Robust Design of Credit Scoring System by the Mahalanobis-Taguchi System

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Abstract

Credit scoring is widely used to make credit decisions, to reduce the cost of credit analysis and enable faster decisions. However, traditional credit scoring models do not account for the influence of noises. This study proposes a robust credit scoring system based on Mahalanobis-Taguchi System (MTS). The MTS, primary proposed by Taguchi, is a diagnostic and forecasting method using multivariate data. The proposed approach's effectiveness is demonstrated by using real case data from a large Taiwanese bank. The results reveal that the robust credit scoring system can be successfully implemented using MTS technique.

Key Words: MTS, robust design, credit scoring, signal to noise ratios, orthogonal arrays

1. Introduction

With the rapid development and changes of the credit industry, credit products play a more important role in the economy. New self-service channels like the Internet and automated telephone banking give customers different choices between credit institutions, without time and regional limitations. As a result, institutions are facing an increased competition. Therefore, financial institutions are always looking to reduce their costs. Credit scoring models provide the essential part of effective decision support systems.

Credit scoring is widely used for credit granting, but it is a very challenging financial problem [20]. The advantages of credit scoring include reducing the cost of credit analysis, enabling faster credit decisions, closer monitoring of existing accounts, and prioritizing collections [2]. In the last few decades, several quantitative techniques have been used for developing credit scoring systems, for instance: linear discriminant analysis (LDA) and logistic regression (LR), decision trees, k-nearest neighbor (k-NN), and neural networks (N.N.). However, these models do not take into account the environmental factors as well as other potential noise factors. As a consequence, those models may lead to inaccurate predictions.

The Mahalanobis-Taguchi System (MTS) was primary proposed by Taguchi as a diagnosis and forecasting method. It combines Taguchi's methods of quality engineering with Mahalanobis' statistical measure of distance. The MTS transfers the Taguchi methods into multivariate domains and provides a recipe for the analysis of multivariate statistical data [9]. Taguchi listed a number of areas of application for the MTS, including manufacturing inspection and sensor systems, patient monitoring, fire detection, weather forecasting, credit scoring, and voice recognition [17]. MTS has been applied to picture identification [10], medical studies for identification of patients [18], inspection and classification in manufacturing [9], and yield prediction. However, relatively little empirical research has been carried out on the effectiveness of the MTS on financial applications. In such a case, an analysis to establish credit evaluation based on MTS is developed for application in the credit industry.

The main objective of this study is to design a robust credit scoring system based on the MTS that is insensitive to the noises. In this study, MTS is employed as a classification system to recognize customers' credit, to select important credit characteristics, and to provide more information about the abnormality of the applicants. This study is organized as follows:

- Section 2 reviews the credit scoring system.
- Section 3 describes the detail of Mahalanobis-Taguchi System.
- Section 4 develops the robust design of credit scoring model based on MTS.
- Section 5 presents a detailed case study.
- Section 6 provides conclusions.

2. Credit Scoring

Credit scoring as a method of credit evaluation has been used in practice for more than fifty years. Essentially credit scoring is a way of recognizing the different groups in a population. The original meaning of "credit scoring" is that a score is assigned to each person. Using historical data and quantitative techniques, credit scoring tries to discriminate the effects of various applicant characteristics on delinquencies and defaults. For making consumer credit decisions, credit scoring models are not the only way for handling the large numbers of transactions. However they produce more accurate classifications than subjective judgmental assessments by experts [6].

A variety of methods for credit scoring has been developed to help credit decisions, including linear discriminant analysis [13], logistic regression [7], decision trees models [3], k-nearest neighbor models [5][8], and neural network models [4][19][22].

The classic linear discriminant analysis (LDA), one of the first credit scoring models, is based on the Bayesian classification procedure, which assume that two classes have normal distribution with equal covariance matrices. Due to the categorical nature of credit data, the covariance matrices of the creditworthy and non-creditworthy customers are not equal, and the data is not usually normal distributed. The fitness of LDA for credit scoring has been criticized. The LDA cannot be optimal if these assumptions are not satisfied.

