Classification of Company Credit Rating Using Artificial Neural Network with Data Factorization

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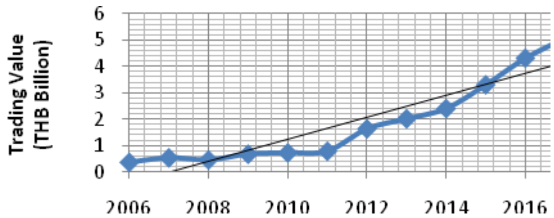
Abstract **- The objective of this study is to classify company credit rating applying an Artificial Neural Network (ANN) model incorporating with a Principle Component Analysis (PCA) technique for the purpose of extracting common factors from a large panel of input variables in order to overcome the multicollinearity problem in the financial figures. The rating reports are collected from a provided website of TRIS Rating (Thailand) Co., Ltd in September, 2018. The data set consists of 183 companies classified into 6 different levels of rating (AAA, AA, A, BBB, BB, and lower than B respectively). To construct the ANN model, 60% of the sample will be used as a training set and the remaining will be assigned to play a role as a testing set. With a pre-adjustment process, the Augmented Dickey Fuller test will be applied to each time series of the 26 selected financial figures. Then, a panel of standardized financial figures will be extracted. With 26 nodes of input layers and 53 nodes in 3 hidden layers, 80.91% of the company's credit rating was correctly classified with the training set. In addition, the overall accuracy of the proposed ANN model was improved by 3.28% when they were applied with the testing set. With the empirical findings of this study, we can infer that the ANN model with data factorization would effectively provide constructive results in classifying the company credit rating.**

Keywords **- Credit Rating, Financial Ratio, Classifying, Artificial Neural Network, Extracting**

I. INTRODUCTION

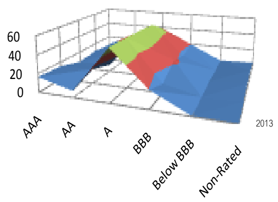
The analysis of company credit rating has largely drawn Thai investor's interests since the Securities Exchange Commission (SEC) officially authorized unrated companies to raise funds through the financial markets, especially the bond markets. Fig. 1, remarkably shows the Thai corporate bonds continuously grew since year of 2008 and intensively rose since year 2011 until now. For the year of 2017, the corporate bonds repeatedly increased with 17.55% from the previous year.



Source: Summary Report 2017, Thai Bond Market Association.

Fig. 1 Trading Value (average trading per day) in corporate bonds (THB billion)

In term of rating, the proportion of non-rated bonds in 2017 shown on Fig. 2, doubly declined from 6.1% to 3.4% of the total issuance amount. The major shrink was largely due to the concerning of investors on the default of non-rated bonds that they already have seen during the last year. With this situation in the bond market, the issuance of credit rating becomes a crucial feature for bond stakeholders (issuers, investors and government officers) as a proxy measure of company riskiness. The credit rating is assumed to be an indicator reflecting characteristics and capabilities of bond issuers in order to respect the term of bond obligations for a repayment of interest and principle. As results, the company credit rating significantly provides a considerable contribution to investors for various uses. Most importantly, they crucially provide useful information to estimate the amount of risk at a low cost. Moreover, brand image would also be improved as the company credit rating rise up.



Source: Summary Report 2017, Thai Bond Market Association.

Fig. 2 Long-Term Corporate Bonds Issuance Classified by Rating

On the other hands, the company credit rating is generally costly to acquire. During the committee of rating agencies analyse all gathered quantitative and qualitative information, the analysis processes and relevant evidences used to support decision making of the rating committee are firmly confidential. In addition, rating agencies need large amount of investments in human resources and time to execute an extensive analysis of company's credit risk. Therefore, the models used to assess company credit rating become a black box. Consequently, most of conventional techniques provided very unfavourable results on predicting the company credit rating.

Fortunately, the common information used to indicate company's creditworthiness is their financial figures because their recent financial information would be reflected by its past performance. As results, the current financial figures may significantly be assumed to influence the company future performance as well. Nevertheless, the financial figures naturally relate with each other. Therefore, they may cause a serious complication which is a multicollinearity problem. This trouble would happen when they are performed in any applications of regression analysis. In consequence, we will apply the Principal Component Analysis (PCA) in this study to extract the common factors from a panel of company financial figures to prevail over the fundamental problem of multicollinearity in the variable selection process.

