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Artificial Neural Network Model for Predicting Insurance Insolvency

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ABSTRACT
In addition to its primary role of providing financial protection for other industries the insurance industry also serves as a medium for fund mobilization. In spite of the harsh economic environment in Nigeria, the insurance industry has been crucial to the consummation of business plans and wealth creation. However, the continued downturn experienced by many countries, in the last decade, seems to have impacted negatively on the financial health of the industry, thereby rendering many insurance companies inherently distressed. Although there is a regulator to monitor the insurance companies in order to prevent insolvency and protect the right of consumers this oversight function has been made difficult because the regulators appeared to lack the necessary tools that would adequately equip them to perform their oversight functions. One such critical tool is a decision making model that provides early warning signal of distressed firms. This paper constructs an insolvency prediction model based on artificial neural network approach which could be used to evaluate the financial capability of insurance companies.

Keywords: *Insurance, Financial protection, Artificial neural network, Insolvency, Ratio analysis, Training, Prediction model, Early warning signal*

INTRODUCTION
The role of insurance in providing financial protection in the economy is well established. Over the years, the provision of cover by insurance companies has been crucial to the consummation of business plans and, by extension, wealth creation. However, the ability of the industry to continue to effectively play its assigned role in the economy seems to be diminishing and is now severely threatened, first, by poor level of capitalization and, second, by dearth of technical capability to handle emerging issues. In Nigeria, for instance, it is found that, in some years, the quantum of reported claims for some insurance companies is greater than their paid-up capitals (NAICOM, 2002); a clearly undesirable development. If this trend continues the industry may collapse with serious consequences for the entire economy. This, in part, had led to a series of upward reviews of the capital base of insurance companies between 1997 and 2005. In spite of the recapitalizations, however, insolvency in the insurance industry has become a recurrent issue and matter for public concern.

When an insurance company is insolvent, the impact can be pervasive, impacting negatively on employees and threatening the stakes of shareholders and policy holders. In the life business, for instance, an insured’s pension and his future plans may be completely jeopardized.

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In other classes of insurance business a firm without appropriate insurance cover may be put out of business. It is, therefore, important to be able to detect early warning signs of distress in an insurance company before insolvency sets in.

Insurance insolvency is a global phenomenon. In the United States and in Europe many insolvency cases appeared after the insurance cycles of the 1970s and 1980s (Zuleyka et al., 1995). Unlike developing economies where a 'do-nothing' strategy appears to be the adopted approach, the more advanced economies have carried out several surveys to identify the main causes of insurers' insolvency. For instance, the Muller Group Report (1997) identified major causes of insurance insolvencies in the European Union. As a means of mitigating the problems identified, many insurance companies, especially the prime movers in the group, have developed internal risk models for a number of purposes.

In the property/liability insurance business a number of empirical studies have used statistical models based on insurers' financial data to predict insolvencies (Trieschmann and Pinches, 1973, 1977; Harmmelink, 1974; Eck, 1982; Hershbarger and Miller, 1986; Harrigton and Nelson, 1986; BarNiv and Smith, 1987; Ambrose and Seward, 1988; BarnNiv and Raveh, 1989; BarNiv, 1989; BarNiv and McDonald, 1992). The models have impressive ability to predict insolvencies in the industry. For example, Trieshmann and Pinches (1973) reported that their MDA model correctly classifies 92 percent of insolvent firms two years prior to the determination of their insolvency. Some of the studies are based on the assessment of the companies' financial ratio over 100 years (Zheng, Howard and Parker, 1997).

Other studies of financial insolvency in property – liability insurance, for example, include those of BarNiv and McDonald (1992), Ambrose and Seward (1988), and Cummins, Grace and Philips (1999). Adopting Z-score and Multiple Discriminant Analysis (MDA), Altman (1968) proposed that an insurance company with a Z-score greater than 2.675 can be regarded as solvent while one less than 2.675 is at risk of insolvency. However, a report in The Banker (1993) advised against indiscriminate use of the Z-score method because of its inability to account for key variables, principal of which is fraud.