Logistic regression (LR), essentially a linear with a sigmoid function, is the approach of choice in predicting dichotomous data. Probability interpretation is easier to understand, because the output is in between 0 and 1. Some research shows that logistic regression demonstrates better performance than linear discriminant analysis in credit scoring [22]. However, LR is only useful when the observed outcome is restricted to two values. Another disadvantage is that it cannot handle interactions between the variables.

The third major technique is using decision trees. Decision trees are effective because they are easy to use, meaningful, and can reflect the impact of combinations of factors. Their main disadvantage is that sample sizes must be large to obtain statistically sound probability estimates at each node.

Another approach applied to credit scoring is k-nearest neighbor (k-NN) method. Henley and Hand applied the k-NN method, a nonparametric statistics, to the credit scoring problem [5] .The advantage of k-NN is that speed of training is very fast, however the disadvantage is that the speed of application is slow, and the transparency is opaque.

The motivation for using neural networks is because LDA assumes the variables are multivariate normal. LDA could lead to erroneous results when this assumption is not satisfied. Desai *et al.* [4] explored the ability of neural networks, such as multiplayer perceptions and modular neural networks, on scoring credit applications in the credit union environment. West [22] investigated the credit scoring accuracy of several neural networks. Although neural networks are powerful, their uses for practical problem solving are limited due to their intrinsic opaque, black box nature, because they are not transparent. Therefore, credit analysts cannot understand them. Whether or not these scoring models are reasonable is often suspicious.

Many of the previous studies attempt to improve the accuracy of credit scoring model. However, the above credit scoring models do not account for the influence of noises. Noises may result from the card issuer's policy change, different marketing channels or bank administrators. This will cause the scoring models to be sensitive to the external environment or policy variations. Therefore, the accuracy of credit scoring is reduced. In such a case a robust credit scoring system to establish correct credit risk management is required for the safe operation of issuer bank.

3. Mahalanobis-Taguchi System

The Mahalanobis-Taguchi System (MTS) is a pattern information technology that helps quantitative decisions by constructing a multivariate measurement scale using data analytic methods. In essence, MTS is a diagnostic and forecasting tool for identifying each item's degree of abnormality, based on the multivariate data of "normal" and "abnormal" groups of items. The main objective of MTS is to make accurate predictions in multidimensional systems by constructing a measurement scale.

A typical multidimensional system used in MTS is as shown in Figure 1. $X_1, X_2,\ldots,X_n$ are the variables, which define "normal" of a condition. These variables are used to construct the Mahalanobis space (MS). The output should be as close to the true state of the condition as possible. The true state of the condition represents the degree of abnormality. In the figure, the noise factors are the changes in usage environment, such as different manufacturing environments or different places of measurement [15].

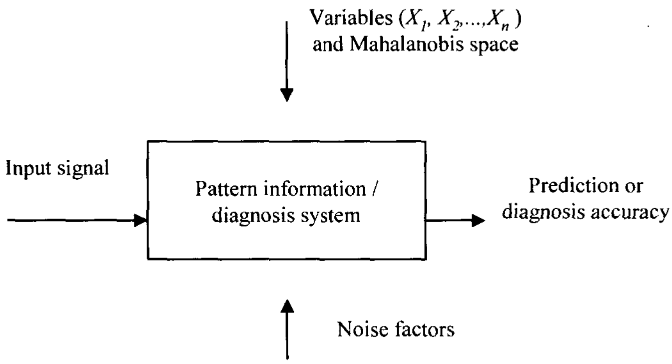

Figure 1. Mahalanobis-Taguchi System

The basic procedure of MTS algorithm can be divided into four stages:
The first stage is to identify a "normal" group as a reference point for the measurement scale. In order to construct a measurement scale, we need to collect a set of "normal" observations and standardize the variables to calculate the Mahalanobis Distance (MD). The following is the formula used to calculate MD:

$$MD_j = D_j^2 = (1/k) Z_{ij}^T C^{-1} Z_{ij} \tag{1}$$

Where $i = 1, 2 \ldots k$, $j = 1, 2 \ldots n$

$Z_{ij} = \dfrac{(X_{ij} - \bar{x}_i)}{S_i}$ = The standardized vector obtained by standardized values of X_{ij}

Z_{ij}^T = Transpose of standardized vector= $(Z_{1j}, Z_{2j}, \ldots, Z_{kj})$

C^{-1} = Inverse of correlation matrix.

