Evaluating Loans Using a Combination of Data Envelopment and Neuro-Fuzzy Systems

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ABSTRACT

A business organization's objective is to make better decisions at all levels of the firm to improve performance. Typically organizations are multi-faceted and complex systems that use uncertain information. Therefore, making quality decisions to improve organizational performance is a daunting task. Organizations use decision support systems that apply different business intelligence techniques such as statistical models, scoring models, neural networks, expert systems, neuro-fuzzy systems, case-based systems, or simply rules that have been developed through experience. Managers need a decision-making approach that is robust, competent, effective, efficient, and integrative to handle the multi-dimensional organizational entities. The decision maker deals with multiple players in an organization such as products, customers, competitors, location, geographic structure, scope, internal organization, and cultural dimension [46]. Sound decisions include two important concepts: efficiency (return on invested resources) and effectiveness (reaching predetermined goals). However, quite frequently, the decision maker cannot simultaneously handle data from different sources. Hence, we recommend that managers analyze different aspects of data from multiple sources separately and integrate the results of the analysis. This study proposes the design of a multi-attribute-decision-support-system that combines the analytical power of two different tools: data envelopment analysis (DEA) and fuzzy logic. DEA evaluates and measures the relative efficiency of decision making units that use multiple inputs and outputs to provide non-objective measures without making any specific assumptions about data. On the other hand fuzzy logic's main strength lies in handling imprecise data. This study proposes a modeling technique that jointly uses the two techniques to benefit from the two methodologies. A major advantage of the DEA approach is that it clearly identifies the important factors contributing to the success of a decision. In addition, I also propose the use of a neuro-fuzzy model to create a rule-based system that can aid the decision-maker in making decisions regarding the implications of a decision. One of the important characteristics of neuro-fuzzy systems is their ability to deal with imprecise and uncertain information. The neuro-fuzzy model integrates the performance values of a set of production units derived by ranking using DEA to create IF-THEN rules to handle fluctuating and uncertain scenarios. Thus, a decision maker can easily analyze and understand any decision made by the neuro-fuzzy model in the form of the easily interpretable IF-THEN rules.

Keywords: Benchmarking, Data Envelopment Analysis, Neuro-Fuzzy Systems, Decision Support System.

1. INTRODUCTION & MOTIVATION

A business organization's objective is to make better decisions at all levels of the firm to improve performance. Typically organizations are multi-faceted and complex systems that use uncertain information. Therefore, making quality decisions to improve organizational performance is a daunting task. Organizations use decision support systems that apply different business intelligence techniques such as statistical models, scoring models, neural networks, expert systems, neuro-fuzzy systems, case-based systems, or simply rules that have been developed through experience. Managers need a decision-making approach that is robust, competent, effective, efficient, and integrative to handle the multi-dimensional organizational entities. The decision maker deals with multiple players in an organization such as products, customers, competitors, location, geographic structure, scope, internal organization, and cultural dimension [46]. Sound decisions include two important concepts: efficiency (return on invested resources) and effectiveness (reaching predetermined goals). However, quite frequently, the decision maker cannot simultaneously handle data from different sources. Hence, we recommend that managers analyze different aspects of data from multiple sources separately and integrate the results of the analysis. This study proposes the design of a multi-attribute-decision-support-system that combines the analytical power of two different tools: data envelopment analysis (DEA) and fuzzy logic. DEA evaluates and measures the relative efficiency of decision making units that use multiple inputs and outputs to provide non-objective measures without making any specific assumptions about data. On the other hand fuzzy logic's main strength lies in handling imprecise data. This study proposes a modeling technique that jointly uses the two techniques to benefit from the two methodologies. A major advantage of the DEA approach is that it clearly identifies the important factors contributing to the success of a decision. In addition, I also propose the use of a neuro-fuzzy model to create a rule-based system that can aid the decision-maker in making decisions regarding the implications of a decision. One of the important characteristics of neuro-fuzzy systems is their ability to deal with imprecise and uncertain information. The neuro-fuzzy model integrates the performance values of a set of production units derived by ranking using DEA to create IF-THEN rules to handle fluctuating and uncertain scenarios. Thus, a decision maker can easily analyze and understand any decision made by the neuro-fuzzy model in the form of the easily interpretable IF-THEN rules. The rest of the paper is organized as follows; Section II we provide a literature review of previous studies on financial statement analysis, Section III discusses the data envelopment analysis model and the neuro-fuzzy model, Section IV provides an empirical analysis of our results, and Section V summarizes and concludes our study.

2. LITERATURE REVIEW

Neural Networks and Neuro-Fuzzy Literature

Many studies highlight the use of artificial neural systems in business applications. Anders, Korn, and Schmitt [1] use statistical inference techniques to build neural network models to explain the prices of call options on the German stock index DAX. They show that statistical specification strategies lead to parsimonious networks that have a superior out-of-sample performance when compared to the Black-Scholes model. Ntungo and Boyd [41] report that out-of-sample neural network trading returns for corn, silver, and Deutsche mark futures contracts are positive and at about the levels as the returns with ARIMA models. Desai and Bharati [12] test the efficacy of neural networks in predicting returns on stock and bond indices. They find that the neural network forecasts are conditionally efficient with respect to linear regression models for large stocks and corporate bonds, whereas the evidence is not statistically significant for small stocks and intermediate-term government bonds.