Financial ratios have served as the main plank for modeling insurance company failure prediction. Variants are hybrids of ratios and Linear Discriminant Analysis (LDA), ratios and Logistic Regression (LR), Artificial Neural Network Simulation using back-propagation and Expert Systems. Econometricians have, however, found these traditional methods somewhat inadequate in identifying and estimating key parameters (Hawley et al., 1990; Zhu, 1996). Our aim in this study, therefore, is to attempt to construct a model that can mitigate this difficulty and be used to predict insurance company insolvency in an artificial neural network framework. It is expected that both the insured and the regulator would benefit from the early warning signals to be derived from the use of the model.

Theoretical Framework

Artificial Neural Network (ANN) refers to an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information (Ajibola et al., 2011). An ANN, usually configured for a specific application, is composed of a large number of highly interconnected parallel processing elements, called neurons, working in unison to solve specific problems, through a learning process. However, learning in ANN involves the modification of the inference rules following the arrival of new information thereby adjusting to the synaptic connections that exist between the neurons much like the biological systems.

Hypothetically, a neural network is made up of very simple computational units, or neurons. An artificial neuron is an eclectic simulation of biological neuron, and it consists of its own dendrites, synapses, cell body and axon terminals. It receives stimulation from nearby cells, or from its environment, and generates a modified action potential or nerve signal (Ajibola et al., 2011).

According to Stergious and Siganos (2007), ANN approach has a unique capability for deriving meaning from complicated or imprecise data and is useful in detecting patterns or trends that are too complex to be noticed by humans or other computer techniques. The network is able to learn how to change the interconnections, improve performance, recognize patterns, and develop generalizations by training rule process through experience, rather than from programming (Brockett et al., 1994). Agatonovic-Kustrins et al. (2000), explained that an ANN is formed from hundreds of single units, artificial neurons or processing elements connected with coefficients (weights), which constitute the neural structure and are organized in layers,. Each processing element has weighted inputs, transfer function and outputs. Figure 1 is the architectural framework of the commonly used artificial neural network consisting of layers of input units connected to layer of hidden units which are connected to a layer of output units.

The behavior of an ANN depends on both the weights and the input-output (transfer function) that is specified for the units (Stergious and Siganos, 2007). These functions fall into one of three categories namely: linear, threshold and sigmoid functions. The transfer function of a neuron is chosen to have a number of properties which either enhance or simplify the network containing the neuron (Duch and Jankwoski, 2001). For instance, any multilayer perception using linear transfer function has an equivalent single layer network, a non linear function. A non-linear function is therefore necessary to gain the advantage of a multilayer network. During the training phase, the model learns how to use some of the fields in a record to predict the value of another field (Nguyen, 2005). Once it is trained and tested, it can be given new input information to predict an output.

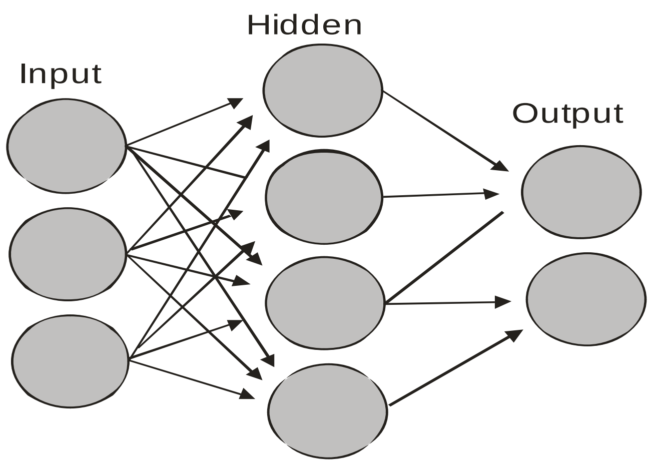

Figure 1: A simple artificial neural network architecture

Data Collection and Key Ratio Selection

The data for the study were obtained from the financial statements of registered insurance companies, the Statistical Reports of the National Insurance Commission (NAICOM), the Nigerian Stock Exchange Fact-Book and the Nigeria Insurance Association (NIA). The reports from these sources indicate that out of the 118 Insurance Companies registered between 2000 and 2007 only forty-nine companies survived the recapitalization exercise. Nineteen others failed due to incurred liabilities and bad management.

