Methods and Indexes to Monitor the Economic Crisis (A Review)

Saiful Bahri Mohd Lod
Mahmoud Khalid Almsafir
Islam Faisal Bourini
Graduate Business School, College of Graduate Studies, Universiti Tenaga Nasional (UNITEN), Jalan IKRAM-UNITEN, 43000 Kajang, Selangor, Malaysia.
bahrie88@yahoo.com
mahmoud@uniten.edu.my
islambourini@gmail.com

Article Info

Received:15th September 2012
Accepted:24th September 2012
Published online:1st October 2012

ISSN: 2231-8275

Abstract

The ability in forecasting the future state of financial condition and predicting the incoming economic crisis has become very crucial in preparing the countries towards economic downturn. Therefore, a necessary preventive action can be taken much earlier in order to avoid more severe outcome. The purpose of this paper is to evaluate and analyse some of the classifiers that have been used all over the world to predict the possibility of such crisis. Those classifiers that will be covered are Fuzzy Logic (FL), Neural Network (NN), Genetic Algorithm (GA), Data Envelopment Analysis (DEA) and Support Vector Machine (SVM). The study analyses multiple published papers and researches that has been conducted within 1996-2012 period. The first criterion will be in accordance to the individual description, method and analysis of each classifier, followed by the gap analysis of the multiple in-scope classifiers studies that have been observed. Referring to the review that has been done, the findings show that the Fuzzy Logic (FL), Neural Network (NN), Genetic Algorithms (GA), Support Vector Machines (SVM), and Data Envelopment Analysis (DEA) can be used in predicting the financial crisis. It can also be evidenced that there is still a lack of study that combines those classifiers in producing a better, more efficient and accurate method.

1. Introduction

The history of economic crisis throughout the globe has been recorded since 1930s. There are multiple of events in which the crises have been evidenced started with United State in 1929, Spain in 1977, Latin Americas in 1980s, Turkey and Asia in 1997-1998 to the recent one, United States in 2008 (Reihart and Rogoff, 2008). The crises have contributed to a significance impact to the economic and financial situation not only to affected countries but also indirectly impacted those countries around it. Realising the criticality of avoiding such economic 'disaster' to reoccur, many financial researcher around the world have worked on building the preventive mechanism to act upon it. However, they soon realise that preventing alone is not good enough to avoid it. They have learnt to acknowledge the importance of developing a workable mechanism that not only prevent but predict and forecast before the crisis is actually taken place. Prevention is better than cure. This is the main objective that drives the creation of predictive classifier to forecast the future of the financial situation and condition.

Based on the Oxford Dictionary Online (Oxford Dictionaries, 2012), a method can be described as a particular procedure for accomplishing or approaching something, especially in a systematic or established way. On contrary, an index can be referred to a sign or measure of something. In the mean time, crisis can be defined as a time of intense difficulty or danger. Therefore, in short, the topic is basically discussing about the procedure, approach or measurement that can be utilized in order to forecast and monitor the danger in economy of a particular country, even the world.

There are many studies of the methods and indexes that have been conducted in determining the economic situation and predict the possibility of incoming crisis. The research of this subject matter has evolved tremendously as many have aware on the severity that can be caused by the financial crisis. The evolution has transformed the efficiency and effectiveness of the predictive method in which the algorithms are performed and calculated in a computer-based application instead of a traditional and manual statistic calculation.