In this study, we try to examine the relationships between the company financial information and their credit rating awarded by TRIS Rating (Thailand). Assuming the existence of these relationship, we will apply an Artificial Intelligence (AI) technique, named Artificial Neural Network (ANN), to classify the type of company credit rating. Because of their ability to learn complex relationships hidden in the data set without any prior knowledge, the ANN outperforms any conventional techniques of statistical analysis such as linear regression, logistic regression, discriminant analysis and etc.

With the corroboration of the ANN and PCA, we would expect that the empirical results from this study would provide a reasonable benchmark model used to assess company credit rating. In addition, they would considerably reduce the transaction cost occurring on the information gathering process for evaluating risk regarding on corporate bond investment.

II. LITERATURE REVIEWS

The concept of credit rating originally invented since the year of 1860, which H.V. Poor published the key financial figures of the railroad companies in the USA. Almost fifty years later on, J. Moody, who is the establisher of Moody's Investor service, improved the method of rating by assigning the alphabetical symbols to corporate bonds issued by the US railroad companies. After the great depression in 1930, bond credit rating significantly becomes widespread in the US where all commercial papers and corporate bonds were rated accordingly. Until now, we have seen many credit rating agencies established around the world in order to provide corporate risk status to bond stakeholders.

The evolution of Thai credit rating agencies have been started from year 1993 where Thai Rating and Information Services Co., Ltd was firstly established. Then, they were renamed as TRIS Corporation Ltd. (TRIS) in 2002 in order to reconstruct their corporation. The credit rating operation was entirely moved to TRIS Rating as a separate entity. With outstanding contributions of TRIS Rating, Thailand's leading credit rating agency, to Thai debt capital market, S&P Global Rating, the world's leading provider of credit-risk report, acquired a 49% share in TRIS Rating from TRIS Corporation in June 2016. With a collaboration with the world leading credit provider, TRIS credit rating capability become significantly strengthen and provide wide range of services for Thai debt capital market.

However, the transaction cost of awarding credit rating is considerably significant since rating agencies need to perform an intensive due diligence process for targeted company. Therefore, the agency need large amount of investments in human resources and time to execute an extensive analysis of the company credit risk. In addition, rating agencies do not fully disclose all relevance information used to support their decision on assigning credit rating since they are considered as their intellectual properties.

With the suggestion of [1], rating agencies practically use company financial ratios to compose the decision on assigning company credit rating because it can be used to identify the company's solidity and profitability. The study of [2] also ensured that the accounting information and the market risk exposure were blended. As results, accounting statements could be used to value the exposure of securities as well as company rating.

The studying of credit assessing model may began with the study of [3] that applied key accounting ratios of both bankruptcy companies and the companies normally operated to estimate the model by using univariate analysis. With the ratio of cash flow to total liability, the model provided a great contribution to explain the company's failure 5 year in advance.

However, the most obviously seen model in literatures on credit assessing is the study of [4], called "Z-Score Model". This model employed key financial ratios to classify company default probability in the logistics regression analysis. In addition, there are several studies for example [5-8] that revised the Z-Score Model in order to encounter the diverse environment and contributed an invaluable knowledge in credit assessment.

Unfortunately, the inherent features of the financial figures obviously correlate with each other. Consequently, directly applying those financial figures into the regression model will seriously cause multicollinearity problem. As results, the estimated values from the regression model will be considered as spurious results claimed by [9].

To overcome this problem, [10] suggested applying the Principle Component Analysis (PCA), which is a method of observing correlation matrix, variance influence factor and eigenvalues of the correlation matrix. In addition, the exanimated results of [11] provided supported evidences to the use of PCA in extracting common factors from a data rich environment before employing the logistic regression analysis to classify the company's default risk.

With the breakthrough of artificial intelligence (AI) technologies, the adoption of conventional techniques of statistical analysis whose variables necessarily require several restrictive assumptions such as normality, linearity and independent is diminished. In addition, the study of [12-15] suggested applying the Artificial Neural Network (ANN) to avoid that inability of the conventional statistical analysis. Especially, the study of [12] suggested developing the use of soft computing methods for several financial applications such as bankruptcy prediction. Those methods include the probabilistic neural networks and back propagation neural network. In the other areas of finance, there are studies of [16-19] that provided concrete results of ANN for predicting bond rating, bankruptcy, financial distress and credit union financial distress respectively. With the invaluable results of the previous works, we would develop our framework further on combining the principle component analysis for extracting the common factors and the artificial neural network to classify the company credit rating.