Zhang and Hu [64] illustrate the use of neural networks in forecasting UK pound/U.S. dollar exchange rate. They report that neural networks outperform linear models, particularly when the forecast horizon is short. Zhang, Hu, Patuwo, and Indro [63] show that neural networks are significantly better than logistics regression models in bankruptcy prediction. Indro, Jiang, Patuwo, and Zhang [23] show that neural networks outperform linear models in forecasting the performance of mutual funds that follow value, blend, and growth investment styles. Thus, all the above-mentioned studies provide mixed evidence regarding the potential of neural networks to analyze, evaluate, and predict many financial systems. Wong, Wang, Goh, and Quek (1992) illustrate the use of fuzzy neural systems for stock selection. Derrig and Ostaszewski (1995) provide an overview of fuzzy pattern recognition techniques and used those techniques in clustering for risk and claims classification. Turtle and Gill (1994) illustrate the use of fuzzy logic in international cash management. Selwyn (1999) compares the benefits of using neurofuzzy systems and neural networks for credit-risk evaluation. Malhotra and Malhotra [36] use neurofuzzy systems to evaluate consumer units/decisions. They find that the neuro-fuzzy system performs better than the multiple discriminant analysis approach to identify bad credit applications. In addition, Malhotra and Malhotra [35] also find that the neural network models consistently perform better than the multiple discriminant analysis models in identifying potential problem units/decisions. Angelini et. al. [2] show that artificial neural networks show promising results in evaluating credit risk. Wu [56] illustrates several data mining algorithms, i.e., Backpropagation Neural Network (BPNN), decision tree, logistic regression and Monte Carlo simulation in credit-scoring problem. Hu et. al. [22] illustrate the use of neural network to evaluate credit risk in relation to the retail industry. Trinkle et. al. [55] illustrate the use of neural networks in developing credit risk models. Baesens et.al. [3] illustrate the use of neural networks for extracting rules and creating decision tables for credit risk evaluation. Charlton, et. al. (2010) illustrate the use of neuro-fuzzy systems to identify chemical parameters including isotopic ratios, biogenic amines, and rare earth elements that discriminate between vintages and grape varieties for wines produced in a particular country. Fernandes, et. al. [15] illustrate the use of Adaptivr Network-based Fuzzy Inference Systems (ANFIS) that classifies the mammaographic images of calcification region of interest as benign or malign. Bekiros [5] use hybrid neurofuzzy system for decision-making and trading under uncertainty. Pinthong, et. al. [45] illustrate the use of hybrid genentic algorithm and neurofuzzy computing to determine the optimal reservoir releases in Pasak River Basin, Thailand. Zhou et. al. [65] use neurofuzzy approach to discover knowledge for predicting customers' attitude toward Internet retailers in relation to traditional retailers. Yang et. al. [58] illustrate the use of neuro-fuzzy systems in early detection and assessment of a surface mount assembly problem for cost-effective manufacturing. This study extends previous studies by applying DEA models and neurofuzzy systems to analyze consumer units/decisions.

Data Envelopment Analysis Literature

Recently, many studies have illustrated the use of DEA, a non-parametric methodology to analyze different aspects of business entities. The details of the DEA model are discussed in the next section. In contrast to other methodologies, DEA is one of the methods that have traditionally been used to assess the comparative efficiency of homogenous operating units such as schools, hospitals, utility companies, sales outlets, prisons, and military operations. More recently, it has been applied to banks [17] and mutual funds ([29], [13] [37], [39]).

Murthi, Choi, & Desai [39] examine the market efficiency of the mutual fund industry by different investment objectives. They use a benefit/cost non-parametric analysis where a relationship between return (benefit) and expense ratio, turnover, risk, and loads (cost) is established. They also develop a measure of performance of mutual funds that has a number of advantages over traditional indices. The DEA portfolio efficiency index (DEPI) does not require specification of a benchmark, but incorporates transaction costs. The most important advantage of DEA method as compared to other measures of fund performance is that DEA identifies the variables leading to inefficiencies and the levels by which they should be changed to restore the fund to its optimum level of efficiency. McMullen and Strong [37] applied DEA to evaluate the relative performance of 135 US common stock funds using one, three, and five-year annualized returns, standard deviation of returns, sales charge, minimum initial investment, and expense ratio. They illustrate that DEA can assist in selecting mutual funds for an investor with a multifactor utility function. The DEA selects optimum combinations of investment characteristics, even when the desired characteristics are other than the two-factors specified in Capital Market Theory. The DEA enable the user to determine the most desirable alternatives, and pinpoint the inefficiencies in a DEA-inefficient alternative. Galagedera and Silvapulle [13] use DEA to measure the relative efficiency of 257 Australian mutual funds. The further investigate the sensitivity of DEA efficiency to various input-output variable combinations. They find that more funds are efficient when

DEA captures a fund's long-term growth and income distribution than a shorter time horizon. In general, the overall technical efficiency and the scale efficiency are higher for risk-aversive funds with high positive net flow of assets.

Haslem and Scheraga [21] use DEA to identify efficiencies in the large-cap mutual funds in the 1999 Morningstar 500. They identify the financial variables that differ significantly between efficient and inefficient funds, and determine the nature of the relationships. They use Sharpe index as the DEA output variable. They find that the input/output and profile variables are significantly different between the Morningstar 500 (1999) large-cap mutual funds that are DEA performance-efficient and inefficient. Basso and Funari [4] propose the use of DEA methodology to evaluate the performance of mutual funds. The proposed DEA performance indexes for mutual funds represent a generalization of various traditional numerical indexes that can take into account several inputs and outputs. They propose two classes of DEA indexes. The first class generalizes the traditional measures of evaluation using different risk indicators and subscription and redemption costs that burden the fund investment. The second class of indexes considers a multiple inputs-outputs structure. Thus, they monitor not only the mean return but also other features such as stochastic dominance and the time lay-out. Morey and Morey [38] present two basic quadratic programming approaches for identifying those funds that are strictly dominated, regardless of the weightings on different time horizons being considered, relative to their mean returns and risks. They present a novel application of the philosophy of data envelopment analysis that focuses on estimating "radial" contraction/expansion potentials. Furthermore, in contrast to many studies of mutual fund's performance, their approach endogenously determines a custom-tailored benchmark portfolio to which each mutual fund's performance is compared.

