

CHAPTER II

REVIEW OF LITERATURE

The review of literature relating to **‘A comparative study of the prediction models of industrial sickness with specific reference to Principal Component Analysis based Multiple Discriminant model and Evolutionary Neural Networks model’** is discussed under the following headings.

- A. Definition of industrial sickness;
- B. Growth of industrial sickness in India;
- C. Causes of industrial sickness in India and
- D. Prediction models of industrial sickness
 - (i) Early period;
 - (ii) Univariate analysis;
 - (iii) Multivariate analysis;
 - (iv) Logit and Probit analysis;
 - (v) Recursive Partitioning Algorithms;
 - (vi) Neural Networks and
 - (vii) Other Models.

A. Definition of industrial sickness:

Sickness in industries has been viewed differently. It is a well known fact that there is no unanimity on what constitutes a sick unit. Walter (1957) and Donaldson (1962) have termed it as the technical insolvency when a firm is unable to meet its maturing obligations. Altman (1968) however interpreted industrial sickness in a stricter sense as either bankruptcy or liquidation of firms when the firm ceases its operations. The Small Industries Development Organisation (1968) defined a sick unit as “a unit having less than 25 percent capacity utilization”

The Report of the Study Team of the State Bank of India (1971) defined a sick unit as “one which fails to generate internal surplus on a continuing basis and depends for its survival on frequent infusion of external funds”. In 1976, the Industrial Credit and Investment Corporation of India defined a sick industry as one whose financial viability is threatened by certain adverse factors relating to management, market, labour relation, fiscal burden etc. The Financial Bill of 1977, had a clause which defined a sick unit as one whose 50 percent or more of capital resources are wiped out by losses. The Reserve Bank of India (1978) contends that a sick unit is a unit which has incurred cash losses for one year which is likely to continue in the current year as well

as the following year and which has an imbalance in its financial structure i.e. where the ratio of current assets to current liabilities is less than 1:1 and the debt-equity ratio is worsening.

However, Lal (1979) has indicated two stages for sickness of an industrial firm. An industrial unit becomes sick if it is operating at less than break even point, where it is unable to meet its cost and depreciation and the unit which has eroded its capital and reserves is considered to have reached an advanced stage of sickness.

According to the Sick Industrial Companies Act 1985, a sick unit has been defined as a company where the accumulated losses at the end of any financial year result in erosion of 50 percent or more of its peak net worth during the immediately preceding five financial years.

The Sick Industrial Companies Act was amended in 1993 which ultimately defined a sick industrial company as a company being registered for not less than 5 years and which has at the end of any financial year accumulated losses equal to or exceeding its entire net worth.

The Sick Industrial Companies Amendment Act (2002) redefined a sick industrial unit as “an industrial company, which has

(i) accumulated losses in any financial year which are equal to 50 percent or more of its average net worth during four years immediately preceding such financial year (or)

(ii) failed to repay its debts within any three consecutive quarters on demand made in writing for its repayment by a creditor or creditors of such companies

Thus in defining industrial sickness three different views can be identified.