III. RESEARCH OBJECTIVES

The aim of this study is to construct a classification model for company credit rating applying the Artificial Neural Network (ANN) model. However, the input variables in the ANN model will be firstly extracted by the Principle Component Analysis (PCA) technique in order to overcome the multicollinearity problem in the panel of financial figures. The input variables used to supervise the ANN model included the common factors extracted from a large amount of key financial ratios calculated from company's accounting statements. These financial figures composed of the ratios measuring the company's liquidity, efficiency, profitability and leverage.

IV. CONCEPTUAL FRAMEWORK

As the centre of our attention is closely focused more on classifying the company credit rating awarded by TRIS rating (Thailand) with the Artificial Intelligence (AI) technique, named Artificial Neural Network (ANN). However, the common factors used in the input layer of ANN need to be firstly extracted from a large panel of financial figures by the method of PCA as illustrated in Fig. 3.

- **Dependent Variables:** The company credit rating assigned by TRIS Rating (Thailand). The rating can be grouped into 6 different categories which each category contains different risk level as shown in the Table I, where 1 is defined to be the company pertained the lowest default risk (AAA), 4 is defined to be the company pertained the moderate default risk (BBB+, BBB, BBB-) and 6 is defined to be the company pertained the greatest default risk (lower than B+) respectively.

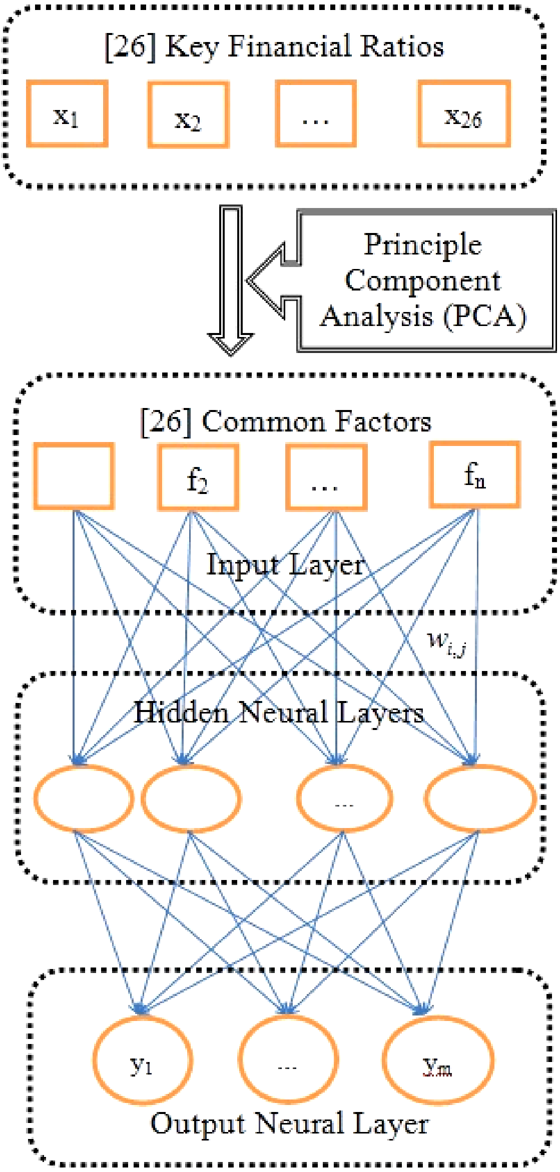


Fig. 3 The Conceptual Framework of Classifying the Companies' Credit Rating by ANN with PCA

- **Independent Variables:** we specifically selected 26 popular financial ratios calculated from the most recent company's accounting statements published on SEC's website in order to construct the input layer for the ANN model, which each selected value ideally captures the fundamental behaviour of the company's profitability, efficiency liquidity and gearing. The selected ratios are composed of current ratio, quick ratio, times interest earn, cash conversion ratio, total debt to total equity, current assets to total assets, total debt to total assets, total equity to total assets, solvency ratio, quick assets to total assets, net sales, inventory to current assets, sales to net worth, assets turnover, cash to total assets, inventory turnover, account receivable turnover, sales to total assets, account payable turnover, gross profit margin, net profit margin, return on assets, operating profit margin, return on equity, retain earning to total assets and pretax margin.

