD is the Exposure at default. Both PD and LGD are expressed in percentages while EAD is in monetary units (e.g. dollars). Effort is made to estimate the probability of default for every loan, thereby enhancing the assessment of its potential cost and accurately measuring the portfolio risk.

To minimize portfolio loss, a credit institution must be able to predict its loan default rate or at best minimize its portfolio default within an acceptable error margin. Banks are therefore required to set aside a particular percentage of their liquid assets to meet expected losses (EL). The percentage is largely determined by the expected default risk, often expressed as probability of default on each loan and useful for determining the portfolio loss distribution.

While predicting credit default can be carried out using traditional econometric techniques, incorporating expert knowledge into the estimation procedure has been faced with several challenges. This necessitates the use of fuzzy inference system for predicting loan default and allows expert knowledge to be incorporated in the credit appraisal process, while making available to credit officers, linguistic rules that would be useful in their credit ratings and assessments. In our sample case, the credit analyst is offered a Pareto optimal solution set, expressed in easily understandable linguistic rules.

Figure 2 shows a typical fuzzy inference system with five steps. Crisp input values are fuzzified in the first step to determine their respective membership functions (the measure of belief in the fuzzy indicator). In the second step, the inference system combines the fuzzy indicators as described by the fuzzy rule structure in the system. An output value (rule-strength) is produced by each rule showing its impact on the system. All the rules are later weighted based on their respective value and aggregated together to give a single output, in the case of a sugeno type system or a set of linguistic consequents, if it is a mamdani type.

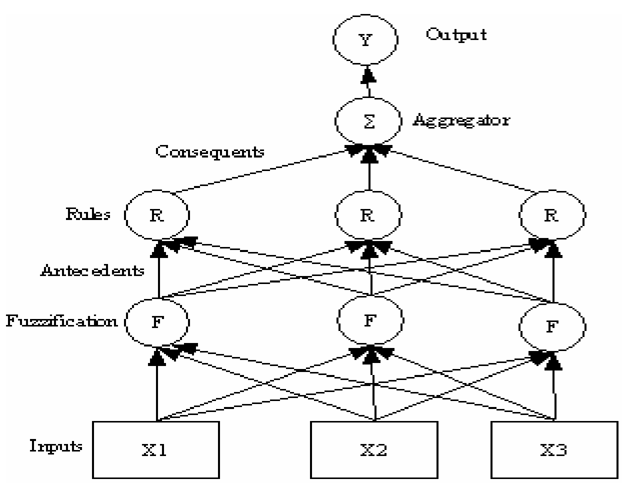

Fig. 2: Fuzzy Inference System

In this study, we use the Tagaki-Sugeno [21] approach because it is more tractable and the main focus is on estimating a crisp output, from which we were able to optimize the generated linguistic rules. This is empirically specified in equation (4),

$$\begin{aligned}
&R^1: If(CDRC \text{ is } High_1^1 \text{ and } OE \text{ is } High_2^1 \text{ and } WC \text{ is } High_3^1),\\
&\qquad then\left(Y = Y^1 = c_0^1 + c_1^1 CDRC + c_2^1 OE + c_3^1 WC\right)\\
&R^2: If(CDRC \text{ is } High_1^2 \text{ and } OE \text{ is } Medium_2^2 \text{ and } WC \text{ is } High_3^2),\\
&\qquad then\left(Y = Y^2 = c_0^2 + c_1^2 CDRC + c_2^2 OE + c_3^2 WC\right)\\
&R^{12}: If(CDRC \text{ is } Medium_1^{12} \text{ and } OE \text{ is } High_2^{12} \text{ and } WC \text{ is } Low_3^{12}),\\
&\qquad then\left(Y = Y^{12} = c_0^{12} + c_1^{12} CDRC + c_2^{12} OE + c_3^{12} WC\right)\\
&R^{27}: If(CDRC \text{ is } Low_1^{27} \text{ and } OE \text{ is } Low_2^{27} \text{ and } WC \text{ is } Low_3^{27}),\\
&\qquad then\left(Y = Y^{27} = c_0^{27} + c_1^{27} CDRC + c_2^{27} OE + c_3^{27} WC\right)
\end{aligned} \tag{4}$$

where the input variables are CDRC (Capital Debt Repayment Capacity), OE (Owner's Equity) and WC (Working Capital) while High, Medium and Low are the fuzzy terms. Y^i is the consequence or output of rule *i* while the c^i_j 's are the parameters determined endogenously. The number of rules is determined by x^n where x is the number of inputs and there are n input membership functions. In the estimation process, the triangular membership function was used for the inputs while the linear membership was used for the output.