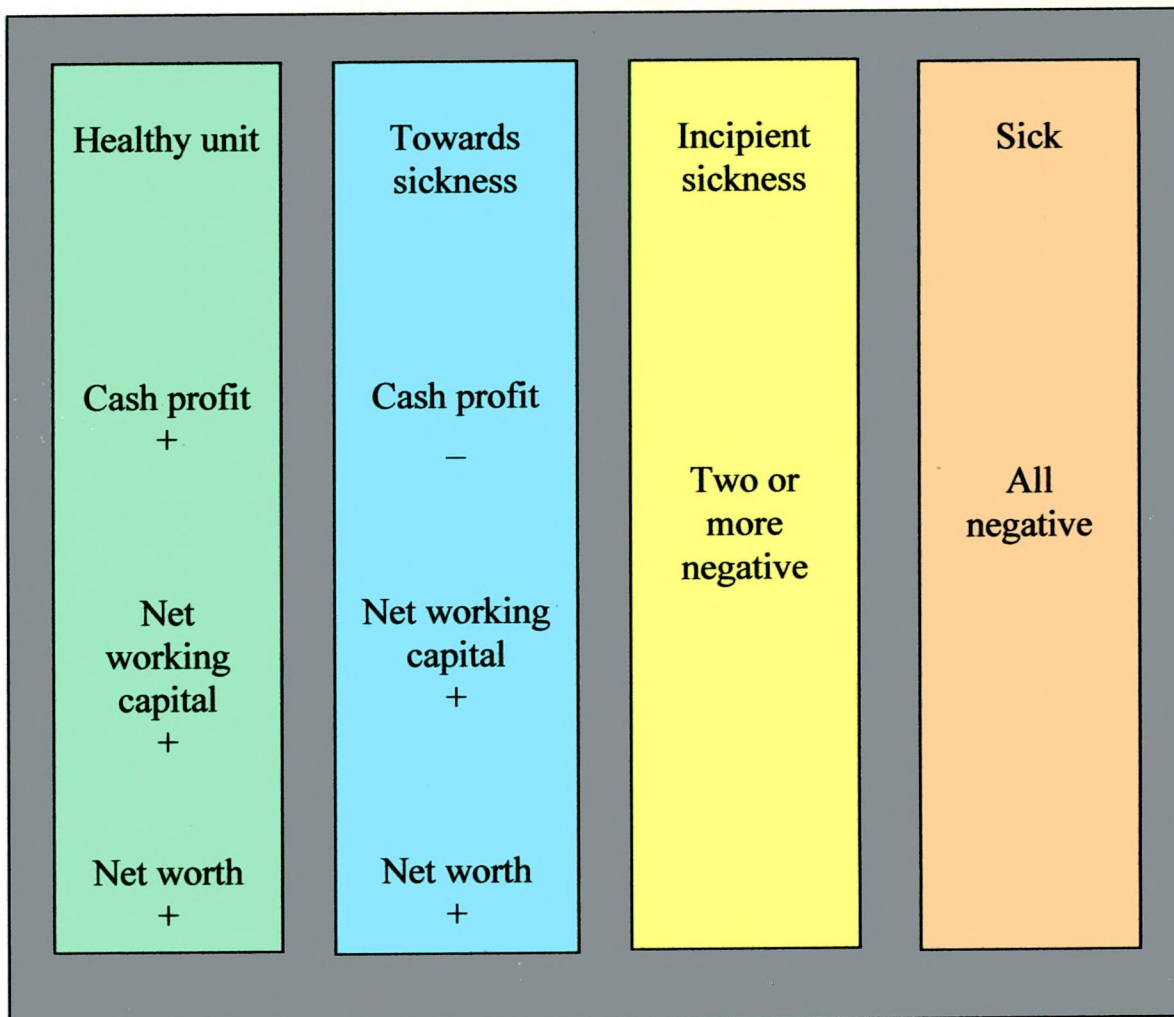
- (i) At the Government level in India, industrial sickness is marked only when a unit is on the verge of closure throwing a large number of people out of employment;
- (ii) At the lending financial institutions level, the problem gets recognized when the non-payment of installments borrowed by firms start and
- (iii) From the shareholder's point of view an enterprise is sick if it fails to pay reasonable dividends while the share value drops down

Industrial sickness is thus an organic process, experienced in the life process of a unit. Companies do not go sick overnight. The process of sickness is gradual. (Srivatsava and Yadav, 1986)

The process of industrial sickness is illustrated in Figure I

FIGURE I.

PROCESS OF INDUSTRIAL SICKNESS



Initially a healthy unit may show good cash profit and may possess a positive value of cash profit, net working capital and net worth. As it moves towards sickness, cash profit becomes negative, though the firm may continue to pay its loan installments to the lending institutions. As sickness grows deeper two or more of the financial parameters become negative. These negative values indicate sickness.

B. Growth of industrial sickness in India:

The phenomenon of industrial sickness both in the Non-SSI sector and in the small scale sector has been alarming in recent years in India. In the pre-liberalization period (1980-92) the number of sick Non-SSI units rose from 1401 units in 1980 to 2427 units in 1992, which in the post liberalization period increased further to 3317 units in 2001. Consequently the bank credit locked up in these sick units also increased from Rs.1502 crores in 1980 to Rs.9241 crores in 1992, which further rose to Rs.21, 270 crores in 2001. On the other hand, in the small scale industrial sector, the number of sick units showed a hike from 23,149 units in 1980 to 2, 33,441 units in 1992, which further increased to 2, 49,630 in 2001. Correspondingly the bank credit locked up in these sick units also exhibited an increase from a mere Rs.306 crores in 1980 to Rs.3346 crores in 1992 and to Rs.4506 crores in 2001.

The growth of industrial sickness however among the Non-SSI units in the last two decades had been very disturbing. An overview of the growth of industrial sickness among the Non-SSI units, revealed the following facts.

- (i) Fluctuations have been noticed in the sick Non-SSI units where the number has raised from a mere 1401 units in 1980 to 3317 units in 2001, showing an increase by 130 percent.