2. Literature Review

It can be evidenced that the experimentation and testing of the predictive classifiers has been conducted since 1990s or even earlier such as Discriminant Analysis (DA), Neural Network (NN) and Case-Based forecasting to monitor financial crisis (Jo and Han, 1996). Each literature review would have come out with certain conclusion in related to the model that has been used. One of the classifiers with a good review is Support Vector Machine (SVM). Many researchers agree that based on the experiment that they have conducted, Support Vector Machine (SVM) has proved that it is a highly promising model due to its nature that minimizes the upper bound of the generalization error rather than the training error, the use of fewer free parameters and its ability to provide a unique, optimal and global solutions (Ahn , Oh, Kim and Kim , 2011; Tay and Cao, 2001; Kim, 2003). There are also multiple research verdicts that show that SVM has performed better in predicting the financial crisis when it was compared against Back-Propagation Neural Network Model (BPNN) (Chen and Shih, 2006; Khin, Lee and Kim, 2005; Ding, Song and Zen, 2008; Lee, 2009). In addition, an integrated SVM is claimed to work better compared to the individual Support Vector Machine (SVM) model (Sun and Li, 2012). However, based on different experiment on Back-Propagation Neural Network Model (BPNN) and Support Vector Machine (SVM), it has been observed that both are equally comparative result with 80% of accuracy (Huang, Chen, Hsu, Chen and Wu, 2004).

The other method that has been commonly used for such purpose is a Logit Model. Based on the Working Paper that has been presented, it is stated that Logit is one of the promising method to forecast economic failure (Boyd, Nicolo and Loukoianova, 2009). It is also mentioned that when Logit is integrated with other models, its integration would give a better and more accurate outcome (Canbas, Cabuk and Kilic, 2005). In contrary, when it is compared against Trait Recognition, the Trait Recognition would outperform Logit (Kolari, Glennon, Shin and Caputo, 2002).

Fuzzy Cerebellar Model Articulation Controller (FCMAC) is another model that can be adopted for forecasting purpose. The performance of FCMAC is highly encouraging as a bank failure classification and early warning system (Ng, Quek and Jiang, 2008; Alam, Booth, Lee and Thordarson, 2000). Apart from those, there is also a Hazard Model also can be used for such purpose (Molina, 2002).

Despite of that, Neural Network (NN) is another frequent statistical predictive classifier tested by the researchers. The model can be classified into several types such as Probabilistic Neural Network (Yang, Platt and Platt, 1999), Artificial Neural Network (Celik and Karatepe, 2007), Principal Component Neural Network (Ravi and Pramodh, 2008) and Probabilistic Neural Network (Ogut, Aktas, Alp and Doganay, 2009; Wu, Liang and Yang, 2008).

Another predictive models available are Discriminant Analysis (Jo and Han, 1996), Genetic Algorithms (Min, Lee and Han, 2006; Wu, Tzeng, Goo and Fang, 2007), Multivariate Discriminate Analysis (Wu, Liang and Yang, 2008), Multicriteria Decision, K-Nearest Neighbor, Interactive Dichotomizer 3 (ID3), Case-based Reasoning (CBR), Data Envelopment Analysis (DEA) (Demyanyk and Hasan, 2010), Data Envelopment Analysis (DEA) (Cielen, Peeters and Vanhoof, 2004; Kao and Liu, 2004) and Ensemble (Kim and Kang, 2010).

There is also evidence that the integration of two or more classifiers has been done. For example, the integration of Discriminant Analysis, Neural Network and Case-Based Forecasting produced higher prediction accuracy compared to individual results (Jo and Han, 1996). Other case is the use of Genetic Algorithms to improve both a feature subset and parameter of SVM simultaneously for bankruptcy prediction (Min, Lee and Han, 2006; Wu, Tzeng, Goo and Fang, 2007). Apart from that, there is also a study of Multivariate Statistical Analysis, Logit, Discriminant analysis and Probit (Canbas, Cabuk and Kilic, 2005) and Ensemble and Neural Network (Kim and Kang, 2010).

The integration study of multiple methods also compares the performance of two or more methods. Some of those study are the comparison of Logit against Trait Recognition (Kolari, Glennon, Shin and Caputo, 2002), Neural Networks against Genetic Algorithms (Back, Laitinen and Sere, 1996), Support Vector Machine against Back Propagation Neural Network (Ding, Song and Zen, 2008) and Probabilistic Neural Network against Multivariate Discriminate Analysis (Wu, Liang and Yang, 2008).