With this specification, the consequence is a linear equation, and c_i *'s* are a total of 108 parameters (i.e. four parameters per rule for the twenty seven rules). This indicates the impact of each variable and the bias in the respective rules. This specification makes it easy to obtain the overall output as a weighted average of the consequents (Y^i) thus

$$\hat{Y} = \frac{\sum_{l=1}^{27} w^l Y^l}{\sum_{l=1}^{27} w^l} \tag{5}$$

where w^l is defined as

$$w^l = \prod_{i=1}^{p} \mu_{F_i^l}(x_i) = \mu_{F_i^l}(CDRC) * \mu_{F_i^l}(OE) * \mu_{F_i^l}(WC) \tag{6}$$

and denotes the truth value of the output or $Y=Y^l$ proposition. F_i^l can be High, Medium or Low when the input variables are fuzzified, while the right hand expression simply denotes the intersection of the membership functions of the three input variables, CDRC, OE and WC. The variable w^l is identical to a nonlinear interaction term between the three variables in traditional regression analysis. So, there are twenty seven nonlinear parameters (one for each of the rules) in this case, making a total of 135 parameters (with the 108 linear parameters) that are tuned simultaneously The high number of estimates make this optimization procedure computationally challenging for traditional econometric procedures. In this study, an elitist fuzzy dominance based multi-objective hybrid of a genetic algorithm and simplex algorithm [8] is used to optimize the fuzzy rules over a range of risk tolerance levels (delta).

3. MULTI-OBJECTIVE OPTIMIZATION

Most real world problems involve optimization of multiple conflicting objectives at the same time. Conventional methods to solve such problems would generally assign weights to each of the objectives that reflect their relative importance in the problem. However, it is often difficult to find the weights capable of accurately indicating the actual problem. Moreover, it is not always advisable to combine all the objectives into a single objective since this makes it impossible for us to explore the simultaneity inherent in the real life problem. Therefore, to solve these types of problems in a purely multi-objective sense we need to use the concepts of Pareto optimality.

3.1 Pareto Optimality

Consider a multi-objective optimization problem, where we have n number of competing objectives to be minimized with each objective specified as O_i, i=1,…,n. A is said to dominate B when the following condition is satisfied: $A \succ B$ iff $O_i(A) \le O_i(B)\ \forall\, i$, and $\exists\, i$ such that, $O_i(A) < O_i(B)$. The dominance relationship is denoted as $A \succ B$, stating that A is preferred to B. In microeconomic theory, this hypothesis of rationality assumes

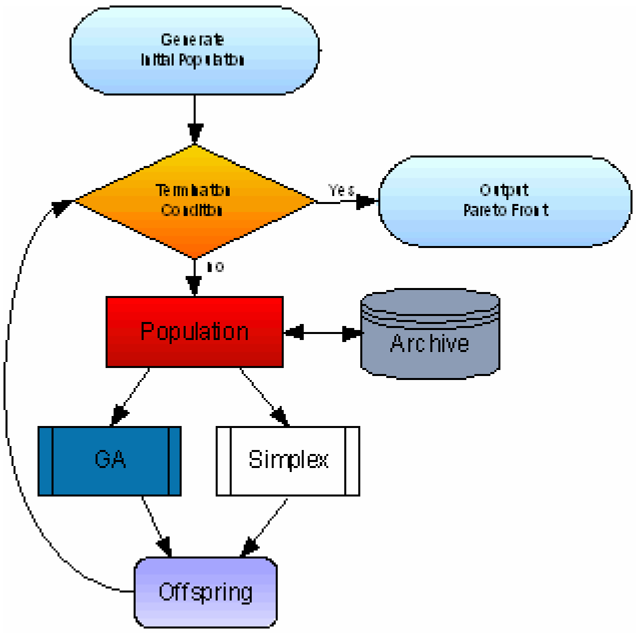

Fig. 3. Flowchart of FSGA Algorithm

completeness and transitivity [15]. Completeness ensures that a decision maker has a well-defined preference when faced with two alternatives, while transitivity implies that the preference of the individual cannot circle (i.e. he cannot prefer option A to B, B to C and also prefer C to A).