Zhu [66] uses data envelopment analysis to develop a multi-factor financial performance model that recognizes tradeoffs among various financial measures. Kao and Liu [27] compute efficiency scores based on the data contained in the financial statements of Taiwanese banks. They use this data to make advanced predictions of the performances of 24 commercial banks in Taiwan. Pille and Paradi [44] analyze the financial performance of Ontario credit unions. They develop models to detect weaknesses in Credit Unions in Ontario, Canada. Neal [40] investigates X-efficiency and productivity change in Australian banking between 1995 and 1999 using data envelopment analysis and Malmquist productivity indexes. It differs from earlier studies by examining efficiency by bank type, and finds that regional banks are less efficient than other bank types. The study concludes that diseconomies of scale set in very early, and hence are not a sufficient basis on which to allow mergers between large banks to proceed. Paradi and Schaffnit [43] evaluate the performance of the commercial branches of a large Canadian bank using data envelopment analysis. Chen, Sun, and Peng [9] study the efficiency and productivity growth of commercial banks in Taiwan before and after financial holding corporations' establishment. They employ a data envelopment analysis approach to generate efficiency indices as well as Malmquist productivity growth indices for each bank. Howland and Rowse [21] assess the efficiency of branches of a major Canadian bank by benchmarking them against the DEA model of American bank branch efficiency. Sufian [53] uses DEA approach to evaluate trends in the efficiency of the Singapore banking sector. The paper uses DEA approach to distinguish between technical, pure technical and scale efficiencies. Lin, Hu, and Hsiao [30] study the relative efficiency of management in the Taiwanese banking system through DEA. The goal is to estimate the competitiveness of each bank and managerial efficiency is to show the efficiency variation of each bank through Malmquist index. Bergendahl and Lindblom [6] develop principles for an evaluation of the efficiency of a savings bank using data envelopment analysis as a method to consider the service orientation of savings banks. They determine the number of Swedish savings banks being "service efficient" as well as the average degree of service efficiency in this industry.

Hoon and Chunyan [19] analyzed the productive efficiency of the railway services in 19 Organization for Economic Cooperation and Development (OECD) countries. They report that railway systems with high dependence on public subsidies are less efficient than similar railways with less dependence on subsidies. Cowie and Riddington [10] evaluate the efficiency of the European railways through the use of a production frontier approach. Yu and Lin [60] uses a multi-activity network DEA model to simultaneously estimate passenger and freight technical efficiency, service effectiveness, and technical effectiveness for 20 selected railways for the year 2002. Lozano & Gutierrez [33] illustrate the slacks-based measure of efficiency of 39 Spanish airports using DEA. Liu & Liu [32] illustrate the use of DEA in evaluating and ranking the research and redevelopment performance of Taiwan's government-supported research institutes. Saranga & Moser [50] develop a comprehensive performance measurement framework using the classical and two-stage Value Chain Data Envelopment Analysis model.

3. METHODOLOGY

This section illustrates the DEA model, the neuro-fuzzy model, and the hybrid neuro-fuzzy and DEA model.

The Data Envelopment Analysis Model

The Data Envelopment Analysis (DEA) (Charnes et al., 1978) is a widely used optimization-based technique that measures the relative performance of decision-making units that are characterized by a multiple objectives and/or multiple inputs structure. The DEA methodology measures the performance efficiency of organization units called Decision-Making Units (DMUs). This technique aims to measure how efficiently a DMU uses the resources available to generate a set of outputs. The performance of DMUs is assessed in DEA using the concept of efficiency or productivity defined as a ratio of total outputs to total inputs. Efficiencies estimated using DEA are relative, that is, relative to the best performing DMU or DMUs (if multiple DMUs are the most efficient). The most efficient DMU is assigned an efficiency score of unity or 100 percent, and the performance of other DMUs vary between 0 and 100 percent relative to the best performance.

The main objective of the DEA methodology is to define a valid measure of comparison among peer DMUs so as to determine the relative position of the peer DMUs. Thus, the DEA establishes an empirical standard of excellence or best practices. Therefore, after establishing the frontier, or best practices, for benchmarking, we can measure a set of new DMUs relative to the benchmark (frontier). However, on encountering a new DMU that outperforms the existing benchmarks, the DEA generates a new efficiency frontier. The model (1) uses all the

DMUs under evaluation, including the best-practice frontier and the new DMUs under study. As a result, we do not have the same benchmark (frontier) for the new DMUs. Thus, the new best-practice frontier does not directly compare the new DMUs to the established standard. Zhu (2003) modifies and extends the original DEA method as a benchmarking tool so that the new DMUs are evaluated against a set of given benchmarks (standards). Let E* represent the benchmarks or the best-practice identified by the DEA. Based upon the input-oriented CRS envelopment model, we have the following model:

$$Min\ \delta_o^{CRS}$$

subject to

$$\sum \lambda_j x_{ij} \leq \delta_o^{CRS} x_{io}^{New},\ i = 1,\ldots,m,$$

$$\sum \lambda_j\ y_{rj} \geq y_{ro}^{New}\ r = 1,\ldots,s, \qquad (1)$$

$$\lambda_j \geq 0,\ j \in E^*,$$

where a new observation is represented by DMU_o^{New} with inputs x_{io}^{New} (i=1,…,m) and outputs y_{ro}^{New} (r=1,….,s). The superscript of CRS indicates that the benchmark frontier composed by benchmark DMUs in set E* exhibits CRS. Model (2) measures the performance of DMU_o^{New} with respect to benchmark DMUs in set E* when outputs are fixed at current levels. Similarly, we can have an output-oriented CRS envelopment model that measures the performance of DMU_o^{New} in terms of outputs when inputs are fixed at their current levels.