In terms of the indexes used, it can be evidenced that most studies had been utilising the Financial Report in its experimentations (Alam, Booth, Lee and Thordarson, 2000; Back, Laitinen and Sere, 1996; Cielen, Peeters and Vanhoof, 2004; Erdogen, 2008; Kao and Liu, 2004, Kim and Kang, 2010; Rebeiro, Lopes and Silva, 2010; Wu, Tzeng, Goo and Fang, 2007; Yang, Platt and Platt, 1999; Ogut, Aktas, Alp and Doganay, 2009). Other type of indexes used are including Stock Market Information (Chen and Shih, 2006; Kim, 2003), Credit Rating Analysis (Huang, Chen, Hsu, Chen and Wu, 2004), International Finance Corporate Investable's Index (Johnson, Boone, Breach and Friedman, 2000), NAZDAQ Index (Lee, 2009) and Loan Loss Provission for the Period (PLAQLY) (Tung, Quek and Cheng, 2004).

There is also some studies that concentrate on specific financial ratios such as Liquidity Ratios (Ding, Song and Zen, 2008), Activity Ratios (Canbas, Cabuk and Kilic, 2005; Sun, 2012; Cielen, Peeters and Vanhoof, 2004), Profitibility Ratios (Canbas, Cabuk and Kilic, 2005; Celik and Karatepe, 2007; Ding, Song and Zen, 2008; Sun, 2012; Wu, Liang and Yang, 2008), Liabilitiy Ratios (Ding, Song and Zen, 2008; Sun, 2012; Cielen, Peeters and Vanhoof, 2004), Capital Ratios (Celik and Karatepe, 2007; Ding, Song and Zen, 2008), Growth Ratios (Ding, Song and Zen, 2008; Sun, 2012; Cielen, Peeters and Vanhoof, 2004) , Structure Ratio (Sun, 2012, Per Share Ratios (Sun, 2012), Debt Asset Ratios (Wu, Liang and Yang, 2008; Cielen, Peeters and Vanhoof, 2004), Inventory Ratios (Wu, Liang and Yang, 2008; Cielen, Peeters and Vanhoof, 2004), Receivables Ratios (Wu, Liang and Yang, 2008, Total Asset Turnover (Wu, Liang and Yang, 2008, Earning Index (Wu, Liang and Yang, 2008, Cash Flow Index (Wu, Liang and Yang, 2008, Non-Performing Ratios (Celik and Karatepe, 2007) and Equity Ratios (Celik and Karatepe, 2007).

2.1 Fuzzy Logic (FL)

The concept of Fuzzy Logic (FL) has been developed based on the mathematical framework by modelling the human experiential in any particular domain (Kumar and Ravi, 2007). The method formulates the knowledge of the domain expert and fuzzy algorithm in order to generate the fuzzy inference systems. According to Kaneko, there are three distinctive steps that will be undertaken in the experimentation of Fuzzy Logic algorithms. The first step is to calculate the Index Value based on certain specific financial ratios such as Current Ratio, Debt Ratio, Fixed Assets, Inventory Turnover, Receivable Sales, Fixed Asset Turnover and Net Worth Turnover. The second step is to calculate the Total Value by using the fuzzy IF-THEN fuzzy rules. The final step is to construct the fuzzy sets, membership function and 3 Dimensional graphs to reflect the performance of the indexes for diagnosis (Kaneko, 1996).

The Total Value is calculated using the formula below:

$$\text{Total Value} = \sum_{i=1}^{n} x1 \, . \, w1 \, / \, \sum_{i=1}^{n} w1,$$

where x1 is the number of membership while w1 is the weight of each financial ratio, i is 1 and n is the number of financial ratio.