The average vector of MD_j in "normal" group is located at the origin, and is approximately equal to 1.0. The zero point and unit distance provide a scaled reference point.

The second stage in MTS is validation of the measurement scale. For validating the scale, the known observations outside of the MS are considered. If the scale is good, then these observations should have MDs that correspond to the abnormal conditions, and their MDs should have lager values.

In third stage, represents the screening stage, orthogonal arrays (OA) and signal to noise ratios (SN) are used to identify the most important variables in order to reduce the dimension of the variable space. A designed fractional factorial experiment is used as a search algorithm for optimizing the MTS. The OA is used to as an optimization technique to find the combination of variables that maximize the SN ratio. If we run an experiment that classifies a number of known applicants, then the classification rate is not a sufficient measure because it tells nothing about the robustness of the system. The performance of each experiment is therefore measured as an SN ratio [9].

There are many SN ratios formulas in the Taguchi's method. However, the MTS usually suggests using the "larger-the-better" SN. The following is the formula for calculating SN.

$$SN = -10 \log \left[(1/t) \sum_{j=n+1}^{n+t} \left(\frac{1}{MD_j^{\,2}} \right) \right] \tag{2}$$

The reason to use the "larger-the-better" SN is because the MD in "abnormal" observations is usually larger than the MD in "normal" observations. Taguchi and Rajesh [16] also suggest using dynamic SN. To use dynamic SN, we need to know the degree of severity of each "abnormal" observation in advance. We use M_j to represent the degree of severity of t abnormal observations.

Larger values of M_j indicate a greater degree of abnormality. The purpose of this phase is to select important variables to make the "abnormal" MD more appropriate to reflect the degree of severity.

For the known variables X_i, we use $\overline{SN^+}$ to represent the average SN ratio from all the experimental results when X_i is included as a variable. $\overline{SN^-}$ represents the average SN ratio from all the experimental results when X_i is excluded as a variable. A "gain" represents the difference between these two values, i.e. $\overline{SN^+} - \overline{SN^-}$. If the "gain" is positive, keep the variable; if not, then exclude it. The "gain" is a method of measuring the degree of improvement.

In stage 4, diagnosing and forecasting future items with the MTS scale are based on useful variables. By using these important variables, the measurement scale is redefined and used for diagnosing and forecasting new items.

4. The MTS-Based Credit Scoring Model

The aim of the MTS-based credit scoring model is to design a "robust" system for recognizing the credit of customers, to select important characteristics for credit, and to measure the degree of severity of non-creditworthy applicants based on this scale.

The procedure is described as the following steps:

Step1: Problem definition

For recognition and classification of the credit of customers, we must define the "normal" and "abnormal" customer according to the purpose of this study.

Step 2: Define response values, identify noise factors and choose control factors

In MTS, the construction of a MTS scale is entirely at the discretion of the decision maker [15]. The response value is the Mahalanobis distance that is calculated by the variables of "normal" observations. In credit scoring system, the noise factors that will disturb the function of a system are impossible to control, such as different marketing channels, different application organizations and different card reviewing and approving departments. According to the domain knowledge of credit scoring, the examples of control factors are age, marital status, education, occupation and salary.

Step 3: Pre-process the credit data

Due to the mixture of variables like nominal, ordinal, interval, and ratio scale in credit data, we need to pre-process the data prior to the first step of the MTS. The pre-processing includes handling outliers, re-coding nominal and ordinal scale, and deleting the observations with mistakes or missing data in the original codes.