A solution is said to be Pareto-optimal if it is not dominated by any other candidate in the solution set. That is, with *n* solution candidates (s^1, s^2…,s^n) in a given solution set S, and s^p defined as a Pareto-optimal solution, the Pareto Front (Γ) is given as:

$$\Gamma = \{s^p \in S \mid \forall\, s \in S,\ s^p \succ s\} \tag{7}$$

3.2 Fuzzy Dominance based Simplex-GA Hybrid Algorithm (FSGA)

We used the Fuzzy Dominance Based Genetic Algorithm-Simplex Hybrid Algorithms [8] that is based on the concept of fuzzy dominance. Unlike other multi-objective approaches that assume a crisp dominance measure for Pareto ranking, a degree of dominance referred to as "Fuzzy dominance" is adopted here. This facilitates the hybridization of the genetic algorithm with other local optimization techniques such as Nelder-Mead simplex, which is not possible with other traditional methods.

In this algorithm, dominance is determined using fuzzy membership functions. The distance between the two individual solution candidates on each objective is determined and those closer to the Pareto front are preferred to (dominated) solutions that are far away. The closer a solution candidate is to the Pareto front the less dominated it is in the solution set and the lower is its fuzzy dominance value. The fuzzy membership function makes it possible to determine the degree by which each solution is dominated by other solutions in the population. This allows ranking the individuals and selecting the non-dominated solutions based on their dominance measure.

A value in the range of [0, 1] is assigned to each individual in a population with the non-dominated solutions in the Pareto front assigned lowest values and the dominated solutions are assigned higher values. By definition, if we let S be a population of solutions, where each solution minimizes the error of misclassification and each is contained in a set of solutions U. Suppose s_i is fuzzy dominated by another, s_f, the degree of dominance is denoted by:

$$s_f^{\,dom}(S \,{}^{F}\!\!\succ s_i) = \bigoplus_{s_f \in S} s_f^{\,dom}\left(s_f \,{}^{F}\!\!\succ s_i\right) \tag{8}$$

where $\oplus$ and $\prec^F$ represents t-conorm and fuzzy dominance respectively. Fuzzy dominance in this respect $\left(s_f \prec^F s_i\right)$, indicates that s_f has a smaller misclassification error than every s_i in the solution set.

In the multi-objective fuzzy dominance based optimization routine, a hybrid of the Nelder-Mead simplex algorithm and the genetic algorithm (GA) is used. Both are derivative free algorithms. At each generation a part of the population is used to populate the simplex and GA is populated using tournament selection as shown in Figure 2. While the simplex conducts a local search by utilizing local search space information, the GA is a global search technique that attempts to ensure that the process is not trapped in a local minimum by searching through the entire solution space. This has been proven to provide faster convergence in comparison with other state of the art algorithms. For GA, selection is done using binary tournament selection. This involves randomly selecting two individual solution candidates, among which the least dominated ones are selected for populating the next generation population. There are many different types of crossover operations: Single point, two-point, uniform, convex etc. We have used convex crossover in the current problem. The mutation operator introduces a fractional change, typically 0.2 or less, in given solutions to test their robustness. The crossover rate is set at 0.8 and a mutation rate of 0.1 is used.

Elitism is used to archive the best solution candidates (Pareto front solutions): any other solution candidate in the population does not dominate them. The elite is not subjected to crossover and mutation but re-introduced into subsequent population for evaluation, to ensure that it is still the best solution candidate. The process is iterated for a desired number of generations or until a pre-specified fitness measure condition is met.

4. OPTIMIZING FUZZY-RULE SET

Using the hybrid algorithm discussed above, the fuzzy rule weights obtained from the fuzzy training in the Adaptive Neuro-fuzzy Inference System (ANFIS) [24] estimations of the dataset are optimized. This is necessary to examine and develop sets of decision rules that can be useful for credit approval. Rules are quite useful because of their linguistic properties, ease of understanding and because they are based on empirical information from customer loan characteristics. The added advantage is that information based on expert advice or experience can be translated and optimized.