TABLE I
RATING CATEGORIES CORRESPONDING TO TRIS RATINGS

Code	Categories	Corresponding TRIS Rating
1	High	AAA
2	Rather High	AA+, AA, AA-
3	Upper Medium	A+, A, A-
4	Medium	BBB+, BBB, BBB-
5	Lower Medium	BB+, BB, BB-
6	Speculative	B+ and Lower

V. DATA

The population of this study are the 207 companies rated by TRIS Rating (Thailand) Co., Ltd, which rating reports were issued on TRIS's website in September 2018. Unfortunately, some companies may not be easily gathered the information since those companies are considered as unlisted, trust and special purpose vehicle (SPV). Therefore, we have only 183 companies used in this study whose accounting information is publicly available on the website. Consequently, the company's annual financial statements and their key financial ratios have been mainly downloaded from the Securities Exchange Commission's website.

VI. RESEARCH METHODOLOGY

In order to construct the ANN model, the sample has been divided into training data and testing data. We randomly selected 60 percent of the sample by using a simple random sampling to be used to supervise the model by applying the method of back propagation with momentum as a learning rule.

In order to gather the variables used as an input layer in the ANN model, we have to extract the common factors from a panel of 26 selected financial ratios. Before extracting the common factors by the method of principle component analysis, the 26 selected financial ratios must contain stationary property as a pre-adjustment process. As a result, the Augmented Dickey Fuller test will be used to examine each time series of financial figures. After that we would standardize the entire variables in order to have mean equal to zero and variance equal to one. Accordingly, the variable denotes a panel of the 26 standardized financial ratios which variance-covariance matrix of the 26 standardized financial ratios denoted as $\Sigma = Cov(x) = xx'$. The common factors (F) can be calculated by:

$$F = v^{-1}\lambda^{-1/2}x = \Phi x \quad (1)$$

where

x denotes the matrix of the 26 standardized financial ratios.

v^{-1} denoted the inversed matrix whose columns are contained by the eigenvectors of Σ.

$\lambda^{-1/2}$ denotes the inversed of diagonal matrix whose elements are the square-roots of the eigenvalues.

Φ denotes the vectors of principal component loadings which can be illustrated as $\Phi = v^{-1}\lambda^{-1/2}$.

F denotes the matrix of common components.

Given the input vector $F = (f_1, f_2, ..., f_n)'$ where n is the number of input components and $Y = (y_1, y_2, ..., y_m)'$ denotes the output vector where m is the number of output units. Each node within adjacent layers is totally connected. In addition, the degree of association between units i and j is denoted as $w_{i,j}$. In order to supervise the multi-layer neural network, the standard algorithm of back propagation is performed which the sum of squared errors ($\psi(w)$) between output and simulated output is minimised.

$$\psi(w) = e'e \quad (2)$$

where

$w = [w_1, w_2, ..., w_N]$ denotes all the weight of the network.

e denotes the vector consisting of all errors of the training sample.

Furthermore, the activation function employed in this study is the tangent sigmoid function which will establish a degree of nonlinearity to the model.

With the algorisms suggested by [15], we randomly load each value of w_i to a small value. Then, we will used the vector $(f_1, f_2, ..., f_n)$ as input layer to the network and computed the output $(y_1, y_2, ..., y_m)$. For each unit of the output k, we will assume $\delta_k = y_k(1-y_k)(t_k - y_k)$, where t_k is the target output of unit k. In addition, for the hidden unit h, we will assign the value of $\delta_h = y_h(1-y_h)\sum_k (w_{h,k}\delta_k)$ and the value of $w_{i,j} = w_{i,j} + \Delta w_{i,j}$, where $w_{i,j} = \eta \delta_j f_{i,j}$ [15]. suggested that learning rate η can be assumed by user. Based on Kolmogorov theory, the number of hidden nodes should be $2N+1$, where N is number of input noses. For the output layer, we can classify company credit rating into 6 categories and each category have one score. Therefore, there are 6 nodes on the output layer. With the R programming [20] and the package "neuralnet" proposed by [21], the proposed algorisms will be performed successfully when the error or gradient converges to some predetermined goal.