Step 4: Sample "normal" observations to construct the MTS measurement scale

In this stage we define "normal" population and sample observations from the population to construct the MTS measurement scale, named the "Full Model MTS Measurement Scale". During the MTS, construction of the MS is very important, because the analysis of classifications is highly dependent on the MS.

Step 5: Validate measurement scale

The known observations outside of the MS used to validate the scale. If the scale is good, then the MD of the abnormal cases should have larger values. If not, we need to reconstruct the MS with different variables. If the MS is not satisfactory, then we need to reconstruct the MS with different observations. In practice, it is impossible to get the abnormal cases' D^2 values to always be "larger" than the normal. Therefore, determining a threshold prior the application of the method is very important. [1].

Step 6: Screen the important variables

To design a robust system, noises must be considered. A better parameter design strategy would be to force noise effects into the experiment in a different manner [14]. The used variables have a major effect on the performance of credit scoring models. Generally, the process of choosing the best set of variables for credit scoring is unsystematic. This study intends to use a systematic approach to choose the best set. Inner and outer OA and SN are used to identify the most important set of variables. The different in SN ratios depends on the previous knowledge about the severity of the conditions outside the MS. According to the value of "gain", the important variables selected tend to be more robust against the noise effects.

Step 7: Construct measurement scale for the Reduced Model

MTS construction measurement scale is based on the important variables. We screen the variables to reduce the numbers of variables in the previous step and re-construct a new MTS measurement scale with reduced variables. This new scale is called the "Reduced Model MTS Measurement Scale".

Step8: Validate new measurement scale

Finally, we evaluate the ability of this new measurement scale.

5. A Credit Scoring Case

One real data set was used to investigate the ability of MTS credit scoring model. Data were collected from one large bank in Taiwan. First, we use the block code provided by the bank to define the credit of customers. A "Blank" block code means the credit history is good. A "U" block code means the account has been past due for more than 180 days and is ready to be closed. We define customers with " blank" block codes as "normal", and "U" block codes as "abnormal". In this study, we use a set of "normal" observations to construct a multivariate measurement scale to forecast future credit of customers.

In next step, response value, control factors, and noise factors must be defined. The response value is the MD that is calculated from the "normal" observations. In this data set, nine variables describe basic customer information: gender, age, marital status, education, and occupation, level in company, residential area, salary, and house ownership. In addition, four variables describe extra information: behavioral variables, credit limit, difference status and marketing channels. In order to protect the confidentiality of the data, we have converted the attribute names to symbolic data. In this study, basic information, behavioral variables, credit limits and difference status are defined as control factors. Marketing channels are treated as noise, because controlling customers' marketing channels are difficult.

In step 3, the pre-processing includes and cleaning the outliers, transforming categorical variables into binary variables, and deleting the observations with mistakes or missing data in the original codes. After the re-coding, there are several control variables: gender, age, marital status, education, position, occupation, location, salary, house ownership or not, cash balance, hi balance, credit limits, and background difference. The only noise variable is marketing channels.

In step 4, we select "normal" observations to construct full model our MTS measurement scale. For evaluating the appropriateness of the constructed models, data were randomly divided into training and testing sets. The training set has 4400 available cases (4000 normal observations and 400 abnormal observations), and the testing set has 1320 available cases (1200 normal observations and 120 abnormal observations). Both sets are shown in Table 1.

The 4000 normal training observations construct the MS. We use formula (1) to calculate the MD of each normal observation in MS. Figure 2 represents the MD distribution of this full model. The MDs range of MS is 0.227-19.237, with an average of 0.9999, we assume rounding, so we consider the average to be equal to 1.