The rule strengths are iteratively generated while the dual objectives of minimizing estimation error and ensuring that a range of risk tolerance level is simultaneously maintained are optimized. The model output is determined by appropriately aggregating and weighting the rules based on their respective rule strengths.

5. DATA DESCRITION

The data used for this study are from the Seventh Farm Credit District's customers' loan database [4]. The data consist of loans from eleven states (Arkansas, Illinois, Indiana, Kentucky, Michigan, Minnesota, Missouri, North Dakota, Ohio, Tennessee and Wisconsin) covered by the bank during the period (1995-2002).

The four variables used in this study are the Default Dummy (DD), Capital Debt Repayment Capacity (CDRC) percentage, Owners Equity (OE) percentage and the Working Capital (WC) percentage. The DD is an indicator that takes a value of unity (1) if loan default is observed and zero otherwise. This definition considers non-payment of principal and/or interest as default when such fell in arrears by 90 days or more [4]. The other three variables used have been found to be important determinants of the probability of default of loans granted by the Seventh Farm Credit District [4] and have been used in other related studies [18].

Table 1 shows the summary statistics of the data used, while Table 2 shows a summary of the parameters used for generating the triangular membership functions used in the Tagaki-Sugeno fuzzy inference system.

Table 1 Statistical Description of the Data

VARIABLE NAME	MEAN	STD	MIN	MAX
Repayment Capacity	153.04	68.08	-70.03	379.86
Owner's Equity (%)	64.16	17.48	11.44	116.82
Working Capital (%)	36.75	67.09	-222.62	305.38
No. of Observations				157853

Table 2 Definition of Linguistic Variables Used**

Independent Variable	Linguistic Variable	Min (%)	Centre (%)	Max(%)
Repayment Capacity	Low	**-71***	-71	144
	Medium	-71	**144***	380
	High	144	380	**380***
Owners Equity	Low	**11***	11	60
	Medium	11	**60***	100
	High	60	100	**100***
Working Capital	Low	**-223***	-223	29
	Medium	-223	**29***	306
	High	29	306	**306***

Note: *The bold values indicate membership value of unity in the respective row
. ** Definition is based on the symmetric triangular membership function

6. RESULTS AND DISCUSSION

A preliminary run of the sample shows the candidate solutions after the first iteration (before training) in figure 4 (Initial Population). The hollow circles represent dominated solutions, while the solid ones represent non-dominated solutions.

After 50 generations, the tuning process produced the Pareto front shown in figure 4 (top). The non-dominated solutions represented with the solid (filled) circles form the Pareto front while all the dominated solutions (hollow circles) are to the right of the Pareto front. Each of the optimal solutions represents an optimal choice to the decision maker in his credit approval/rating process. The advantage of this approach is that the decision maker has a variety of optimal options to choose from. As shown in Figure 4 (middle), the Pareto front has become more pronounced with fewer dominated solution candidates at 100 generations. This gives the credit analyst a set of optimal choices from which he can choose, based on his preferred risk tolerance level.

Based on the specification of the linguistic variables shown in Table 2, twenty-seven rules (equation 2) were generated based on the fuzzy inference system relationship, X^n, giving rise to the maximum number of fuzzy rules in the fuzzy system. X is the number of crisp variables to be fuzzified and n denotes the number of membership functions used. In our specification, X is 3 and n is 3.