$$Max\ \tau_o^{CRS}$$

subject to

$$\sum \lambda_j x_{ij} \leq x_{io}^{New},\ i = 1,\ldots,m,$$

$$\sum \lambda_j\ y_{rj} \geq \tau_o^{CRS}\ y_{ro}^{New}\ r = 1,\ldots,s, \qquad (2)$$

$$\lambda_j \geq 0,\ j \in E^*,$$

Based upon models (1) and (2), we have

$\delta_o^{CRS^*} = 1/\tau_o^{CRS*}$, where $\delta_o^{CRS^*}$ is the optimal value for model (3.12) and $\tau_o^{CRS*}$is the optimal value for model (3.13). Further, model (1) and (2) yields a benchmark for DMU_o^{New}. The ith input and the rth output for the benchmark can be expressed as

$\sum_{j \in E*} \lambda_j^* x_{ij}$, (i^th output),

$\sum_{j \in E*} \lambda_j^* y_{ij}$, (j^th output). (3)

Further, although the DMUs identified as the best-practice benchmarks are given as set E*, the benchmark for each DMU may be different as it is represented by a combination of DMUs associated with the set E* (3). Therefore, models (1) and (2) represent a variable-benchmark scenario.

Thus, the performance of DMU_o^{New}, using model (3) can be interpreted as follows:

$\delta_o^{CRS^*} = 1$ or $\tau_o^{CRS*}=1$ implies that DMU_o^{New} achieves the same performance level as the benchmark in model (3.14).

$\delta_o^{CRS^*} > 1$ or $\tau_o^{CRS*} < 1$ implies that DMU_o^{New} has input savings or output surpluses as compared to the benchmark in model (3.14).

If we allow scale inefficiency, models (1) and (2) can incorporate scale inefficiency by assuming VRS. Therefore, we have the following input-oriented VRS Variable-Benchmark model:

$$Min\ \delta_o^{VRS}$$

subject to

$$\sum \lambda_j x_{ij} \leq \delta_o^{VRS} x_{io}^{New},\ i = 1,\ldots,m,$$

$$\sum \lambda_j\ y_{rj} \geq y_{ro}^{New}\ r = 1,\ldots,s,$$

$$\sum \lambda j = 1 \qquad (4)$$

$$\lambda_j \geq 0,\ j \in E^*,$$

$$Max\ \tau_o^{VRS}$$

subject to

$$\sum \lambda_j x_{ij} \leq x_{io}^{New},\ i = 1,\ldots,m,$$

$$\sum \lambda_j\ y_{rj} \geq \tau_o^{VRS}\ y_{ro}^{New}\ r = 1,\ldots,s, \qquad (5)$$

$$\sum \lambda j = 1$$

$$\lambda_j \geq 0,\ j \in E^*,$$

As we introduce scale inefficiency, unlike models (1) and (2), models (4) and (5) may be infeasible.[1] Thus, we have following two scenarios:

a. If model (4) is infeasible, then the output vector of DMU_o^{New} dominates the output vector of the benchmark in (1).
b. If model (5) is infeasible, then the input vector of DMU_o^{New} dominates the input vector of the benchmark in (2).

Based on the above scenarios, we have four cases:

Case I: When both models (4) and (5) are infeasible, this implies that DMU_o^{New} has the smallest input level and the largest output level as compared to the best-practices benchmark. Thus, DMU_o^{New} offers both input savings and output surpluses.

Case II: When model (4) is infeasible and model (5) is feasible, this implies that DMU_o^{New} has the largest output level as compared to the best-practices benchmark to make model (4)

[1] For more details on the proof of propositions for variable benchmark DEA model refer to Zhu [67].

infeasible. Thus, we use model (5) to calculate the output surplus offered by $\mathrm{DMU}_o^{\mathrm{New}}$.

Case III: When model (5) is infeasible and model (4) is feasible, this implies that $\mathrm{DMU}_o^{\mathrm{New}}$ has the smallest input level as compared to the best-practices benchmark to make model (5) infeasible. Thus, we use model (4) to calculate the input savings offered by $\mathrm{DMU}_o^{\mathrm{New}}$.

Case IV: When both models (4) and (5) are feasible, this implies that we use both the models to determine if $\mathrm{DMU}_o^{\mathrm{New}}$ offers input savings and output surpluses.

Case V: The underperforming DMUs belong to this category. We can use benchmark values to find the source of low performance.

Neuro-Fuzzy Inference System Model:
Fuzzy logic starts with the concept of fuzzy sets. Fuzzy sets describe vague concepts. A fuzzy set admits the possibility of partial membership in it. The degree to which an object belongs to a fuzzy set is denoted by a membership function between 0 and 1. A membership function is a curve that describes how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. Fuzzy logic is a convenient way to map an input space to an output space through the primary mechanism of IF-THEN statements called rules.

The input space for the mapping is input parameters and the output space is the decision variables. For instance, the decision maker is advised to accept or reject a proposition or point out the extent of risk involved. Typically, a fuzzy inference system interprets the values of an input vector and, based on some set of rules, assigns values to the output. Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made, or patterns discerned.