Meanwhile, the fuzzy set used is classified into 5 different categories which are VB (Very Bad), B (Bad), S (So-so), G (Good) and VG (Very Good). The Total Value calculated based on the formula below:

$$T = 500 – (VB/2 + B/4) + (G/4 + VG/2)$$

The Fuzzy Logic methods has been claimed to be good in deriving the human ‘IF-THEN’ rules as it has less computational requirement (Kumar and Ravi, 2007). This has been supported by Harchicha, Jarboui and Siarry in which they agreed that the use of membership and fuzzy set in Fuzzy Logic allows the efficiency level of a particular portfolio in a selected market to be analysed (Harchicha, Jarboui and Siarry, 2011). However, the different choice of the membership function and fuzzy sets might contribute to tits disadvantages as it could lead to different results during the diagnosis (Kuma and Ravi, 2007).

2.2 Neural Network (NN)

The fundamental of Neural Network is developed based on the large number of processing neurons and connections between them (Back, Laitinen and Sere, 1996). It manipulates a value of x into a function of y = f(x) and formulates the best approximation of the function itself. This basic concept of Neural Network has been expanded which resulted the creation of many Neural Network based classifiers such as Probabilistic Neural Network (PNN) (Yang, Platt and Platt, 1999), Back Propagation Neural Network (BPNN) (Huang, Chen, Hsu, Chen and Wu, 2004; Yang, Platt and Platt, 1999), Artificial Neural Network (ANN) (Celik and Karatepe, 2007), and Principal Component Neural Network (PCNN) (Ravi, Pramodh, 2008).

The Probabilistic Neural Network is based on the density estimation method while the Back Propagation Neural Network is using the continuous error feedback between the model and the actual response (Yang, Platt and Platt, 1999). The most common indexes manipulated in this forecasting method would be the Net Cash Flow over Total Asset, Total Debt over Total Asset, Current Liabilities over Total Debt and Total Reserve (Ogut, Aktas, Alp and Doganay, 2009; Wu, Liang and Yang, 2008). In contrary, the Artificial Neural Network can be described as a classifier that processes distributed financial indexes in a parallel instance (Celik and Karatepe, 2007). Those financial indexes used are Non-Performing Loan over Total Loan, Capital over Asset, Profit over Asset and Equity over Asset. The other Neural Network classifier, the Principal Component Neural Network (PCNN) is a hybrid version of Principal Computer Analysis and Neural Network (Ravi and Pramodh, 2008).

2.3 Genetic Algorithms (GA)

Genetic Algorithms (GA) method allows the search in a wide space to be performed effectively. This is due to the fact that the classifier is using multi points of search instead of single search in its procedure (Shin and Lee, 2002). Multiple different financial ratios have been used as the data in executing this technique. Some of the common financial ratios used are Net Income Ratio, Quick Ratio, Liquidity Ratio, Current Liability, Stakeholder’s Equity and Retained Earning. The classifier comprises of seven steps as Figure 1 below:

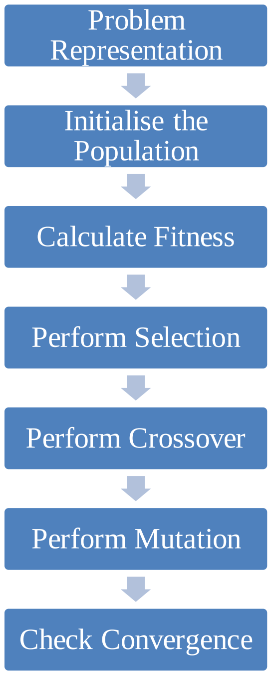

Fig. 1: Basic Steps of GA

Firstly, the problem representation of the particular environment is identified. Then, a population of genetic structure is selected (known as chromosomes) as a starting point of the search. Each of the chromosome is later been evaluated using the fitness defined rule. Based on the result gained, the highly performance chromosomes will be selected and cross-overed among themselves in order to extend the search (Shin and Lee, 2002).