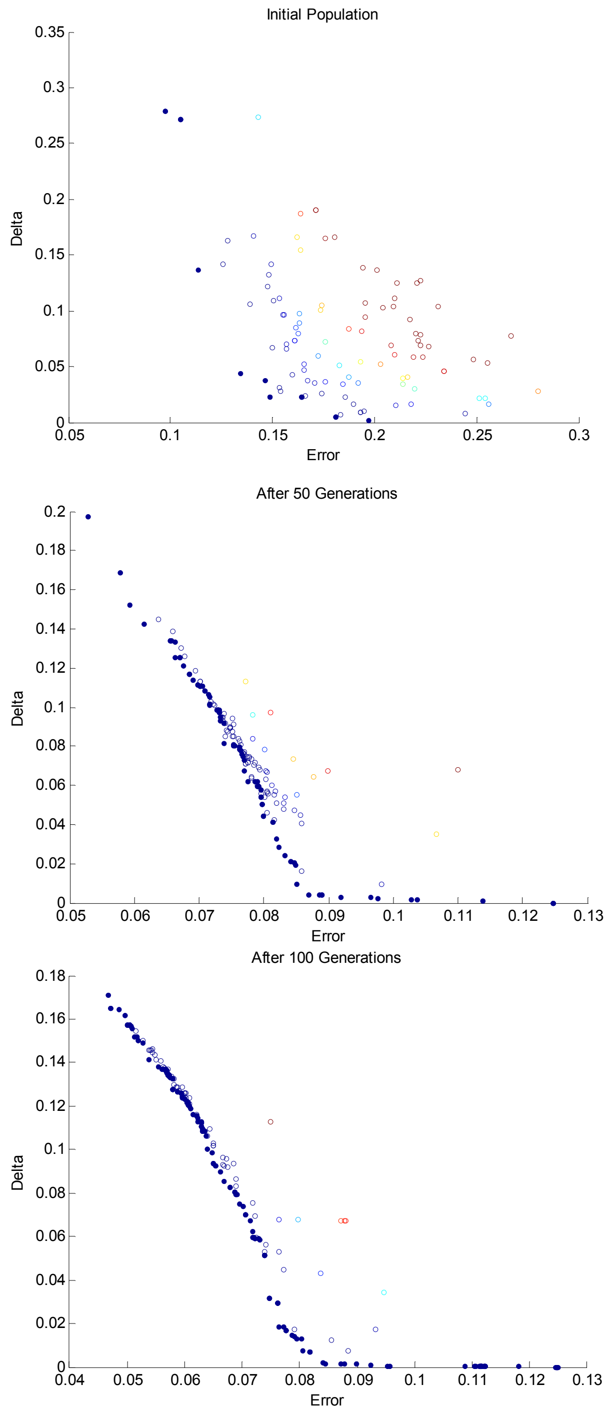

Fig. 4. Plot showing the solutions obtained after 0, 50 and 100 generations. (● - represent the non-dominated solutions, and o – represent the dominated solutions)

The linguistic variables generated from the independent variables after 25 generations are listed in Table 3. The repayment capacity percentage is low with a membership of unity when a

Table 3 Fuzzy Rules at 25 Iterations

Rule Number	Repayment Capacity	Owners Equity	Working Capital	Rule Strength
19	Low	Low	high	0.8755
5	Medium	Medium	Low	0.6275
7	Low	High	Low	0.5491
6	High	Medium	Low	0.5384
25	Low	High	high	0.4985
1	Low	Low	Low	0.4974
15	High	Medium	Medium	0.4937
9	High	High	Low	0.4112
22	Low	Medium	high	0.4011
16	Low	High	Medium	0.3691
24	High	Medium	high	0.3363
13	Low	Medium	Medium	0.3224
18	High	High	Medium	0.3196
14	Medium	Medium	Medium	0.3194
27	High	High	high	0.2840
17	Medium	High	Medium	0.2829
12	High	Low	Medium	0.2389
26	Medium	High	high	0.2291
20	Medium	Low	high	0.2177
23	Medium	Medium	high	0.2107
4	Low	Medium	Low	0.1885
11	Medium	Low	Medium	0.1771
3	High	Low	Low	0.1557
8	Medium	High	Low	0.1419
10	Low	Low	Medium	0.1322
21	High	Low	high	0.1320
2	Medium	Low	Low	0.1277

Table 4 Fuzzy Rules at 50 Generations

Rule Number	Repayment Capacity	Owners Equity	Working Capital	Rule Strength
19	Low	Low	High	0.8644
1	Low	Low	Low	0.6108
5	Medium	Medium	Low	0.6091
22	Low	Medium	High	0.5362
25	Low	High	high	0.5234
7	Low	High	Low	0.5189
15	high	Medium	Medium	0.4678
24	high	Medium	high	0.4024
17	Medium	High	Medium	0.3682
18	high	High	Medium	0.3440
6	high	Medium	Low	0.3293
13	Low	Medium	Medium	0.3162
9	high	High	Low	0.2760
27	high	High	high	0.2582
12	high	Low	Medium	0.2167
26	Medium	High	high	0.2126
23	Medium	Medium	high	0.1864
14	Medium	Medium	Medium	0.1853
4	Low	Medium	Low	0.1456
21	high	Low	high	0.1335
10	Low	Low	Medium	0.1201
8	Medium	High	Low	0.1117
11	Medium	Low	Medium	0.0895
2	Medium	Low	Low	0.0891
3	high	Low	Low	0.0777
20	Medium	Low	high	0.0658
16	Low	High	Medium	0.0348