- (ii) The outstanding bank credit in the sick Non-SSI units showed an increase from Rs.1502 crores in 1980 to Rs.21, 270 crores in 2001, depicting an increase by more than fourteen times.
- (iii) The average outstanding bank credit per Non-SSI sick unit during 1980 to 2001 increased from a mere Rs. 108 lakhs in 1980 Rs.641 lakhs in 2001 depicting a more than five times increase.

The grim condition of the industrial sickness in the Non-SSI units in India is further evident from it's industry wise breakup. In 2001, the five major industrial groups of textiles, engineering, electricals, chemicals and iron and steel accounted for 78.5 percent of the total locked up bank credit in their sick units. In spite of all the development efforts put forth by the Government, the intensity of the sickness among the Non-SSI units was more stringent in India showing little signs of abatement. Therefore apart from developing a coherent framework setting out the causes and symptoms of industrial sickness in this sector, a systematic body of knowledge is required to forewarn the firms of their impending failure to minimize if not to eliminate such losses.

C. Causes for industrial sickness in India:

A study conducted by the Federation of Indian Chamber of Commerce (1978) entitled "Industrial sickness – Dimensions and

Perspectives” on 637 Indian large scale units revealed that deficiency in management was responsible for 52 percent cases of sickness. Market recession and environmental factors came second with 23 percent. The other causes were technical factors and faulty initial planning (14 percent), infrastructural factors such as power cuts and shortage of critical inputs (9 percent) and labour troubles (2 percent).

The study conducted by the Planning Commission under Seventh Five Year Plan (1985-90), showed that 44 percent of the cases of industrial sickness occurred due to management incompetence, followed by production problems (32 percent) and marketing and other problems (24 percent).

According to the study by the Reserve Bank of India (1998), the main reasons for industrial sickness in Non-SSI units were internal factors such as deficiencies in project management and short coming in project appraisal, as also external factors like non-availability of raw materials, power storage, transport bottlenecks, increase in overhead costs, market condition, Government policies and lack of modernization.

D. Prediction models of industrial sickness:

A large number of researchers have worked on the prediction of industrial sickness. As a result, numerous theories have evolved in an effort to distinguish between firms that fail and that do not fail. Altman (1993) stated that 59 studies have been conducted in 19 countries

while Dimitras, Zankis and Zopoundis (1996) noted that 47 studies have been conducted in 11 countries. These studies have developed authentic models to predict potential industrial sickness, as an early warning screen. The major differences among these sickness prediction studies have been the differences pertaining to sample selection, selection of method, selection of specific ratios to develop a model etc.

At the beginning of the research period of sickness prediction, there were no advanced statistical methods or computers available for research (Fitzpatrick 1932). Jones (1989) stated that lack of a foundational theory does not necessarily handicap bankruptcy prediction research. Scott (1981) stated that the corporate bankruptcy prediction is both explainable theoretically and feasible empirically.

(i) Early period:

Prediction of industrial sickness based on ratio analysis can be dated back to 300 BC, when Euclid conducted an analysis of the attributes of ratios in Book V of his Elements. However its real use began in 1870 when the commercial banks in the USA began to request financial statements for lending purposes. The banks studied various ratios and preferred current ratio most.

In 1919, Alexander Wall of USA criticized banks for solely relying on current ratios for their lending decisions, since current ratios alone can never provide complete financial deals to a firm. Wall's study was thus a

forerunner to the fact of using more than one ratio. He used seven different ratios from thousand firms to establish his analysis.

Subsequently James Bliss attempted on presenting the first system of ratios that were related in a logical way. Bliss' work became the stepping-stone for the introduction of ratio analysis. (Horrigan 1968)

(ii) Univariate analysis

Univariate statistical techniques were the first to be used to distinguish between sick and non-sick firms. Univariate analysis examined the predictive ability of various financial ratios considering only one ratio at a time.

Paul Fitzpatrick (1932) developed a study using 13 ratios of 19 sick and matching non-sick firms, during a nine-year period of 1920-29. He concluded that impact of three ratios namely net profit to net worth, net worth to debt and net worth to fixed assets were the best predictors of failure. Winakor and Smith (1935) examined 183 firms, which failed between 1923-31 for ten years prior to failure. Twenty one financial ratios of each of the firms were examined which inferred that the ratios of net working capital to total asset were the most authentic indicator of failure. Saulinier (1938) in his study concluded that borrowing firms with poorer current ratios and net worth to debt ratios were susceptible to loan default.