The extraction rule that is used to encode the string is:

String {VAR_{1i}, VAR_{2i}, VAR_{3i}, VAR_{4i}, VAR_{5i}, L/G_{1k}, $L/G_{2k,}$ $L/G_{3k,}$ $L/G_{4k,}$ $L/G_{5k,}$ C_1, C_2, C_3, C_4, C_5,}

Where VAR is the Data, i is Variable Number, L is Less Than, G is Greater or Equal To, k is 1 and C is Cutoff Value.

The accuracy of Genetic Algorithms has been approved by various different experiments such as Etemadi, Rostamy and Dehkordi in 2009, Min, Lee and Han in 2006 and Wu, Tzeng, Goo and Fang in 2007. This is because GA is using multi points of search that reduce the local convergence, directly work with the parameter set characters and manipulates probabilistic rules instead of determistic rules (Shin and Lee, 2002).

2.4 Data Envelopment Analysis (DEA)

Data Envelopment Analysis forecast the financial performance by segregating the cases into efficient and inefficient group (Cielen, Peeters and Vanhoof, 2004). Therefore, the differences of the segments can be observed and analysed accordingly. This method utilises various financial ratios such as Equity Ratio, Cash Ration, Inventories Ratio, Gross-Return Ratio, Net Return Ratio, Quick Ratio, Current Ratio and Financial-debt Ratio. The Data

Envelopment Analysis model omits the sign of reversion between the segments and can be represented as below (Cielen, Peeters and Vanhoof, 2004):

Min $z = 1C_1f_1 + 1C_2f_2$ subjected to

$A'y - A'x - d_1 \leq b$

$B'y - B'x - d_2 \geq b_1$

$d_1 \leq Mf_1$

$d_2 \leq Mf_2$

$x, y, d_{1,} d_2 \geq 0$

where $f_{1,} f_2$ are binary factors, x, y, and b are free, M is a huge number and C_1, C_2 are the cost coefficients.

It has been evidenced that Data Envelopment Analysis is able to determine the performance efficiency of the banking industry (Kao and Liu, 2004). It is also proved to be better in term of accuracy, cost, deployment and comprehensibility (Cielen, Peeters and Vanhoof, 2004). On contrary, there is also a disadvantage that has been reported in which due to its nature of ex post factor; the banking industry might not be able to take action appropriately as the forecasting is based on 'former' factor (Kao and Liu, 2004).

2.5 Support Vector Machines (SVM)

Support Vector Machine manipulates the pattern recognition based on the statistical learning theory of Vapnik in 1998 by finding the maximum margin hyper plane (Ahn, Oh, Kim and Kim, 2011). The Support Vector Machine classifier is based on the condition below (Ahn, Oh, Kim and Kim, 2011; Ding, Song and Zen, 2008):

$$y_i(w^T x_i + b) \geq 1, \quad I = 1, 2, \ldots, N$$

There are many different ratios that have been utilised as an input during the implementation of Support Vector Machine such as Current Ratio, Acid Test Ratio, Cash Ratio, Inventory Turnover, Current Asset Turnover, Total Asset Turnover and many more (Ding, Song and Zen, 2008).

2.6 Gap of Multiple In-Scope Classifiers Studies

Based on the review that has been performed on 40 articles, it can be evidenced that number of studies that have been conducted involving multiple in-scope classifiers are quite limited. This is because the representation of those studies is only about 17% out of the total number of the articles. Those representations can be further divided into two categories; Integration and Comparison. The integration means that the article is combining a few in-scope methods in its study while the comparison differentiates several methods to prove which one is more superior in forecasting the crisis.