customer's repayment capacity is -71 percent (i.e. his repayment capacity is low). At 144 percent, the customer has a medium repayment capacity, while a repayment capacity of 380 percent translates to high. Values between these extremes vary in their membership of the respective linguistic variable. This specification implies that a customer with repayment capacity of -71 percent, owners equity of 11 percent and working capital of -223 percent is modeled as having a low repayment capacity, low owners equity and low working capital (membership values of the linguistic variable are all unity at these values of the independent variables). While this specification follows the statistics of the data used in this study, the linguistic variable definitions can also be standardized in line with credit analysts' experience, industry standard and or the appropriate credit institution's credit policy.

Tables 3-8 show the fuzzy rules optimized at different generations. Each of these results represents a solution rule-set obtained at the Pareto front of respective iteration. At twenty-five generations (Table 3), the low-low-high rule has the highest rule strength. This suggests that low repayment capacity, low owners equity and high working capital percentages is the best indicator of default out of the rule set. This is followed by the medium-medium-low rule with 0.6275 rule strength. This rule indicates that medium repayment capacity, medium owners' equity and low working capital percentages is a good indicator of default status. At this intermediate optimization point, the medium-low-low (medium repayment capacity, low owners equity and low working capital percentages) rule is shown to be the worst indicator of default status.

The medium-low-high rule and the low-high-medium rule are shown to be the worst indicators of default at 50 generations (Table 4), while the medium-high-low rule and the low-high-medium rule are the worst two indicators of default status with 0.0745 and 0.0334 rule strengths at 75 generations (Table 5).

After 100 iterations (Table 6), the three best rules are the low-low-low, the low-low-high and the medium-medium-low with 0.8289, 0.7607 and 0.6390 rule strengths respectively. The low-low-low rule shows that low repayment capacity, low owners' equity and low working capital percentages is the best indicator of whether a loan would default or not. This relationship is shown in three optimal solution rules (Tables 6 – 8).

7. CONCLUSIONS

It is interesting to note that the best indicators of default status are observed when repayment capacity and owners equity are low and the working capital is either low or high. While this gives an easy to understand, easy to use rule-of-thumb for credit appraisal, it is also in consonance with some previous studies. For instance, earlier studies using logistic regression ([4],[18]) reported that loan default is inversely related with owners' equity. Also, the two worst rule indicators are low repayment capacity, high owners' equity and medium working capital or medium repayment capacity, low owners' equity and high working capital.

Table 5 Fuzzy Rules at 75 Generations

Rule Number	Repayment Capacity	Owners Equity	Working Capital	Rule Strength
19	Low	Low	high	0.8904
1	Low	Low	Low	0.6355
5	Medium	Medium	Low	0.6003
22	Low	Medium	high	0.5259
25	Low	high	high	0.5246
7	Low	high	Low	0.5241
15	High	Medium	Medium	0.4838
24	High	Medium	high	0.3782
17	Medium	high	Medium	0.3709
6	High	Medium	Low	0.3499
18	High	high	Medium	0.3307
13	Low	Medium	Medium	0.3143
9	High	high	Low	0.2800
27	High	high	high	0.2625
12	High	Low	Medium	0.2161
26	Medium	high	high	0.2146
23	Medium	Medium	high	0.1845
4	Low	Medium	Low	0.1499
21	High	Low	high	0.1327
10	Low	Low	Medium	0.1207
14	Medium	Medium	Medium	0.1198
20	Medium	Low	high	0.0904
11	Medium	Low	Medium	0.0878
2	Medium	Low	Low	0.0875
3	High	Low	Low	0.0874
8	Medium	High	Low	0.0745
16	Low	High	Medium	0.0334

Table 6 Fuzzy Rules After 100 Generations (A)