Ratios have been the basis of previous analyses. In that regard, Dorsey et al. (2002) described 26 financial information and ratios that have been useful for bankruptcy studies. Other analysts have used varying numbers of these ratios. The highest number was used by Frydman et al. (1985). Altman (1968; 1983) regrouped Dorsey's twenty six (26) factors into five major ratios. This modification appears to be widely accepted by analysts (Coats and Fant, 1993) and is therefore adopted in this study.

The companies used in the study are insurance companies that are based in Lagos State. These companies were selected for two reasons: First, more than 80% of insurance companies in Nigeria have their head offices in Lagos and over 63 percent of the companies that failed between 2000 and 2007 were located in Lagos. Second, involving insurance from the same locality increases the sample's homogeneity.

The sample consists of insurers' data four years prior to their failure. As a control measure (training data set), a failed insurer was matched with a successful insurer in terms of size and accounting years, that is, asset size, number of branches, age, and charter status. Since the analysis of credit risk was the historic starting point for formal ratio analysis, we adopted total assets/total liability as a measure of liquidity ratio in the current study. Although ratio analysis can be a powerful tool of financial management, previous studies have shown that financial ratios are not free from certain limitations. Some of these limitations for financial institutions were mentioned in Ibiwoye (2010). Other limitations are discussed in the following paragraph.

Although ratios can be used as a tool to assist financial analysis, they are not predictive as they are usually based on historical information. Again, although they help to focus attention systematically on important areas and summarize information in an understandable form and assist in identifying trends and relationships, they do not reflect the future perspectives of a company, as they ignore future action by management. They can be easily manipulated by window dressing or creative accounting and may be distorted by differences in accounting policies. When an analyst fails to take inflation into consideration in applying ratio analysis, comparisons can be distorted, thereby resulting in inappropriate conclusions. A comparison with industry averages may also be difficult for a conglomerate firm since it operates in many different market segments. Seasonal factors may further distort ratios and thus must be taken into account when making ratios are used for financial analysis. To the extent that it is not always easy to tell that a ratio is good or bad, it may only be used as an additional tool to back up or confirm other financial information gathered. Further, different operating and accounting practices may distort comparisons. Finally, using the average of certain ratios for companies operating in a specific industry to make comparisons and draw conclusions may not necessarily be an indicator of good performance; perhaps, a company should aim higher. In the light of these observations, we have only used financial ratio analysis as a basis for the authentication of Artificial Neural Network model.

RESEARCH METHOD

In training an ANN, the traditional procedure involving four (4) or more stages may not be applicable in our case since the application package, Stuttgart's Neural Network Simulator (SNNS), has inbuilt mechanism that incorporate ANN training sub-processes into its data processing routine. The procedural considerations for the neural networks techniques for the simulation of insolvency in insurance industry were, therefore, conducted under the following subheadings:

- ✓ tuning the network
- ✓ data preprocessing
- ✓ training of the network

The steps are considered in their order of application in the ANN algorithm.

Tuning of the Parameters for the Artificial Neural Network

Traditionally, the training of a neural network analysis commences with the tuning of its parameters. It is essential to identify the set up parameter for the network. Some parameters considered are:

- ✓ the number of input layers
- ✓ the size of hidden layers
- ✓ the learning constant, β
- ✓ the momentum parameter, α
- ✓ the range, format and bias of data presented to the network, and
- ✓ the form of the activation function (sigmoid is used here).