The integration study covers the integration of Genetic Algorithms and Support Vector Machines (Min, Lee and Han, 2006; Wu, Tzeng, Goo and Fang, 2007) as well as Genetic Algorithms and Neural Network (Sun, He and Li, 2011). Meanwhile, the comparison study can be observed in the experiments covering Support Vector Machine and Neural Network (Ding, Song and Zen, 2008; Lee, 2009; Ogut, Aktas, Alp and Doganay, 2009) as well as Algorithms and Neural Network (Back, Laitinen and Sere, 1996). The coverage of such studies can be illustrated in the Table 1 below:

Table 1: Multiple In-Scope Classifiers Studies Coverage

	Fuzzy Logic	**Neural Network**	**Genetic Algorithms**	**Data Envelopment Analysis**	**Support Vector Machines**
Fuzzy Logic		-	-	-	-
Neural Network	-		-	-	-
Genetic Algorithms	-	√		-	-
Data Envelopment Analysis	-	-	-		-
Support Vector Machines	-	√	√	-	

3. Methodology

This writing is developed by studying and reviewing multiple published papers and researches that have been conducted from 1996 to 2012 from all aver the world such as China (Ying and Michael, 2010), Taiwan (Chen and Shih, 2006), Korea (Kim and Kang, 2010), Turkey (Canbas, Cabuk and Kilic, 2005; Celik and Karatepe, 2007), United States (Kolari, Glennon, Shin and Caputo, 2002; Yang, Platt and Platt, 1999; Demyanyk and Hasan, 2010) and Spain (Rebeiro, Lopes and Silva, 2010). Those published papers has been produced based on multiple different strategies such as Review Paper (Johnson, Boone, Breach and Friedman, 2000; Kumar and Ravi, 2007), Empirical Study (Kolari, Glennon, Shin and Caputo, 2002; Back, Laitinen and Sere, 1996), Credit Rating Analysis (Huang, Chen, Hsu, Chen and Wu, 2004), Empirical Study (Demyanyk and Hasan, 2010), Annual Report Analysis (Cielen, Peeters and Vanhoof, 2004), Financial Ratio Analysis (Canbas, Cabuk and Kilic, 2005; Kao and Liu, 2004; Tung, Quek and Cheng, 2004, Lee, 2009; Sun and Li, 2012).

The review is also extended into two main criteria. The first criterion is the description, method and analysis of individual classifier. Meanwhile, the second criterion is to analyse the integration and comparison of two or more classifiers in determining the same objective. Although most of the study done either testing on individual classifier or comparing it with others, there are also evidence that the integration of two or more classifiers been done. The result is surprisingly better and more accurate compared to individual test. Despite of the

Integration study of multiple methods, there are also various studies that have been conducted in comparing the performance of two or more methods. The comparison study has deduced which classifier is more superior and better in predicting financial crisis.

Considering that the scope of the study is vastly wide and varied in terms of methods and techniques, this review will be using the study of Kumar P. R. and Ravi V. in 2007 as a baseline of the methods that will be further evaluated. Those classifiers appraised in the article are Fuzzy Logic (FL), Neural Network (NN), Genetic Algorithms (GA), Case-Based Reasoning (CBR), Rough Sets, Support Vector Machines (SVM), Decision Trees, Data Envelopment Analysis (DEA) and Soft Computing Techniques (SC). The models that will be further discussed (in-scope) will only be the Fuzzy Logic (FL), Neural Network (NN), Genetic Algorithms (GA), Support Vector Machines (SVM), and Data Envelopment Analysis (DEA).

4. Recommendation

In referring to the observation from Section 2.6 above, it can be recommended that more studies can be further conducted and explored in order to cover or fill up the under study of classifiers integration and comparison. This is because there could be a various possibilities for integration or differentiation studies to take place involving multiple combination of the rest of the classifiers. Such study will contribute to a great benefit in determining what the performance is like when those classifiers are differentiated or combined together. Therefore, a more efficient and accurate predictive classifiers can be created.