The k-fold cross validation is employed to notify the behaviour of the neural network model when new data is joined. We then compute the root mean square error (RMSE) of each observation of the test set. With these procedures, they will be ensured that the proposed results will not contain of any sample bias and can be used to investigate for the robustness of the model.

VII. EMPRIRICAL RESULTS

Employing principle component analysis to extract the common factors from a large panel of various types of the financial ratios, we assume these 26 common factors to be input variables in the ANN Model. To supervise the model, we randomly select 60 percent of the total sample to be a training set and the rest is assumed to be a test set.

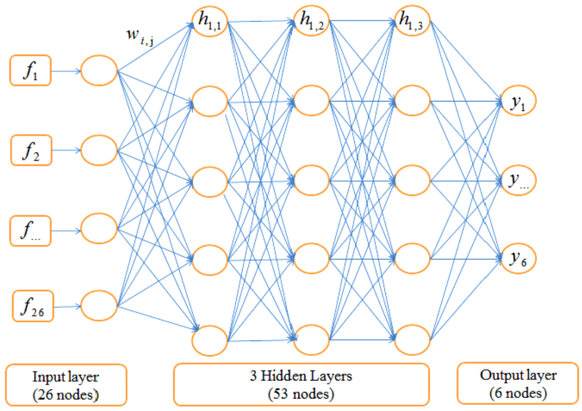


Fig. 4 The Architecture of ANN Used in the Analysis

The constructed ANN model is composed of 26 nodes included in an input layer. Based on the Kolmogorov theory, the numbers of hidden nodes are 53 nodes and there are 6 nodes on the output layer. Furthermore, we assigned the ANN model to have 3 hidden layers illustrated in Fig. 4. However, the network may possibly be other combinations of neuron in this case.

To correct the weights, we initially adjust the learning rate from a relatively low value which starts from the value of 0.2 and notch up to 0.5. In addition, we assign the momentum value at a relatively high level, which is 0.8, in order to control the errors of adjusting the weight in the current case. Moreover, we set the error limit at 0.1 as a criterion to stop training and to prevent network from an over-training problem. In addition, we initially set the weights of neural network as 88 throughout the study.

TABLE II
NUMBER OF COMPANY CLASSIFIED BY THE ANN MODEL BASED ON THE COMPANY RATING WITH THE TRAINING SET

Observed Company's Rating	Predicted Company's Rating					
	1	2	3	4	5	6
1	8	2	0	0	0	0
2	1	6	2	0	0	0
3	0	2	31	4	0	0
4	0	0	3	33	5	0
5	0	0	0	0	10	2
6	0	0	0	0	0	1
Overall Percentage	80.91					

As we already stated earlier, 60% of the entire dataset (183 companies) were selected as a training set. After the supervision of neural network with a training set, 80.91% of the 110 companies were correctly classified.

TABLE III
NUMBER OF COMPANY CLASSIFIED BY THE ANN MODEL BASED ON THE COMPANY RATING WITH THE TEST SET

Observed Company's Rating	Predicted Company's Rating					
	1	2	3	4	5	6
1	2	1	0	0	0	0
2	0	5	2	0	0	0
3	0	1	21	4	0	0
4	0	0	1	30	3	0
5	0	0	0	0	3	0
6	0	0	0	0	0	0
Overall Percentage	83.56					

Applying the proposed ANN model with the testing set (40% of the entire dataset), 83.56% of the remaining 73 companies were correctly classified. The overall accuracy was improved by 3.28%.

VIII. DISCUSSION AND CONCLUSION

This study examines the implication of the Artificial Neural Network (ANN) model whose input variables are applying the benefit of the Principle Component Analysis (PCA) in extracting the common factors from a data rich environment of the financial ratios. We found from the empirical results that the ANN model provide an outstanding performance in classifying the company credit rating. With 26 nodes of input layers and 53 nodes in 3 hidden layers, 80.91% of the company's credit rating was correctly classified with the training set. In addition, the overall accuracy of the proposed ANN was improved by 3.28% when they were applied with the testing set. As results, the ANN model with PCA can capture concealed relationships between financial information and the company credit rating assigned by rating agencies. With the empirical findings of this study, we can infer that the ANN with data factorization would effectively provide constructive results in classifying the company credit rating.

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(Arranged in the order of citation in the same fashion as the case of Footnotes.)

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