The output layer has a single unit, which represents the expected change for the prediction problem. One middle layer is used in our analysis. We have chosen a modest number of neurons possible for our ANN simulation to allow for generalization. A major setback associated with the use of too many neurons in an exercise is the problem of memorization of patterns that may in turn result in an inability of the neural network to efficiently and effectively carry out accurate predictions outside the training data (Ajibola et al., 2011).

The Processing of the ANN Data

According to Ajibola et al. (2011), the preprocessing of the acquired raw data is required for the neural network to function. The sigmoid activation function is used for data preprocessing in this paper. The steps involved in preprocessing of the raw data are:

a. Presenting a derived data *di* from the raw data by setting

$$d_i = P_{i+1} - P_i \tag{3}$$

where P_k is the row matrix representing the data on level k of the ANN data.

b. The next step is to normalize the derived data, viz:

$$t_i = \frac{d_i - \mu}{\sigma} \tag{4}$$

where μ = mean and σ = standard deviation.

c. In image processing, edge can be detected by accenting change with the function $\left(\frac{a-b}{a+b}\right)$, where a and b are adjacent pixel values. This enables feature detection and will be used to accent change in the data:

$$s_i = \frac{P_{i+1} - P_i}{P_{i+1} + P_i} \tag{5}$$

Therefore, all columns from the last (feature detection) procedure are appended with the columns from the previous (squashing) procedure. This doubles the number of columns.

Modeling the ANN

The network is simulated using the back propagation algorithm. The weights are initialized with random floating point numbers in the range [–1, 1] and the error function used is the mean square error, ε, defined as:

$$\varepsilon = \frac{1}{T}\sqrt{\sum_{i=1}^{T}\left(\sigma_i - t_i\right)^2} \tag{6}$$

where T is the number of output units, σ is the network output and t is the desired target output. This error will be propagated backward for each training pattern and for each epoch. The back propagation algorithm used is as given below.

The back propagation algorithm

Step 1: Read first input pattern and associated output pattern

$$\text{CONVERGE} = \text{TRUE} \tag{7}$$

Step 2: For input layer, assign as net input to each unit in its corresponding element in the input vector. The output for each unit is the net input.

Step 3: For the first hidden layer units – calculate the net input and output

$$net_j = W_o + \sum_{i=1}^{n} x_i Wij \quad (8)$$

$$\sigma_j = \frac{1}{1+\exp(-net_j)} \quad (9)$$

W_o = initial weight values, x_i = input vector and $W = \{W_{ij}\}$ is the weight matrix.
Step 4: For the output layer units – calculate the net input and output.

$$net_j = W_o + \sum_{i=1}^{n} x_i Wij \quad (10)$$

$$\sigma_j = \frac{1}{1+\exp(-net_j)} \quad (11)$$

Step 5: Is the difference between target and output pattern within tolerance? If No,
THEN CONVERGE = FALSE (12)

Step 6: For each output unit calculate its error,
σj = (t j - σj) σj (1 - σj) (13)

Step 7 For last hidden layer calculate error each unit

$$\sigma_k = \sigma_j\left(1-\sigma_j\right)\sum_k \delta_k W_{kj} \quad (14)$$

Repeat Step 7 for all subsequent hidden layers.

Step 8 For all layers, update weights for each unit,

ΔWij (n + 1) = β(δj σj) + αΔWij (n) (15)

(last pattern is presented) CONVERGE – TRUE STOP
Read next input pattern and associated output pattern and
GOTO Step 2.

The Artificial Neural Network Simulation

We have used the data, in Table 1, for the training. The learning rate of the ANN is 0.0004 while its error tolerance is 0.0002. The number of cycles used is 500 while the ANN architecture of 7 6 1 was used. In Figure 2, we have shown the behavior of the simulated ANN based on our algorithm. The ANN graph (series 1) clearly show that the Insurance companies under consideration failed since all the points on the simulation curve fall below threshold line (series 2). Figure 3 is the graphical interpretation of the data in Table 1 giving a visual presentation of the pattern of distribution of the two sets of data.