5. Conclusion

In summary, it can be concluded that there are many classifiers that can be utilised in predicting the financial situation in a particular market. Each classifier would have each own strengths and weaknesses. This review has evidenced two important findings. Firstly, each individual in-scope classifier that described above has been proven to be a dependable method in forecasting the financial crisis (Kumar and Ravi, 2007). Secondly, it can be observed that there is still a plenty of room of improvement need to be taken care of in studying the integration or differentiation of multiple classifiers. Perhaps once there are more studies have been conducted, a better result can be generated which eventually will be used to prevent the financial crisis around the globe.

References

Ahn, Oh, Kim, Kim, (2011). Usefulness of Support Vendor Machine to develop an Early Warning System for Financial Crisis. Expert Systems with Applications Vol, 38. 2966 - 2973.

Alam, Booth, Lee, Thordarson, (2000). The Use of Fuzzy Clustering Algorithm and Self-Organizing Neural Networks for Identifying Potentially Failing Banks: An experimental study. Expert Systems with Applications Vol, 18. 185 - 199.

Back, Laitinen, Sere, (1996). Neural Networks and Genetic Algorithms for Bankruptcy Predictions. Expert Systems with Applications Vol, 11. 407 - 413.

Boyd, Nicolo, Loukoianova, (2009). Banking Crises and Crisis Dating: Theory and Evidence. IMF Working Paper.

Canbas, Cabuk, Kilic, (2005). Prediction of Commercial Bank Failure via Multivariate Statistical Analysis of Financial Structures: The Turkish Case. European Journal of Operation Research Vol, 166. 528 - 546.

Celik, Karatepe, (2007). Evaluating and Forecasting Banking Crises through Neural Network models: An application for Turkish Banking Sector. Expert Systems with Applications Vol, 33. 809 - 815.

Chen, Shih, (2006). A Study of Taiwan's Issuer Credit Rating System using Support Vector Machines. Expert Systems with Applications Vol, 30. 427 - 435.

Cielen, Peeters, Vanhoof, (2004). Bankruptcy Prediction Using a Data Envelopment Analysis. European Journal of Operation Research Vol, 154. 526 - 532.

Demyanyk, Hasan, (2010). Financial Crises and Bank Failures: A review of prediction methods. Omega Vol, 38. 315 - 324.

Ding, Song, Zen, (2008). Forecasting Financial Conditions of Chinese Listed Companies based on Support Vector Machine. Expert Systems with Applications Vol, 34. 3081 - 3089.

Erdogen, (2008). Bankruptcy Prediction of Turkish Commercial Banks using Financial Ratios. Applied Mathematical Science Vol, 2. 2973 - 2982.

Harchicha, Jarboui, Siarry, (2011). A Fuzzy Logic Control using a Differential Evolution Algorithm aims at Modelling the Financial Market Dynamics. Information Sciences Vol, 181. 79 – 91.

Huang, Chen, Hsu, Chen, Wu, (2004). Credit Rating Analysis with Support Vendor Machines and Neural Networks: A Market Comparative Study. Decision Support Systems Vol, 37. 543 - 558.

Jo, Han, (1996). Integration of Case-Based Forecasting, Neural Network, Discriminant Analysis for Bankruptcy Prediction. Journal of Banking & Finance Vol, 28. 2353 - 2368.

Johnson, Boone, Breach, Friedman, (2000). Corporate Governance in the Asian Financial Crisis. Journal of Financial Economics Vol, 58. 141 - 186.

Kaneko, (1996). Building a Financial Diagnosis System based on Fuzzy Logic Production System. Computers Ind Engng Vol, 31. 743 – 746.

Kao, Liu, (2004). Predicting Bank Performance with Financial Forecasts: A case of Taiwan Commercial Banks. Journal of Banking & Finance Vol, 28. 2353 - 2368.

Kim, (2003). Financial Time Series Forecasting using Support Vector Machine. Neurocomputing Vol, 55. 307 - 319.

Kim, Kang, (2010). Ensemble with Neural Networks for Bankruptcy Prediction. Expert Systems with Applications Vol, 37. 3373 - 3379.