Table 1. Credit Card Samples

Credit Rating	Normal	Abnormal	Total
Training samples	4000	400	4400
Testing samples	1200	120	1320
Total	5200	520	5720

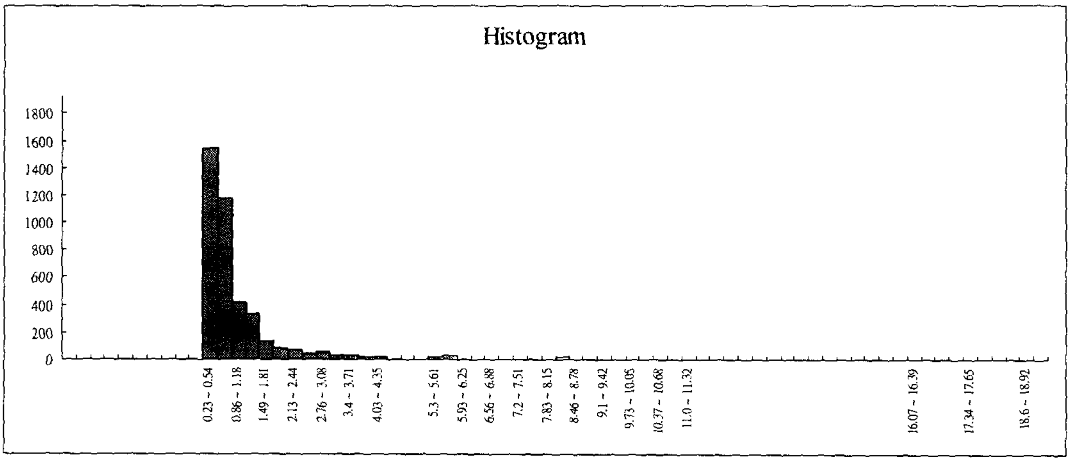

Figure 2. The Mahalanobis Distributions of the Full Model

In step 5, we select abnormal observations to validate the measurement scale. The training abnormal observations were selected. The MD values of abnormal observations ranged from 0.752 to 42.978. A threshold is needed to differentiate the two groups, because we cannot clearly differentiate between the normal and abnormal groups. Prior to deciding the threshold, we examine the relationship between MD and the group. In Table 2, we divide all MDs into different groups and perform the chi-square test, the result is

$\chi^2 = 2437.647$, $df = 2$, $p = 0.000$. When we set α=0.05, we find that MD and the group are obviously related.

Table 2. Relationships of the "MD" and the "Group"

MD / Group	Below 2	2.01-4	Over 4.01
Normal	3638(90.95%)	264(6.6%)	98(2.45%)
Abnormal	51(12.75%)	44(11%)	305(76.25%)

Bovas *et al.* [1] mentioned that the selection of the scale and a cutoff value is crucial for the application of MTS. According to Otsu [11] to derive the optimal threshold t*, for a two-class model, the MD space must be divided into two class C_1 and C_2, representing acceptable and unacceptable samples with a threshold *t*. The discriminating criterion maximizes the inter-class variance σ_B^2. When the threshold is 4.2, the maximum inter-class variance is 4040.037. For the training data set, the type I error and type II error are 2.325% and 24.5 % respectively, and the total classification accuracy rate is 95.66%. Figure 3 shows the MD of all the observations from the training samples in Table 1.

Figure 4 shows the MD of all the observations from testing samples in Table 1. The MDs distribution for the 1200 normal observations is 0.235-17.424. The distribution for the 120 abnormal observations is 1.14-105.561. By applying a threshold of 4.2, the total classification accuracy rate reaches 96.06%.