Merwin (1942) used over 900 continuing and discontinuing small firms which failed during the period 1926-36 and analyzed the ratio differences for six years prior to sickness. He found three ratios to be sensitive predictors of failure. They were current ratio, net working capital to total assets and net worth to total debt.

Hickmen (1958) identified interest-earning ratios and the net profits to sales ratio as useful predictors of the default experience of corporate bond issues during 1900-1943. Moore and Atkinson (1961) concluded that the ability to acquire credit was closely related to several ratios. Seiden (1962) inferred that some financial ratios like net working capital to total assets were inversely related to the index of trade credit difficulties.

All the above studies, pertaining to univariate analysis used financial ratios as inputs for examining the economic activity. However these studies were more descriptive and were not confined to the normative problem of predicting corporate failure.

The first pioneering attempt to predict industrial sickness was initiated by Beaver (1966). He examined the predictive power of 30 different financial ratios up to 5 years prior to sickness. A univariate bankruptcy prediction model was developed and tested on financial data of 79 failed and 79 non-failed firms selected on a matching design. Beaver's research underlined three main defects of ratio analysis for

bankruptcy prediction. Firstly, not all ratios predict sickness with identical degree of accuracy. Secondly, ratios were successful more in predicting non-sick than sick firms. Thirdly financial ratios should be complemented by frequency distributions and likelihood ratios while taking decisions.

(iii) Multivariate analysis

The main significance of the multivariate approach to predict industrial sickness is the simultaneous consideration of several financial ratios in the process of prediction.

Tamari (1966) conducted the first multivariate study using the weighted composite of several ratios to indicate the possibility of failure. In 1968, Altman attempted at finding out the effect of using different combinations of financial ratios to predict business failure. He used Multiple Discriminant Analysis (MDA) as an analytical tool. He used a sample of 33 failed and matching non-failed firms and applied a five variable model using data of one year prior to failure. The model correctly classified 95 percent of total sample one year prior, which diminished to 36 percent for data five years prior to failure.

Deakin (1972) made an attempt to develop an alternative model based on a sample of 32 failed and a matching 32 non-failed firms by applying five financial ratios in each of the years prior to failure. The

study concluded that discriminant analysis had a higher degree of accuracy upto three years in advance to failure.

Marc Blum (1974) developed a Failing Company Model (FCM) to assess the probability of business failure. A twelve variable discriminant model was applied to a paired sample of 115 failed and 115 non-failed firms to evaluate predictive accuracy of the model. The model predicted corporate failure with an accuracy of 93-95 percent one year prior to failure, 80 percent two years before and 70 percent thereafter upto five years prior to failure.

Taffler and Tishaw (1977) developed a Z model for the prediction of a firm's insolvency. A linear discriminant analysis was applied to a sample of 46 failed and 46 non-failed firms, using eighty financial ratios. He concluded that four ratios-profit before tax to current liabilities, current assets to total liabilities, current liabilities to total assets and credit interval ratio measure the risk profile of the firm. Moyer (1977) retested Altman's bankruptcy prediction model using financial data of firms with assets ranging between \$15 million and \$1 billion for the period of 1965-1975. He concluded that a better explanatory power would be got from the model, if the market value of equity to the book value of debt and sales to total assets variable were eliminated from the model. Altman, Haldeman and Narayanan (1977) conducted a study on a sample of 53 bankrupt firms, out of which

29 were manufacturing and 24 were retail firms, and 58 non-bankrupt firms out of which 32 were manufacturing and 26 retail firms, using seven financial ratios. They concluded that this model, which they called it as Zeta model, was more accurate up to five years prior to failure, with 90 percent accuracy in predicting sickness one year prior and 70 percent up to five years. Fredriklust (1978) made an attempt to predict business failure based on testable financial theory of corporate failure. He identified the failure prediction variables of liquidity, profitability, solvability, variability of liquidity and variability of profitability over time, industry variables and general economic variables. The model correctly predicted 92.5 percent of sickness, one year prior to failure, which there after reduced to 70 percent for data five years prior to sickness.

Booth (1983) used a multivariate model with decomposition measures to predict financial distress. Forty two failed companies along with a matching 35 non-failed companies were considered and concluded that decomposition measures possessed different attributes for failed and non-failed companies. Fulmer, Moon, Gavin and Eswin (1984) studied 30 failed and non-failed smaller firms, chosen from manufacturing and retail industries. The model showed an overall classification accuracy of 91 percent and 88 percent, one and two years prior to sickness respectively. Casey and Bartczek (1985) developed a model using six accrual based

financial ratios and three cash flow ratios. They concluded that the classification accuracy had not improved in any way by incorporating the operating cash flow variables.