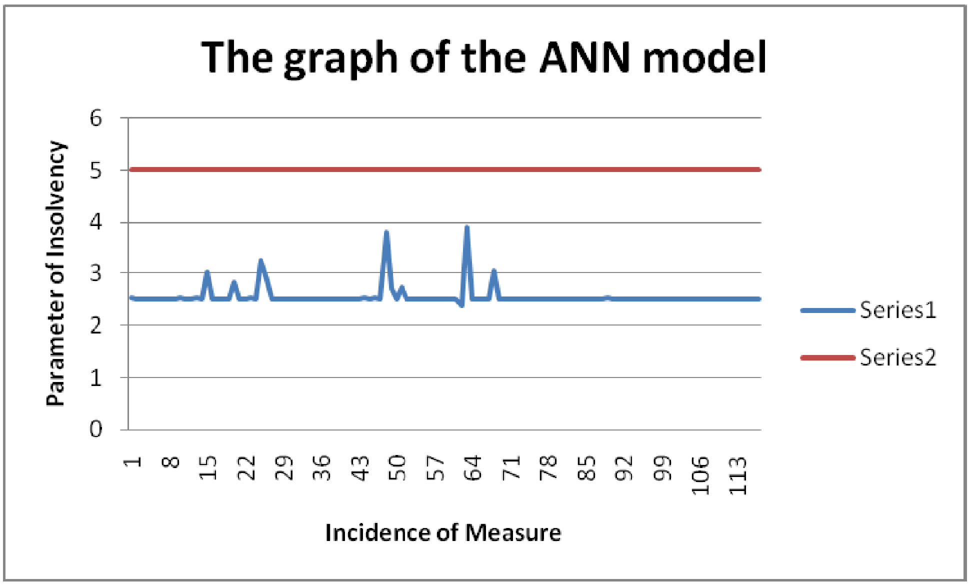

Figure 2: ANN analysis of insolvency of insurance industry

Table 1: Data for both calculated and ANN model for insolvency in insurance industry

Serial Number	Actual Value	Predicted Values	Serial Number	Actual Value	Predicted Values	Serial Number	Actual Value	Predicted Values
1	1.0966	2.5323	40	5.7501	2.5271	79	4.2154	2.5275
2	1.4994	2.5278	41	6.1298	2.5276	80	3.1592	2.5275
3	1.6899	2.5283	42	1.8106	2.5278	81	2.4843	2.5276
4	0.2531	2.5287	43	6.8695	2.5276	82	2.0606	2.5284
5	1.7678	2.5277	44	1.3238	2.5325	83	5.8592	2.5210
6	2.5153	2.5276	45	1.9946	2.5277	84	4.9839	2.5278
7	2.1448	2.5276	46	1.3676	2.5310	85	1.5579	2.5277
8	1.2245	2.5284	47	2.2823	2.5276	86	2.6187	2.5276
9	1.2286	2.5283	48	2.2432	3.8107	87	0.1644	2.5285
10	1.2179	2.5313	49	1.7072	2.7216	88	2.8401	2.5276
11	3.8786	2.5276	50	2.3254	2.5276	89	1.2313	2.5319
12	3.1592	2.5275	51	3.9795	2.7380	90	5.0690	2.5281
13	1.2986	2.5322	52	1.5339	2.5279	91	1.7335	2.5280
14	2.3992	2.5279	53	1.1091	2.5283	92	3.2396	2.5281
15	1.5682	3.0299	54	1.8799	2.5283	93	1.1320	2.5297
16	2.0720	2.5277	55	1.1725	2.5289	94	7.1011	2.5276
17	3.0985	2.5276	56	3.7661	2.5276	95	5.8817	2.5272
18	1.3527	2.5282	57	1.2750	2.5285	96	2.1932	2.5277
19	1.1831	2.5285	58	2.4695	2.5276	97	2.5991	2.5279
20	1.7109	2.8293	59	6.8143	2.5276	98	2.8721	2.5275
21	3.0565	2.5276	60	1.6428	2.5289	99	2.0591	2.5276
22	2.9874	2.5271	61	7.3162	2.5263	100	9.5610	2.5275
23	1.0015	2.5320	62	5.5994	2.3964	101	2.7278	2.5277
24	8.4592	2.5265	63	1.5545	3.9093	102	6.5599	2.5267
25	1.6902	3.2767	64	1.6053	2.5278	103	1.6611	2.5279
26	3.6568	2.8909	65	1.3678	2.5296	104	3.7882	2.5276