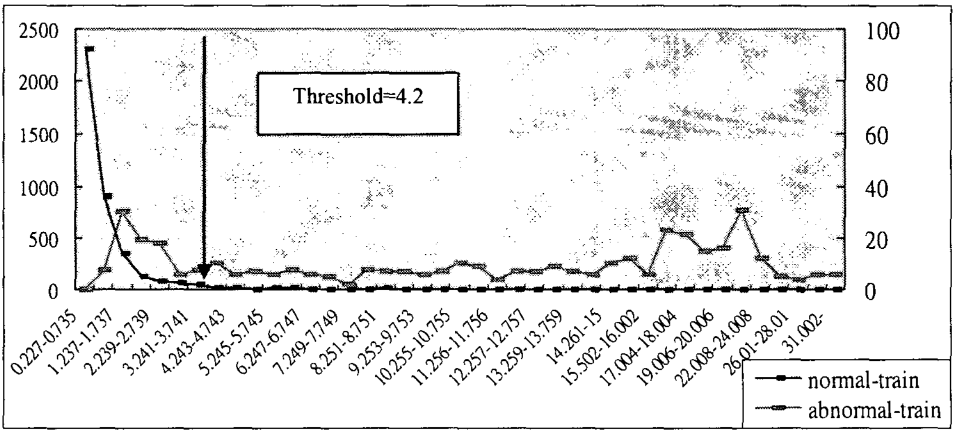

Figure 3. The Mahalanobis Distributions of the "Full Model"- Training Samples

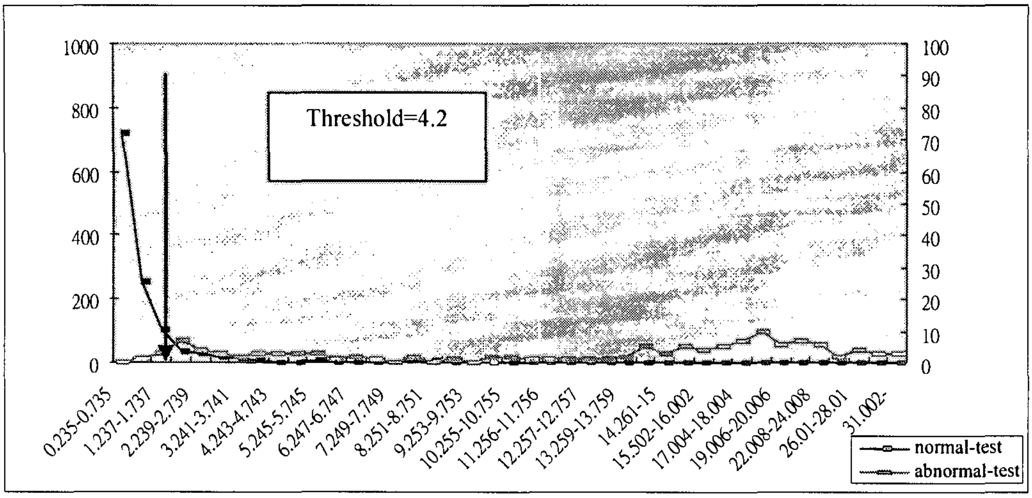

Figure 4. The Mahalanobis Distributions of the "Full Model"- Testing Sample

In step 6, we screen out the numbers of variables, OA and SN are used to identify the most important variables that relate to creditworthiness. There are up to 24 control factors in the previous step's full model. We will screen the important variables for prediction by applying $L_{32}(2^{31})$ OA. This fractional factorial design can accommodate up 31 factors with 32 runs. We assign the 24 variables to the array. In this study, marketing channel is viewed as a noise factor. Due to the limitation of this samples, we randomly selected 100 abnormal samples, 39 samples from channel1, and 61 samples from channel2. The MD values are calculated for all 100 abnormal samples, and for all combinations of the 24 variables indicated by the rows of the OA. Table 3 shows the detailed OA allocation, MD and SN ratio for each sample. Here "1" includes variable and "2" excludes the variable. Additionally, we apply "large-the-better" SN ratio to analyze the data.

We calculated the corresponding SN ratio for each variable. The result is the factorial effect diagram shown in Figure 5. Therefore, the important variables are gender, age, marital status, education, level in company, credit limits, location, house ownership, cash balance, hi balance, and background difference. The important occupations are occupation 2, occupation 3, occupation 5, occupation 6,and occupation 7. The important variables needed to determine where a customer should have good or bad credit.