Similarly Aziz, Emanuel and Lawson (1988) formulated cash flow models using discriminant method and logit analysis. Based on five year data prior to failure, five cash flow variables were taken as inputs in both the models. However logit model depicted better results than the discriminant model. In 1993, Altman again revised his original Z score model to a four variable Z^{11} score model where he altered the Z score and the cut off points. The model was useful in industries where the financing of assets varied between firms.

Grice and Ingram (2001) conducted a study on Altman's, 1968 Z score model. The study comprised of 148 distressed and 824 non-distressed firms under the sample for the period 1985-87 and about 148 distressed and 824 non-distressed firms under the sample for the period 1988-1991. The study concluded that the prediction accuracy of Altman's model declined significantly from 83.5 percent to 57.8 percent which showed the fact that financial distress is influenced by time. Another inference was that the overall predictive accuracy was greater for manufacturing than non- manufacturing companies.

(iv) Logit and Probit analysis

One of the major limitations of the discriminant analysis was that it assumed equal probability based on sample proportions (Jones, 1987). Therefore many researchers switched over to conditional probability models to avoid this problem. The two statistical analysis, multiple logistic regression (logit) and probit provided the required conditional probability. They were solved by maximum likelihood techniques. These two techniques have been used as alternatives to discriminant analysis (Gentry et al., 1985)

Martin (1977) was the first to use logit analysis for prediction of failure in banks. The model used 58 failed and 5575 non failed banks. Twenty five financial ratios were selected and sorted out into four groups. He used six combinations of independent variables and achieved classification accuracy between 87 percent and 96 percent for failed banks and 89 percent for non-failed banks. James Ohlson (1980) used logit model by constructing three models to predict sickness. A sample of 105 bankrupt and matching 2058 non- bankrupt firms with nine financial ratios was used. The models revealed that size was an important predictor to sickness. Rose and Giroux (1984) constructed a new model using 130 ratios and tested 92 firms equally divided between failed and non-failed. Thirty four of these ratios depicted marked differences between failed and

non-failed and the study showed an overall classification accuracy of 92 percent.

Similarly, Christine Zavgren (1985) used logit analysis to 45 failed and 45 non failed firms. Seven ratios were selected. The primary significance of the study was the use of probabilities to measure financial risk.

Gentry, Newbold and Whitfield (1985) combined cash based funds flow components with traditional financial ratios in their model. Eight variables were applied to probit analysis to predict failure and non-failure probability of 33 bankrupt and 33 non-bankrupt firms. They concluded that inclusion of cash based funds flow components resulted in improving prediction accuracy. Lau (1987) developed a logit model and exhibited five financial stages for a firm namely financial stability, omitting or reducing dividend payments, technical default, protection under bankruptcy Act and bankruptcy and liquidation. Ten variables were selected and used in a sample of 350 financially sound firms and 20, 15, 10 and 5 firms in second to fifth stages respectively. The model depicted an overall predictive accuracy of 96 percent one year prior, 92 percent two years and 90 percent three years prior to failure.

Harlan Platt and Marjorie Platt (1990) used logit analysis on a sample of 60 failed and 60 matching non-failed firms. Seven categories of ratios were applied. The overall results exhibited 93 percent predictive

accuracy for failed and 36 percent for non-failed firms. Koh (1991) used probit analysis in a study of 165 failed and 165 non-failed firms and compared the predictive accuracy of the model with the assessment of auditors. While the accuracy rates for probit model was 85 percent for failed and 100 percent for non-failed firms, the accuracy rate for auditors were only 54 percent for failed and 100 percent for non-failed firms.

Johnsen and Melicher (1994) used logit analysis on a sample of 112 bankrupt, 293 non-bankrupt and 255 financially weak firms. The data was applied to two models, one of Altman's 1977 model and another of Beaver (1966). The study concluded that including financially weak classification could reduce misclassification errors.

Lennox (1999) used a logit model based on 949 UK companies and considered the impact of the economic cycle and company size on the probability of failure. The study concluded that logit and probit models were found to perform better than discriminant analysis. Similarly Barnev, Mehrez and Kline (2000) conducted a study to estimate the risk involved in predicting probability of bankruptcy, such as length of time and boundaries by including 101 bankrupt and 1326 non-bankrupt firms.