Neural fuzzy systems aim at providing fuzzy systems with the kind of automatic tuning methods typical of neural networks but without altering their functionality. In neural fuzzy systems, neural networks are used in augmenting numerical processing of fuzzy sets that is utilized as fuzzy rules. Thus, the fuzzy rule-based modeling process devises a logical approach to imitate the process of human decision making using uncertain information. Neural networks calibrate the model structure to get the optimal model. Neurofuzzy computing optimizes the premise and consequent parameters of the fuzzy inference system using available data.

Zadeh (1965) proposed the fuzzy set theory that allows varying degrees of membership functions as compared to the classical set theory with only two values of logic, 0 and 1. Let X be a collection of objects denoted generically by x, then a fuzzy set A in X is a set of order pairs, $A = \{(x, \mu A(x)) \mid x \in X\}$ where $\mu A(x)$ is the degree of membership function of x in A. Thus, the values of $\mu A(x)$ can vary from 0 to 1. The fuzzy inference system works in four steps. In the first step (fuzzification), membership function defines variables. In the second step, fuzzy model uses human knowledge to infer IF-THEN rules. Fuzzy reasoning uses an inference procedure to derive the aggregation from a set of fuzzy rules. The model defines the output of membership function[2] using a linear function that relates input and output variables.

R_i : *IF* X_1 *is* A_{i1} *and* X_2 *is* A_{i2} *and …… and* X_j *is* A_{ij} *THEN*

$Y_i = f_i\,(X_1, X_2, \ldots X_j)\ , i = 1, 2, \ldots n$

where fi is a linear function of the j input variables, Aij is the jth membership function of fuzzy set A corresponding to input variables Xj in the ith IF-THEN rule. Y(X) is the defuzzified output of the fuzzy inference system that is defined as follows:

$$Y(X) = \frac{A_1(X)f_1(X) + A_2(X)f_2(X) + \ldots . A_n(X)f_n(X)}{A_1(X) + A_2(X) + \ldots . A_n(X)}$$

In the neurofuzzy modeling approach, a fuzzy system uses the learning capability of neural networks to improve performance of the fuzzy model. The neural network using two inputs and two rulesmodel optimizes the premise and consequent parameter values in the fuzzy inference system using available data. The learning procedure of the neural network environment fine tunes the membership functions, and generates the fuzzy rules. Jang [24] proposes the Adaptive Network-based Fuzzy Inference System (ANFIS).

4. THE DATA SOURCE AND LDA AND DEA MODELS

This study analyzes a pooled data of four credit unions[3] using data envelopment analysis model and the linear discriminant analysis model. Table 1 displays the total number of applications processed by different credit unions. There are three groups of applicants: applicants who were accepted and were good credits (Group 1); applicants who were accepted, but were not good credits (Group 2); and applicants who applied for a loan, but were rejected (Group 3). Further, the data set also includes information such as the applicant's age, housing, address time, total income[4], number of credit cards, number of dependents, job time, co-maker on other loans, total debt, monthly rent/mortgage payments and total payments[5]. The credit unions use an algorithm to calculate different types of credit rating and a final rating, ranging from 1-4, with loan applicants divided into four credit groups—excellent (1), good (2), marginal (3), and poor (4). However, to analyze loans without any bias, we decided to discard the credit ratings generated by the credit unions. Table 2 displays the summary statistics of the variables used in this study. The data parameters such as the total debt, number of outstanding loans, and total income vary widely.

Table 2: Summary statistics of the variables used in this study to differentiate between good, bad, and outright reject loan applicants.

Statistics	**Total Debt**	**Number of Loans**	**Number of Dependents**	**Total Payments**	**Total Income**	**Job Time (years)**
Mean	$7,952.07	2.91	.97	$606.99	$2,160.53	8.5

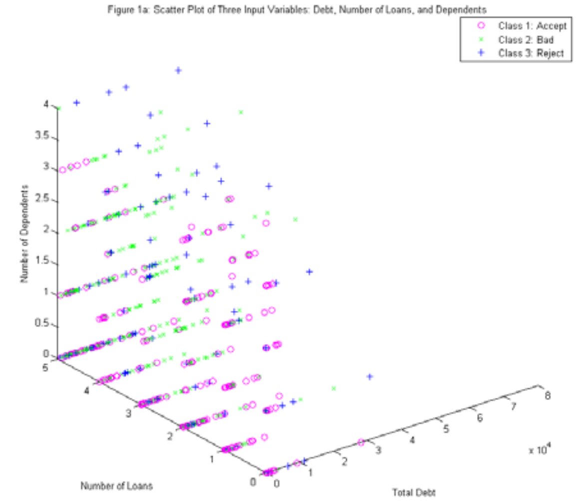
[2] The fuzzy inference system is normally defined following two methods: Mamdani and Assilian (1975) and Takagi and Sugeno (1985). We illustrate the second method.
[3] The credit unions included in our data base are: Jefferson County Teachers Credit Union, Jefferson County Employees Credit Union, Family Security Credit Union, and Steering Credit Union.
[4] Total income includes gross income and other income.
[5] Total payments include payments for rent, automobile loan, and other payments.