Rule Number	Repayment Capacity	Owners Equity	Working Capital	Rule Strength
1	Low	Low	Low	0.8289
19	Low	Low	high	0.7607
5	Medium	Medium	Low	0.6390
6	High	Medium	Low	0.4601
7	Low	High	Low	0.4390
17	Medium	High	Medium	0.4202
15	High	Medium	Medium	0.4164
22	Low	Medium	high	0.4030
24	High	Medium	high	0.4016
9	High	High	Low	0.3532
26	Medium	High	high	0.3509
14	Medium	Medium	Medium	0.3391
27	High	High	high	0.2983
25	Low	High	high	0.2916
18	High	High	Medium	0.2836
13	Low	Medium	Medium	0.2434
23	Medium	Medium	high	0.2412
4	Low	Medium	Low	0.2137
3	High	Low	Low	0.1888
21	High	Low	high	0.1502
10	Low	Low	Medium	0.1121
12	High	Low	Medium	0.1029
2	Medium	Low	Low	0.0598
11	Medium	Low	Medium	0.0514
8	Medium	High	Low	0.0325
20	Medium	Low	high	0.0176
16	Low	High	Medium	0.0113

Table 7 Fuzzy Rules After 100 Generations (B)

Rule Number	Repayment Capacity	Owners Equity	Working Capital	Rule Strength
1	Low	Low	Low	0.8290
19	Low	Low	high	0.7530
5	Medium	Medium	Low	0.6410
6	High	Medium	Low	0.4950
7	Low	High	Low	0.4450
17	Medium	High	Medium	0.4080
15	High	Medium	Medium	0.4050
22	Low	Medium	high	0.4030
24	High	Medium	high	0.4000
9	High	High	Low	0.3670
14	Medium	Medium	Medium	0.3540
26	Medium	High	high	0.3510
27	high	High	high	0.2960
25	Low	High	high	0.2900
18	high	High	Medium	0.2860
13	Low	Medium	Medium	0.2430
23	Medium	Medium	high	0.2390
4	Low	Medium	Low	0.2210
3	high	Low	Low	0.2080
21	high	Low	high	0.1480
12	high	Low	Medium	0.1220
10	Low	Low	Medium	0.1140
11	Medium	Low	Medium	0.0831
2	Medium	Low	Low	0.0555
8	Medium	High	Low	0.0463
16	Low	High	Medium	0.0276
20	Medium	Low	high	0.0222

Table 8 Fuzzy Rules After 100 Generations (C)

Rule Number	Repayment Capacity	Owners Equity	Working Capital	Rule Strength
1	Low	Low	Low	0.8310
19	Low	Low	high	0.7640
5	Medium	Medium	Low	0.6400
6	high	Medium	Low	0.4850
7	Low	High	Low	0.4370
17	Medium	High	Medium	0.4140
15	high	Medium	Medium	0.4130
22	Low	Medium	high	0.4020
24	high	Medium	high	0.4010
9	high	High	Low	0.3550
26	Medium	High	high	0.3460
14	Medium	Medium	Medium	0.3460
27	high	High	high	0.2960
25	Low	High	high	0.2890
18	high	High	Medium	0.2870
23	Medium	Medium	high	0.2460
13	Low	Medium	Medium	0.2440
4	Low	Medium	Low	0.2200
3	high	Low	Low	0.2040
21	high	Low	high	0.1570
10	Low	Low	Medium	0.1200
12	high	Low	Medium	0.1040
11	Medium	Low	Medium	0.0734
2	Medium	Low	Low	0.0543
8	Medium	High	Low	0.0400
20	Medium	Low	high	0.0177
16	Low	High	Medium	0.0072

The key implication of these results is that a repayment capacity of -71 percent, owners' equity of 11 percent and working capital of -223 percent is a strong indication of default. Based on the concept of fuzzy membership function, values close to these are also expected to be strong indicators of default status. The result also shows that low working capital percentage appears to be the most consistent indicator of default status (i.e. considering the best five rules). That is, a business that finds it difficult to meet its daily operational funding needs would find it difficult to honor its debt obligations and therefore might default.

In addition, the result also shows that poor repayment history represented as low repayment capacity and low owners' equity, are key factors that needs to be considered in conducting credit assessment. When both factors are low compared to the credit institutions database, this might be a strong indication of default.

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