Ko, Blocher, Lin, (No Year). Prediction of Corporate Financial Distress: An Application of the Composite Rule Induction System. The International Journal of Digital Accounting Research. 69 - 85.

Kolari, Glennon, Shin, Caputo, (2002). Predicting Large US Commercial Bank Failures. Journal of Economics & Business Vol, 54. 361 - 387.

Kumar, Ravi, (2007). Bankruptcy Prediction in Banks and Firms via Statistical and Intelligent Techniques - A Review. European Journal of Operation Research Vol, 180. 1 – 28.

Lanine, Vennet, (2006). Failure Prediction in the Russian Bank Sector with Logit and Trait Recognition Models. Expert Systems with Applications Vol, 30. 463 - 478.

Lee, (2009). Using Support Vector Machine with a hybrid feature selection method to the stock trend prediction. Expert Systems with Application Vol, 36. 10896 - 10904.

Min, Lee, Han, (2006). Hybrid Genetic Algorithms and Support Vector Machines for Bankruptcy Prediction. Expert Systems with Application Vol, 31. 652 - 660.

Molina, (2002). Predicting Bank Failures using a Hazard Model: The Venezuelan Banking Crisis. Emerging Market Review Vol, 3. 31 - 50.

Ng, Quek, Jiang, (2008). FCMAC-EWS: A Bank Failure Early Warning System based on a Novel Localized Pattern Learning and Semantically Associate Fuzzy Neural Network. Expert Systems with Applications Vol, 34. 989 - 1003.

Ogut, Aktas, Alp, Doganay, (2009). Prediction of Financial Information Manipulation by using Support Vector Machine and Probabilistic Neural Network. Expert Systems with Applications Vol, 36. 5419 - 5423.

Oxford Dictionaries, (2012). http://www.oxforddictionaries.com. 13 August 2012. Available Online.

Ravi, Pramodh, (2008). Threshold Accepting Trained Principal Component Neura Network and Feature Subset Selection: Application to Bankruptcy Prediction in Banks. Applied Soft Computing Vol, 8. 1539 - 1548.

Rebeiro, Lopes, Silva, (2010). High-Performance Bankruptcy Prediction Model using Graphic Processing Units. WCCI. 18 – 23.

Shin, Lee, Kim, (2005). An Application of Support Vendor Machines in Bankruptcy Prediction Model. Expert Systems with Applications Vol, 28. 127 - 135.

Sun, Li, (2012). Financial Distress Prediction using Support Vector Machine: Ensemble vs. Individual. Applied Soft Computing. 2254 - 2265.

Sun, He, Li, (2011). Usefulness of Support Vendor Machine to develop an Early Warning System for Financial Crisis. An International Journal Vol, 38. 2966 - 2973.

Tay, Cao, (2001). Application of Support Vector Machines in Financial Time Series Forecasting. Omega Vol, 29. 309 - 317.

Tung, Quek, Cheng, (2004). Genso-EWS: A novel Neural-Fuzzy based Early Warning System for Predicting Bank Failures. Network Neural Vol, 17. 567 - 587.

Wu, Tzeng, Goo, Fang, (2007). A Real-Valued Genetic Algorithms to optimize the parameters of Support Vector Machines for Predicting Bankruptcy. Expert Systems with Application Vol, 32. 327 - 408.

Wu, Liang, Yang, (2008). Analysing the Financial Distress of Chinese Public Companies using Probabilistic Neural Network and Multivariate Discriminate Analysis. Socio-Economic Planning Sciences Vol, 42. 206 - 220.

Yang, Platt, Platt, (1999). Probabilistics in Neural Networks in Bankruptcy Prediction. J Busn Res Vol, 44. 67-74.

Ying, Michael, (2010). Financial Ratios and the Prediction of Bankruptcy: The Ohlson Model Applied to Chinese Publicly Traded Companies. Proceedings of ASBBS 11.