27	1.7569	2.5278	66	1.1550	2.5302	105	0.3654	2.5275
28	6.9762	2.5278	67	1.8137	2.5277	106	1.5320	2.5278
29	2.8721	2.5276	68	3.8493	3.0600	107	1.8152	2.5276
30	2.0667	2.5278	69	4.6527	2.5275	108	1.9268	2.5277
31	1.9051	2.5277	70	1.6758	2.5279	109	1.8152	2.5276
32	1.6781	2.5277	71	1.9946	2.5277	110	1.4930	2.5293
33	3.4602	2.5277	72	2.4843	2.5276	111	2.3421	2.5277
34	2.9142	2.5275	73	1.5004	2.5281	112	1.3221	2.5283
35	2.1315	2.5276	74	1.9615	2.5278	113	3.9837	2.5275
36	2.5846	2.5275	75	1.7038	2.5281	114	2.0140	2.5282
37	4.5951	2.5279	76	2.6892	2.5276	115	2.8795	2.5270
38	2.2908	2.5276	77	2.6679	2.5276	116	1.3643	2.5283
39	3.8873	2.5276	78	1.8985	2.5280	117	1.2130	2.5283

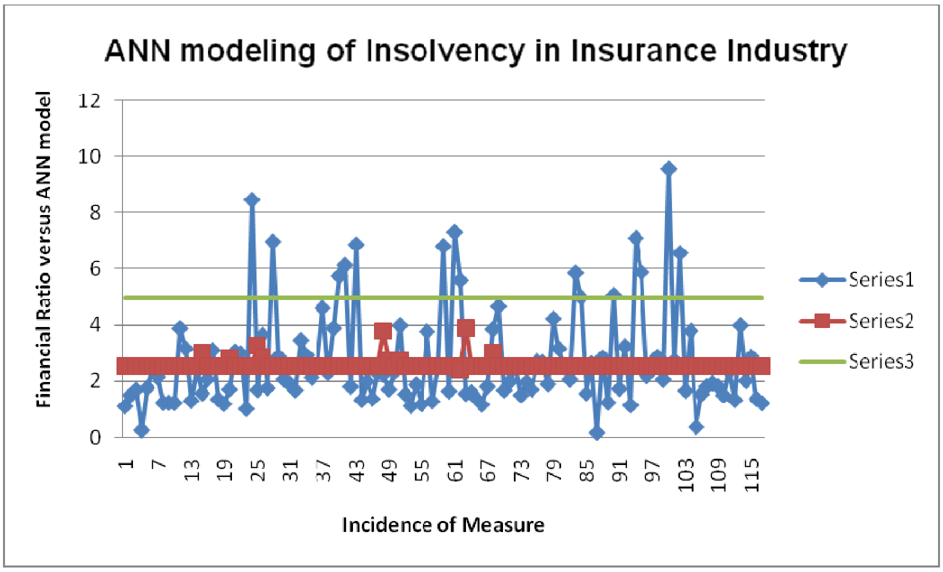

Figure 3: ANN versus Liquidity Ratio analysis

DISCUSSION

This paper takes the statistics of selected insurance companies in Nigeria and investigates their trend of performance with the aim of determining their insolvency status. It considers the dynamism of the insurance industry vis-à-vis their sustainability of insurance business in the face of emerging challenges brought about by globalization. The financial analyses carried out on the data drawn from the financial instruments of the companies under discourse were aimed at determining the overall financial structure of the insurance industry in Nigeria.