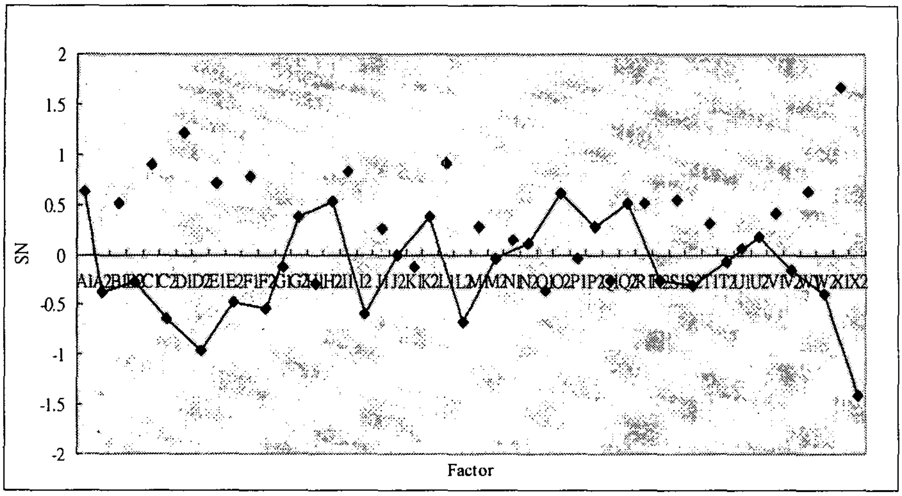

Figure 5. Factorial Effects of Credit

In step 7, we construct reduced the model MTS measurement scale. Figure 6 shows the MDs distribution for this data. The MD distribution for normal training samples is 0.153-27.09 with an average value of 1.

In the last step, we calculated the MD for each observation from the testing samples in Table 1. The results are shown in Figure 7. The MDs distribution for the 1200 "normal" observations is 0.152-24.508,and 1.264-148.769 for the 120 "abnormal" observations. When using a threshold value of 4.2, the classification accuracy rate reaches 95.98% resulting in the new measurement scale.