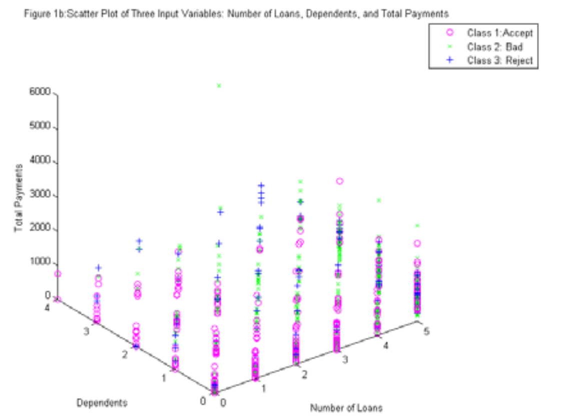
Standard Deviation	$9,306.71	1.82	1.12	$502.60	$1,203.85	8.17
Minimum	$0.00	0	0	$0.00	$0.00	0
Maximum	$70,088	5	4	$5,726	$9,250	38
Median	$4,565	3	1	$511	$1,900	6
Mode	$0.00	5	0	$0.00	$1,900	1

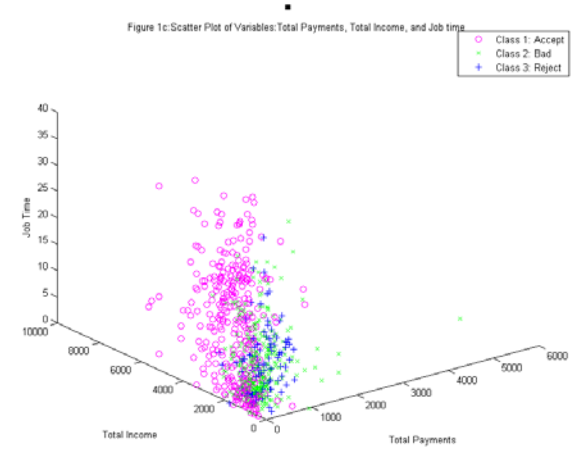
Total payments include payments for rent, automobile loan, and other payments.
Total income includes gross income and other income.

The data set represents a cross section of information for 749 observations. There are three categories of applicants: applicants who were accepted and remained good, applicants who were originally accepted, but turned out to be bad credit, and applicants that were rejected. The applicants who defaulted on their loans should have been rejected by the loan officer. Figure 1 displays the plot of the data space showing the two categories. Figure 1a shows a scatter plot of the variables: total debt, number of outstanding loans, and total number of dependents. Figure 1b shows a scatter plot of the variables: number of outstanding loans, total number of dependents, and total payments. Figure 1c shows a scatter plot of the variables: total payments, total income, and time spent working (years). As illustrated in figures 1a, 1b, and 1c the observations show overlapping clusters. But, as is evident from the figure, each cluster contains data points from all classes. There are no distinct clusters for the three categories of the applicants. Therefore, with overlapping classes, the loan officer is unable to discriminate between good and bad loans. In addition, we cannot expect the traditionally used, LDA model to show a very high prediction rate. The LDA model divides the data space linearly into three parts, corresponding to three classes, respectively. On the other hand, a DEA model uses the best policy loans as benchmark to compare the new loan applications. The next section illustrates the application of the discriminant analysis model and the DEA model (variable benchmark) to discriminate between good and bad loan applications. To illustrate the usefulness of the DEA model, we use the best case scenario for the LDA model where we use the entire data set for prediction. For the DEA model, we first identify 30 (100% efficient) loans using variable return to scale model. Further, we predict the efficiency of the 719 loan applications using variable benchmark DEA model that uses the 30 best policy loan applications as benchmarks.

Section III describes the computational details of the DEA model. In addition, there are many non-computational aspects that are crucial to the application of DEA procedures. Besides the mathematical and computational requirements of the DEA model, there are many other factors that affect the specifications of the DEA model. These factors relate to the choice of the DMUs for a given DEA application, selection of inputs and outputs, choice of DMUs for a given DEA application, selection of inputs and outputs, choice of a particular DEA model (e.g. CRS, VRS, etc.) for a given application, and choice of an appropriate sensitivity analysis procedure (Ramanathan, 2003). Due to DEA's non parametric nature, there is no clear specification search strategy. However, the results of the







analysis depend on the inputs/outputs included in the DEA model. There are two main factors that influence the selection of DMUs – homogeneity and the number of DMUs. To successfully apply the DEA methodology, we should consider homogenous units that perform similar tasks, and accomplish similar objectives. In our study, the loans are homogenous as they compete with each other to get their application sanctioned. Furthermore, the number of DMUs is also an important consideration. The number of DMUs should be reasonable so as to capture high performance units, and sharply identify the relation between inputs and outputs. There are some simple rules of thumb that guide the selection of inputs and outputs, and the number of participating DMUs[6].

Table 1: Description of the credit union consumer loan data used in this study.

Class	Description	Number of Applications
1	Accept	317
2	Accept that turned out to be bad.	329
3	Reject	103
	Total	749

The credit unions included in our data base are: Jefferson County Teachers Credit Union, Jefferson County Employees Credit Union, Family Security Credit Union, an d Steering Credit Union.