Ibiwoye (2010) had drawn attention to the fact that ratios provide little help when considering the effects of economies of scale, the identification of benchmarking policies and the estimation of overall performance measures of firms. This is our main motivation for a search for an alternative and viable approach such as that offered by the ANN methodology. The liquidity ratio analysis is only used, here, as the springboard for determining the threshold of solvency from the ANN simulation. We have raised the threshold of solvency in the industry to 5 (in Figure 2; series 3) as a result of creative accounting (i.e. gross manipulation of accounting figures) typified by unethical practices of fraudulent external auditors associated with declarations made in financial statements of both private and public enterprises the world over, but most especially in a developing economies.

The graph of the ANN simulation model (figure 3; series 2) falls completely below the threshold. This depicts absolute insolvency of the insurance companies under consideration. Moreover, from the perception of probability theory, an incidence of 13 out of 117 data points gives a vivid support to the result of the simulation from our ANN model. The artificial neural network mimics the biological NN in that it harmonizes various inputs into a most desirable output. It is, therefore, the harmonization of all the inputs like management, auditor's report, and external factors such as the government policies and other environmental factors that determine the future status of the insurance companies under study that was reflected in the outcome of the model.

To this end, it can be surmised that the ANN model we have proposed captures the trend of insolvency in the industry in Nigeria. The study can be extended in a future research to examine the adaptive control of insolvency in any financial industry.

CONCLUSION

In this paper, a major headway had been made concerning the modeling of the insolvency that characterizes the failure that befell insurance industry in Nigeria. The new solution technique is ably demonstrated through an interactive ANN simulation modeling. The contribution to existing knowledge includes a mathematical model which describes the insolvency of insurance industry with a view to providing an early warning signal about distressed insurance companies.

REFERENCES

Agatonovic – Kustrins, S. and Beresford R. (2000). Basic Concepts of Artificial Neural Network (ANN) Modeling and Its Application in Pharmaceutical Research, *Journal of Pharmaceutical Biomedical Analysis*, 22 (5), pp. 717-27.

Ajibola, O. O. E., Olunloyo, V. O. S. and Ibidapo-Obe, O. (2011), Artificial Neural Network Simulation of Arm Gait in Huntington's Disease Patient. *International Journal of Biomechatronics and Biomedical Robotics,* 1 (3), pp. 133-140.

Altman, E. I. (1968). Financial Ratio, Discriminant Analysis, and the Prediction of Corporate Failure, *Journal of Finance*, 23 (4), pp. 589-609.

Altman E. I. (1983). Corporate. Distress: A Complete Guide to Predicting Avoidance and Dealing with Bankruptcy, New York: N.Y, John Wiley and Sons.

Altman, E. I., Haldeman, R. G. and Narayanan, P. (1977). ZETA Analysis: A New Model to Identify Bankruptcy Risk of Corporations, *Journal of Banking and Finance*, 1(1), pp. 29-54.

Ambrose, J. M. and J. A. Seward, (1988). Best's Rating, Financial Ratios and Prior Probabilities Networks Performs Nonlinear Discriminant Analysis, *Neural Networks*, Vol. 3, pp. 367-375.

BarNiv, R. (1989). Identifying Financial Distress in the Insurance Industry: A Methodology Inquiry, paper presented at the 1989 Annual Meeting of the America Risk and Insurance Association.

BarNiv, R. and McDonald, J. B. (1992). Identifying Financial Distress in the Insurance Industry: A Synthesis of Methodology and Empirical Issues. *The Journal of Risk and Insurance,* LIX (1992): pp, 543-574.

BarNiv, R. and Raveh, A. (1989). Identifying Finance Distress: A New Non Parametric Approach.

Journal of Business Finance and Accounting, 16 (3), pp. 361-384.

BarNiv, R. and Smith, M. L. (1987). Underwriting, Investment and Solvency, *Journal of Insurance Regulation*, pp. 409-428.