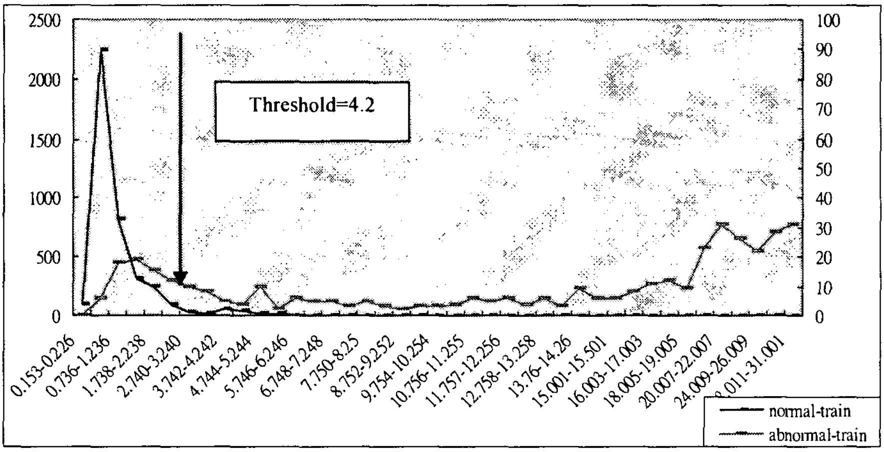

Figure 6. The Mahalanobis Distributions of the "Reduced Model"- Training Sample

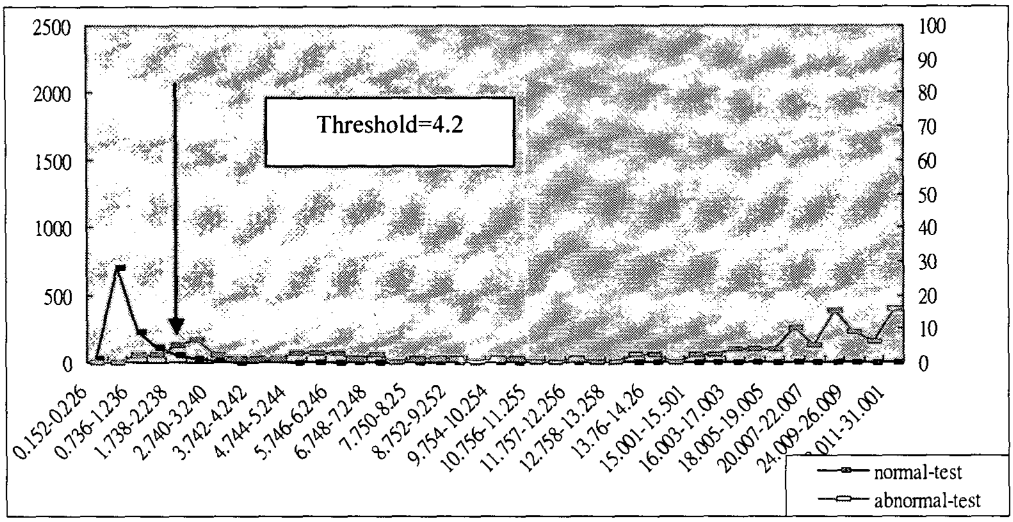

Figure 7. The Mahalanobis Distributions of the "Reduced Model"- Testing Sample

6. Conclusions

Credit scoring is widely used to help banks for deciding whether or not to grant credit to consumers. As mentioned above, many of the previous studies attempt to improve the accuracy of credit scoring model, but they do not mention the "robustness" of the system. This study tried to design a "robust" credit scoring system that is insensitive to noises and to confirm the effectiveness of the proposed system. From the experimental results, we found that the proposed system is robust against the noise. The results also show the classification accuracy rate of the "Full Model" is 96.06%, and the "Reduced Model" is 95.98%, in the MTS measurement scale.

According to Taguchi and Rajesh [15], the main difference of MTS with other techniques is that MTS classifies the new items into normal or abnormal, and the severity of the item can be judged based on the measurement scale; Therefore, we can get more information about the abnormality of the items. In addition, MTS places more emphasis on the robustness of the system and has more flexibility in decision- making. Hence, MTS is applicable in the domain of credit scoring.

Table 3. OA Table and SN ratio

No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	MD		SN
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X								Channel1 Y1-Y39	Channel 2 Y40-Y100	
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1			7.3318
2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2			1.7227
3	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2			2.688
4	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1			3.739
5	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2			0.4343
6	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	2	2	2	2	1	1	1	1			-1.6584
7	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1			-2.223
8	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	2	2	2	2	1	1	1	1	1	1	1	1	2	2	2	2			2.2408
9	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2			1.990
10	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1			3.2426
11	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1			-4.3303
12	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	1	1	2	2	1	1	2	2			2.099
13	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1			-1.6508
14	1	2	2	2	2	1	1	1	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	2	2	1	1	1	1	2	2			-3.9646
15	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	1	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2			-3.4839
16	1	2	2	2	2	1	1	2	2	1	1	1	1	2	2	2	2	1	1	1	1	2	2	1	1	2	2	2	2	1	1			1.8956
17	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2			2.1585
18	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1			-0.0638
19	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2			-0.5867
20	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	1	2	1	2	1	2	1	2			1.0863
21	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1			-1.5959
22	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	2	1	2	1	1	2	1	2			-6.4666
23	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	1	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2			-2.2684
24	2	1	2	2	1	2	1	2	1	2	1	1	2	1	2	2	1	2	1	1	2	1	2	1	2	1	2	2	1	2	1			1.7036
25	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1			-0.2054
26	2	2	1	1	2	2	1	1	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2			-3.3674
27	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2			0.9857
28	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	2	1	1	2	2	1	1	2	1	2	2	1	1	2	2	1			0.8916
29	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2			0.3456
30	2	2	1	2	1	1	2	1	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	2	1	1	2	1	2	2	1			-2.8361
31	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	1	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1			-0.0626
32	2	2	1	2	1	1	2	2	1	1	2	1	2	2	1	2	1	1	2	1	2	2	1	1	2	2	1	2	1	1	2			4.1920

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