To study the outcome of a loan application, we consider six factors: total debt, number of outstanding loans, total number of dependents, total payments, total income, and time spent working (years). Out of these six factors, we specified total debt, number of outstanding loans, total number of dependents, and total payments as input, because the lower these parameters are, the better the chances of a loan are to remain good. All other factors are considered as output factors as a higher value of these variables increases the credit-worthiness of a loan. Finally, the choice of the DEA model is also an important consideration. We should select the appropriate DEA model with options such as input-maximizing or output-minimizing, multiplier or envelopment, and constant or variable returns to scale. DEA applications that involve inflexible inputs or not fully under control inputs should use output-based formulations. On the contrary, an application with outputs that are an outcome of managerial goals, input-based DEA formulations are more appropriate. In addition, for an application that emphasizes inputs and outputs, we should use multiplier version. Similarly, for an application that considers relationship among DMUs, envelopment models are more suitable. Furthermore, the characteristics of the application dictate the use of constant or variable returns to scale. If the performance of DMUs depends heavily on the scale of operation, constant returns to scale (CRS) is more applicable, otherwise variable returns to scale is a more appropriate assumption. In our study, the relationship among these loans is an important consideration as they are all competing with each other to get a loan. Therefore, we select the envelopment models for our analysis. In addition, the focus of the credit union is to sanction loans that have lower input factors such as total debt, number of outstanding loans, total number of dependents, and total payments. Therefore, input-based formulation is recommended for our study. Furthermore, the credit-worthiness of these loans does not depend on the scale of operations, thus variable returns to scale is a safe assumption. Also, the structure of the DEA model (in envelopment form) uses an equation and separate calculation for every input and output. Therefore, all the input and output variables can be used simultaneously and measured in their own units. Further, we use the variable-benchmark model to retain the best-performing loans on the efficiency frontier. However, the DEA model has certain limitations. The DEA model benchmarks effectively with the standard information from a loan applicant. Typically, the loan officer also calculates the ratio of the applicant's total payments to total income and ratio of the applicant's total debt to total income. According to economic rationality, ratio of total payments to net income, ratio of debt to net income affect the decision to accept or reject an application for consumer loans (Fabozzi, 1993). However, the ratios being on a scale of 0 to 1, the DEA model, using the ratios, is unable to discern between good and bad loans. Therefore, in the second stage, we use a neuro-fuzzy model that uses the variable-benchmark efficiency score. The neuro-fuzzy model creates IF-THEN-ELSE rules that can be used by a decision support system.

For the neuro-fuzzy model, we use five variables: Ratio1, Ratio2, number of outstanding loans, time spent working (years), and the DEA efficiency score of a DMU as the factors that can discriminate between a good and a bad decision. As mentioned above, the neuro-fuzzy model works in two stages: training and testing. To adequately train the network, the training sample should be a good representative of the population under study. Thus, the training data should cover the entire expected input data space. Further, we should not train the network completely with input vectors of one class, and then switched to another class; the network will forget the original training. Thus, in accordance with these guidelines, we train the network with a sample of 400 observations. The training set is an unbiased sample with data points from all the three classes. Further, to ensure that the training data covers the entire input space (i.e. learn different characteristics of the applications accepted and rejected), we select observations from all the credit unions. Our selection prevents the network from learning the characteristics of only one credit union that can be misleading. Moreover, to ensure that the network is not trained with vectors from one class or one single credit union, we select the observations randomly. Finally, as there are no preferable membership functions, we create an initial set of membership functions using grid partition method. The built-in function genfis1 of the fuzzy logic toolbox of the MATLAB software is used to create the initial membership function matrix.

[6]The following are the guidelines for DMU model selection:

1. The number of DMUs is expected to be larger than the product of number of inputs and outputs [11] to discriminate effectively between efficient and inefficient DMUs. The sample size should be at least 2 or 3 times larger than the sum of the number of inputs and outputs [49].
2. The criteria for selection of inputs and outputs are also quite subjective. A DEA study should start with an exhaustive, mutual list of inputs and outputs that are considered relevant for the study. Screening inputs and outputs can be quite quantitative (e.g. statistical) or qualitative that are simply judgmental, use expert advice, or use methods such as analytical hierarchy process [59]. Typically inputs are the resources utilized by the DMUs or condition affecting the performance of DMUs. On the other hand, outputs are the benefits generated as a result of the operation of the DMUs, and records higher performance in terms of efficiency. Typically, we should restrict the total number of inputs and outputs to a reasonable level. As the number of inputs and outputs to a reasonable level. As the number of inputs and outputs increases, more number of DMUs get an efficiency rate of 1, as they become too specialized to be evaluated with respect to other units [49].

5. EMPIRICAL ANALYSIS

In this study, we perform the empirical analysis in two stages. In the first stage, we use the minimizing (input-oriented) variable benchmark data envelopment model. As illustrated in Section III, a variable benchmark DEA model uses the best performing loans on the efficiency frontier. Further, the efficiency frontier does not change when a new loan outperforms the identified frontier. The envelopment DEA model modifies the efficiency frontier as new loans are presented, thereby the benchmark changes for the new incoming loans. In this study, we identified 30 best performing loans out of 749 loans. All of these loans are 100% efficient. We use Excel Solver and Visual Basic Application to solve the DEA model. The limitation of Solver for our application was 199 data points. Thus, we solved the DEA model using sets of 199 loan applications. The 30 most outperforming loans are 100% efficient compared to all the other loan applications to calculate the efficiency score. The efficiency score ranges between 0 and 15. Therefore, we assigned a score of 200 to the 30 quality loans and 150 to the loans that had infeasible solution indicating they still offer scope for minimizing input or maximizing output. We use five variables: ratio1, ratio2, number of outstanding loans, time spent working (years), and the DEA efficiency score to train and test the neuro-fuzzy system. We divide the data set into a training set of 400 observations and a predict/test set of 349 observations. The two models were trained with the training sample, and their performance was tested with the test sample. Table 3 displays the size of the train and test sample.