(v) Recursive Partitioning Algorithms (RPA)

Recursive Partitioning Algorithm (RPA) introduced in 1985 is a computerized, non-parametric technique based on pattern recognition that

has the features of both the univariate and multivariate procedures. It is also called as a Classification and Regression Technique (CART). It is an iterative tool which makes no assumptions about the distributions of the independent or dependent variable, thereby does not suffer from the assumptions of both the discriminant analysis and logit analysis (Jones 1987). The model used in RPA is a binary classification tree, which easily explains failure for a specific firm (Nittayagasewat, 1994). Any new object falls from the tree and is placed in a final mode that determines the group to which it belongs and also the probability associated with it (Dimitras et al. 1996). RPA does not require assumptions that the two groups measured have to be overlapping as well as attempting to reduce misclassification costs, has been its greatest advantage (Jones 1987). RPA was found to out perform discriminant analysis (Frydman et al., 1985)

Marais, Patell and Patell (1984) applied this technique to different commercial loan classifications. They compared the probit analysis to RPA using 13 ratio and non-ratio variables. However they failed to establish the superiority of RPA. Frydman, Altman and Kao (1985) were the pioneers in using RPA in comparison to discriminant analysis. Their model used 58 failed and 142 non-failed manufacturing and retailing companies. The results suggested that RPA had superior classification accuracy than discriminant analysis.

Tau (1991) described another method similar to RPA called Interactive Dichotomiser 3 (1D3) which does not use backtracking that is usually used in RPA. ID3 maximizes the probability of the split whereas RPA is designed to minimize misclassification costs. Mckee and Greenstein (2000) used the RPA 1D3 on a sample of bankrupt and non-bankrupt firms, which was proportionate to the actual filings for bankruptcy each year from 1981 to 1989, with six ratios. The study concluded that a higher overall predictive accuracy was seen in RPA than in logit analysis.

(vi) Neural Networks:

A Neural Network (NN) is a computer system made up of a number of simple, highly interconnected processing elements which process information by their dynamic state response to external inputs (Coats and Fant 1993). It is an extension of artificial intelligence and has gained practical significance by the massive parallel processing capability of computers (Altman and Saunders 1997). One of the striking merits of a Neural Network is its capacity to deal with data, which is not independent and linearly separable. The information can be organized and analyzed in such a way that complex relationships between different variables can be analyzed. Neural Networks assist to enter the various patterns into a spreadsheet so that it can be easily adapted to real world problems (Nittayagasetwat, 1994)

Coats and Fant (1991) applied a model containing 47 distressed and 47 healthy firms to test the predictive ability of NN. The model studied the performance of five ratios. The authors inferred that a neural network was more effective than MDA for classifying the firms accurately, as distressed and healthy. Salcenberger, Cinar and Lash (1992) conducted a study of credit institutions and other thrift institutions and compared logit model with a neural network model to determine which model can predict sickness better. In both the models five financial ratios were selected. The sample consisted of a hundred sick and an equal number of non-sick firms during the period 1986-87. The results concluded that NN performed better than logit model.

Tam and Kiang (1992) compared NN with linear discriminant analysis, logit and decision tree model to evaluate the predictive power of each model using bank default data. The sample had 59 failed and 59 non failed banks. The study inferred that the lowest percentage of misclassification errors was found in the NN model compared to other models. Coats and Fant (1993) attempted another study on NN to detect early warning signals of failure, comparing it with discriminant analysis. The sample included 94 distressed and 188 non-distressed firms. Five financial ratios were applied. The results confirmed that NN approach was more effective than discriminant analysis for detection of financial failure.

Back et al. (1994) compared the predictive ability of back propagation network, self organising map and Boltzman machine with each other, in predicting corporate failure. The study found that back propagation network produced better results in predicting corporate failure of Finnish companies. Nittayagasetwat (1994) presented a model with the sample of 173 failed and 1578 non-failed firms in the period 1991-93. The model applied NN and exhibited 80 percent overall classification accuracy. The model also showed that NN performed better than logit and RPA models in predicting industrial sickness.

Serrano-Cinca (1996) used NN to initiate Self-Organising Feature Maps (SOFM) as a financial analysis tool. The model used five financial ratios of 65 bankrupt and 64 solvent firms. The study declared that compared to linear discriminant analysis, SOFM provides graphic information on the financial characteristics of the firm and the type of the firm it resembles.

Lee, Han and Kwon (1996) developed a hybrid NN model to test it's bankruptcy prediction accuracy. The study included 166 Korean firms equally divided between bankrupt and non-bankrupt in the period 1979-92. The model applied 57 financial ratios. The study compared MDA assisted NN, 1D3 assisted NN and a SOFM assisted NN. The results of the study showed that the hybrid NN outperformed MDA and 1D3 assisted NN models.