Brockett, P. L., Cooper, W. W., Golden, L. L. and Utai, P. (1994). A Neural Network Method for Obtaining an Early Warning of Insurer. *Journal of Risk and Insurance*, 6 (3), pp. 402-424.

Coats, P. K. and. Fant, F. L. (1993). Recognizing Financial Distress Patterns Using a Neural Network Tool. *Financial Management,* 22 (3).

Cummins, J. D., Grace, M. F. and Philips, R. D. (1999). Regulatory Insolvency Prediction in Property Liability Insurance: Risk Based Capital, Audit Reason and Cash Flow Simulation. *Journal of Risk and Insurance*, 66 (3), pp. 417-458.

Dorsey, R. E., Edmister, R. O. and Johnson, J. D. (2002). Bankruptcy Prediction Using Artificial Neural Systems. *The University of Mississippi School of Business*, p. 72.

Duch, N. and Jankowski, N. (2001). Transfer Functions Hidden Possibilities for Better Neutral Networks, in 9 th European Symposium on Artificial neutral Networks, Belgium, pp. 81-94.

Eck, J. R. (1982). Detecting Financially Troubled Property-Liability Insurers. *Journal of Business Research*, pp. 445-458.

Frydman, H., Altman, E. I. and Kao, D-L. (1985). Introducing Recursive Partitioning for Financial Classification: The Case of Financial Distress. *The Journal of Finance*, 40, pp. 269-291.

Harmelink, P. J. (1974). Prediction of Bests General Policyholders Ratings. *Journal of Risk and Insurance*, pp. 621-632.

Harrington, S. E. and Nelson, J. M. (1986). A Regression Based Methodology for Surveillance in the property-Liability Insurance Industry. *Journal of Risk and Insurance*, 53 (4), pp. 583-605.

Hawley, D. D., Johnson, J. D. and Dijjotan Raina, D. (1990). Artificial Neutral Systems: A New Total For Financial Decision-Making. *Financial Analysis Journal,* 46 (6), pp. 63-72.

Hershbarger, R.A. and Miller, R. K. (1986). The NAIC Information Systems and the Use of Economic Indicators in Predicting Insolvencies. *Journal of Insurance Issues and Practices*, pp. 21-43.

Ibiwoye, A. (2010). Evaluating Financial Services Productivity: A Comparison of Ratios, Index Numbers and Frontier Methods. *Journal of Economics and Engineering*, February Issue, pp. 50 – 58.

Muller Group (1997), Muller Group Report, Solvency of Insurance Undertakings, Conference of Insurance Supervisory Authorities of the Member States of the European Union.

NAICOM, (2000) (2001) (2002), Nigeria Insurance Statistics and Directory 2000-2002. *National Insurance Commission*, Abuja –Nigeria, pp.15-17, 16-18 respectively.

Nguyen, H-G. (2005). Using Neutral Work in Predicting Corporate Failure. *Journal of Social Sciences*, 1(4), pp. 199-202.

Stergious, C. and Siganos, D. (2007). Neural Networks. Available: www.Doc.k.ac.uk/and/surprise96/journal /Vol4/cs11/report.html

The Banker, (1993). December 13 ABC/INFORM Global, 143, 814.

Trieschemann, J. S. and Pinches, G. E. (1973). A Multi Variable Models for Predicting Financially Distressed P-L Insurers. *Journal of Risk and Insurance*, 40 (3), pp. 327-338.

Zheng, R. Y., Howard, J. and Packer, A. (1997). The Failure Prediction of UK Private Construction Companies. Department of Land and Construction Management, University of Portsmouth, Portsmouth PO13AH, UK.

Zhu, H. Y., and Rohwer, R. (1996). No Free Lunch Cross- validation. *Neutral Computation*, 8 (7), pp. 1421-1426.

Zuleyka, D. M., Jose, F. M., M[a] Jesús, S. V. (1995). See 5 Algorithm Versus Discriminant Analysis, An Application to the Predictions of Insolvency in Spanish, Non-Life Insurance Companies. Universidad Computense de Madrid.