Table 3: Size of train and test sample

Class	Train	Test	Total
1 - Accept	200	117	317
2 – Bad/Reject	200	232	432
Total	400	349	749

The neuro-fuzzy model trains well during supervised training and correctly recognizes loans that were accepted (Class 1) and loans that should be rejected (Class 2 – bad loans, Class 3 – reject). The neuro-fuzzy model initializes the fuzzy inference system (FIS) uses Sugeno-type FIS structure that uses a grid partition structure. The FIS system uses three membership functions associated with each input using generalized bell shaped function. The output function is the linear function. We use genfis1 to create the initial FIS matrix (that stores the fuzzy learning rules). The network is trained with the training sample of 400 observations for 150 iterations. The network trains well with a successful learning rate of 93% for both accept and reject classes with an overall rate of 93%. We test the neuro-fuzzy model on the hold-out sample of 349 observations. The neuro-fuzzy model has a prediction rate of 88% for class 1 (accept loans) and 86% for class 2 (reject loans) with an overall prediction rate of 86%. Table 4 displays the results of training and testing for our neuro-fuzzy model.

Table 4: Predictive rate of Neuro-fuzzy model

Class	Train	Test	Total
1 - Accept	93%	88%	91%
2 – Bad/Reject	93%	86%	89%
Total	93%	87%	90%

6. SUMMARY AND CONCLUSIONS

This study proposes the modeling and development of a multidimensional decision support system that uses a combination of data envelopment analysis and neuro-fuzzy systems. Thus, the decision support system derives benefit from both methodologies to recommend a decision. As illustrated in the literature review section, many studies illustrate the synergy of fuzzy systems and DEA. However, very few studies illustrate the fusion of DEA and ANFIS models. DEA does not require the manager to attach prescribed weights to each input and output. Moreover, DEA modeling does not require prescription of the functional forms that are needed in statistical regression approaches. DEA uses techniques such as mathematical programming that can handle a large number of variables and constraints. As DEA does not impose a limit on the number of input and output variables to be used in calculating the desired evaluation measures, it's easier for managers to deal with complex problems and other considerations they are likely to confront. DEA is a methodology based on the application of linear programming allowing a decision maker to use multiple inputs and outputs measured in different units. DEA identifies good units in a given set of DMUs and provides a measure of inefficiency for all others. The DMUs having the most desirable characteristics are rated a score of one (100% efficient or more for the variable benchmark model), while the DMUs that are inefficient score between zero and one. DEA methodology can identify a bad DMU by comparing its characteristics with a given set of benchmark DMUs having good DMU characteristics. However, DEA does not work well with very small-sized inputs such as income ratios. Further, the variable benchmark DEA model cannot create rules.

Like DEA models, neuro-fuzzy models also do not require restrictive assumptions of the statistical model. Fuzzy logic provides a means of combining symbolic and numeric computations in inference processing. The linkage between neural networks and symbolic reasoning can be established through the membership function of fuzzy logic. The membership function measures the degree of possibility of a concept as related to a numeric quantity. A neural network can be used to synthesize a membership function by training it with instances of the relation. Neuro-Fuzzy systems provide flexibility to the decision-maker to incorporate their own rules in the DEA model to assess DMUs. In addition, neuro-fuzzy model creates rules for the use of decision support system.
Thus, there are two major contributions of the study are:

Theoretical contribution

The DEA is used as one of the popular methods to measure and benchmark the performance of different DMUs. This study proposes the modeling and design of a hybrid methodology based on a combination of the efficiency analysis of DEA and neuro-fuzzy modeling approach. Therefore, we extend the capability of DEA model using neuro-fuzzy models to develop rules that capture the analytical power of DEA modeling methodology. The study extends the traditional DEA model and develops a new class of DEANFIS model using ANFIS model. Thus, the study will contribute to Business Intelligence literature through the development of a new modeling technique that uses a fusion of the two models.

Implications for decision makers

The decision makers can use the combination of DEA and neuro-fuzzy model in many important ways. The Variable Benchmark DEA efficiency scores can identify the units/decisions that are risky. For all units/decisions with less-than-perfect efficiency scores, the DEA model provides the decision maker with an efficiency reference set. Decision makers can analyze and compare these less-than-efficient units/decisions with their corresponding peers to further investigate the pros and cons of approving the units/decisions in question. DEA and neuro-fuzzy modeling systems can help identify good units/decisions that have the desirable or best characteristics. Additional in-depth analysis of these units/decisions can help decision makers and other decision makers identify some rules of thumb that can help a lending organization improve its performance. The decision maker can use the DEA and neuro-fuzzy methodology to identify bad units/decisions without specifying a functional form or some model. Both DEA and neuro-fuzzy models offers significant improvement over statistical methods currently used by decision makers. The statistical model uses expected values assuming statistical distribution, whereas DEA modeling does not require such assumptions. The rules generated by the neuro-fuzzy model provides the rule-based knowledge to the loan officer to accept or reject loans. The quality of units/decisions can be quantified just like economic ratios and quality rating. This quality metric can be calculated by using data envelopment analysis to proxy the multiple input-output models to assess the viability of a unit/decision. The combination of DEA and neuro-fuzzy methodology has opened up the possibility of addressing the performance issue much more broadly than the simplified notion of comparative efficiency measurement. The DEA and neuro-fuzzy techniques can identify different components leading to the identification of good units/decisions, enabling the decision makers to identify the best practices for detecting good units/decisions and their general characteristics. Further, DEA and neuro-fuzzy systems can be used to assess the impact of policy initiatives on sound decision making. The DEA modeling technique can also be used to measure the change over time in the productivity of the industry itself in contrast to that of the decision-making units operating within it. Finally, the DEA and neuro-fuzzy methodology has far reaching implications for decision makers and other decision makers. The development of an efficiency/ rule-based model strengthens the entire examination process by identifying units/decisions more objectively.

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