Jo, Han and Lee (1997) used data from Korean companies. The study applied three forecasting techniques of discriminant analysis, case based forecasting system and NN, to a sample of 544 companies allocated equally between bankrupt and non-bankrupt firms. Twenty one ratios were used in the models. The study concluded that NN outperformed the other two models.

However Serrano-Cinca (1997) used a different model of ANN named Multi-Layer Perception (MLP). The sample used consisted of 37 solvent and 29 bankrupt banks in Spain during the period 1977-85. Nine ratios were used. The study used MLP and compared it with other statistical tools and the results of the study showed that MLP exhibited a better predictive accuracy than other models. Raminder Luther (1998) conducted a study using ANN and compared it with logit analysis. The study included 104 firms registered under chapter 11 of bankruptcy. Thirteen financial ratios were tested, for one year prior to failure. The results exhibited that ANN had a better predictive accuracy than logit model.

In 1999, Zhang, Hu, Patuwo and Indro conducted a study based on 220 firms, divided equally between failed and non-failed firms. Six variables were used. The results exhibited that the overall classification rates of NN were consistently higher than logit model.

Shah and Murtaza (2000) used NN model to accurately predict bankruptcy. A three year analysis was done to determine the financial soundness of a firm. The study comprised of 54 firms that were sound and 60 bankrupt firms in the period 1992-94. Eight ratios were included. The study reported that 73 percent of the firms were accurately classified.

Paul Pompe and Jan Bilderbeek (2005) used a dataset of 1356 failed and 3600 non-failed firms of Belgium. Both MDA and NN methods were applied considering the two aspects of bankruptcy prediction: the influence of the year prior to failure and the effects of a period of economic decline. They concluded that the prediction of bankruptcy one year prior to failure was less successful in timely prediction of failure. Also among the methods, the NN had somewhat better overall performance than MDA.

(vii) Other models

In 1982, Collins and Green compared and evaluated three statistical models namely the multiple discriminant analysis, linear probability model and logistic regression. They pointed that though the assumptions underlying the models were different; the models produced identical and uniformly good results.

Hamer (1983) compared the classification accuracy of linear discriminant analysis and logit analysis, using four sets of variables of Altman (1968), Deakin (1972), Blum (1974) and Ohlson (1980). A

sample of 44 failed and 44 non-failed firms were taken on a matching design for the period 1972-75. The results showed that all four variables sets, predicted failure of firm with identical accuracy. However LDA and logit analysis were better than quadratic model.

In 1985 Casey and Bartczak compared 60 failed companies with 230 non-failed companies. Three variables namely operating cash flow to current liabilities, operating cash flow to liabilities and operating cash flow. The study concluded that none of the cash flow variables could discriminate between the bankrupt and non-bankrupt companies with reasonably good accuracy.

Lo (1986) compared logit against discriminant analysis and found logit technique to be more effective for estimating parameters. Yet both methods had showed similar results under certain distributional assumptions. Thirty eight bankrupt firms and thirty eight matching non-bankrupt firms were tested, using six variables. The results proved that discriminant analysis and logit models were identical in their prediction performance.

In 1988, Emanuel and Lawson tested the predictive accuracy among Altman's Z and Zeta models, a cash flow model and a combined model of the above two. In the first year before failure, the combined model showed better predictive accuracy. However the overall accuracy to discriminate between bankrupt and non-bankrupt firms was the same in

all models. Holeman (1988) compared the univariate model of Beaver (1966) and the multivariate model given by Altman (1968). The study included 84 failed and 84 non-failed firms in the period 1977 to 1980. The results showed that Altman's model yielded an average Type I error of 29.8 percent and Type II error of 31 percent. The Beaver's model however yielded an average Type I error of 40.5 percent and Type II error of 11.9 percent.

The Centrale dei Bilanci in Turin developed a model on LDA in 1988 to identify firms in financial distress. Later it tested the identification of firms using NN. The model included 1000 healthy and 1000 unsound firms. Both the models exhibited over 90 percent classification accuracy. Yet the discriminant technique was showing better accuracy than NN under control period sample.

Dwyer (1992) compared and analysed traditional statistical models (Non-parametric discriminant analysis and logistic regression) and ANN models (back propagation and counter propagation) in predicting corporate bankruptcy. The results of this study found that the logistic regression model and the back propagation network model are the most accurate in classification. While the logit model presented 76.3 percent predictive accuracy, the back propagation network model achieved 78.6 percent accuracy. Altman, Marco and Varetto (1994) compared LDA and NN for distress classification and prediction. The purpose of the

study was to compare the results achieved from NN with the statistical techniques of LDA and its applications.

Dimitras, Zanakis and Zopounidis (1996) reviewed various studies on sickness prediction and classified it according to financial ratios used, industrial sector, data period and country. They considered 158 published articles from 1932 to 1994. They concluded that the most frequently used model was discriminant analysis followed by logit analysis. The solvency and the profitability ratios were more significant.

Mossman, Bell, Swarty and Turtle (1998) compared four bankruptcy prediction models. They were the cash flow model of Emanuel and Lawson (1988), market return model of Clark and Weinstein (1983), Z score model of Altman (1968) and market variation model of Aharoney, Jones and Swary (1980). They concluded that no single model is entirely satisfactory in classifying bankrupt and non-bankrupt firms. The models depicted the best discriminating ability in the year prior to failure. The classifying ability was consistent regarding the cash flow model over the last two or three years prior to failure. The results however showed that the different models could be applied for different decision-making purpose.

Turetsky and Mcewen (2001) studied 2671 companies, which under went a significant decrease in the Cash Flow from Continuing Operation (CFCO) during several years. The study tracked a series of

events that were associated with business failure. They used ex ante procedures to group the firms from initial signal of financial distress (fall in cash flow) and track them through various distress points like dividend reduction, default on loans, troubled debt restructuring etc. Of the 2671 firms, 2360 firms did not fail during the test period and 311 become bankrupt. The study emphasized the heterogeneous nature of financial distress and the potential business failure and the usefulness of accounting information in predicting a trend toward bankruptcy.

Charalambous (2000) compared the predictive performance of three NN methods namely learning vector quantization, radial basis function and the feed forward network with the performance of logistic regression and back propagation algorithm. The study included 139 pairs of bankrupt and non bankrupt US firms for the period 1983-94. The study concluded that NN showed better results compared to logistic regression and back propagation methods.

In the Indian context, a few studies have been carried out to predict industrial sickness. Rao and Sharma (1976) studied industrial sickness applying MDA to a sample of thirty failed textile firms and a matching thirty non-failed firms, using four financial ratios, best discriminating between failed and non-failed firms. They were net worth to total assets, working capital to total assets, retained earnings to total assets and earnings before interest and taxes to total assets.

Bhattacharya and Pandey (1977) studied corporate failure in India using multiple discriminant analysis, as a model to assess the corporate financial strength. Chatterjee and Roy (1978) used the asset growth as an indicator to predict industrial sickness, with a set of auto regression equations.

Gupta (1979) carried out a study on corporate sickness using a sample of 20 sick and 21 non-sick textile companies. Ratios were estimated and tested for each company for each year of a thirteen year period of 1962-74. Five profitability ratios were ultimately selected. The major finding of the study was that ratios relating to net worth were the worst predictors. Companies with inadequate equity base had little reserve strength to put up with adversities. All liquidity ratios were also poor predictors. The current ratio exhibited an error rate three times more than profitability ratios in textile companies.

Kaveri (1980) attempted to predict the borrower's health using a sample of 524 small units comprising good, regular and sick units. The MDA technique was applied using five financial ratios to assign units in the sample to one of the groups viz good, regular and sick. The degree of overall accuracy was 76 percent in the sample one year prior to sickness.

Srivatsava (1981) applied a combination of technical, operational and financial parameters to discriminate sick from healthy units. He developed a linear discriminant function consisting of seven

ratio parameters. The model using three financial ratios showed a predictive accuracy of 85 percent which increased to 90 percent when five ratios were used. When the five financial ratios were combined with the technical and operational ratios, it showed a 100 percent predictive accuracy.

A careful review of the existing literature relating to the present study thus revealed that the existing models of prediction of industrial sickness underlined the conditions of selecting the best set of variables based on a chosen criteria, adopting a matching paired design for selecting the sick and the non-sick companies as well as applying only an isolated model technique in their analysis. As far as research in India is concerned, only statistical methods like the multi-variate discriminant analysis were widely used to predict industrial sickness. There had been little effort to predict industrial sickness using soft computing models like Neural Networks.

Thus as a way of filling up the research gap in India, the current study applied the Principal Component Analysis, which possessed the merit of allowing any number of financial ratios into the model, dispensing with the need to choose the appropriate ratios. Moreover, the current study, trying to compare the Principal Component Analysis based statistical model with MDA as classifier and the soft computing model with ENN as classifier, is based on sample selection, independent of the

industry category, capital employed and size and the models were applied not only to an isolated database but also to a non-isolated database.
