# NEURAL MODEL BASED APPROACH FOR LOAN EVALUATION

by

R.S. Desikan & B. Shekar*

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Indian Institute of Management
Bangalore

*R.S. Desikan, Fellowship student, IIM Bangalore*
*B. Shekar, Assistant Professor, IIM, Bangalore*

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**ABSTRACT**

In this paper, the authors analyze the loan evaluation problem in India. They give a hierarchical decomposition of this problem which facilitates a functional fit of suitable architectures. After motivating the need for a neural approach, they propose a mixed-network architecture that consists partly of expert-system and partly of hybrid neural net independently and justify the need for such a mixed approach at appropriate places.


## 1. INTRODUCTION

In developing countries such as India, the financial institutions and development banks are considered to be the engines of economic development. They endeavour to accelerate the pace of economic growth in conformity with the national objectives. An important pre-requisite for industrial development is the availability of adequate finance. In India, all india financial institutions assist in the funding of industrial projects. 'Term loans' also referred to as 'term finance' represent a source of debt finance which is generally repayable in more than one year but less than ten years. [1,10,15]. They are employed by the companies receiving loans, to finance the acquisition of fixed assets and working capital margin.

The granting of term loans by a typical financial institution is a complex decision making process, involvinf various parameters, many of which are interdependent. This decision making process is suitable for the application of a neural approach.

In this paper, we introduce the 'term loan' evaluation problem and discuss the factors that make the granting of term loans a complex decision making activity. Subsequently, we propose a mixed expert-neural approach for solving this problem.

## 2. TERM LOAN EVALUATION

Term loans are employed mainly for acquiring fixed assets and are repayable over a period of ten years. They are different from short term bank loans which are used to finance short term working capital needs and tend to be self liquidating over a period of time usually less than one year [10 ]. Henceforth, we will refer to 'term loan' as simply 'loan'.

Loan evaluation may be viewed as the assessing of a project report - which is the basis for loan application - by a person who is in no way involved with it. It has to be borne in mind that the project is one whole and it has to be appraised as such. A few deficiencies in one area may be more than made up by the strong points under another head. The evaluating team should, therefore, judge the project as a whole without either laying undue stress on a few weak points or being misled by a couple of strong areas. Projects brought up by inexperienced entrepreneurs are bound to have some drawbacks or deficiencies. Thus, the objective of a good evaluation is to improve and revamp the project with the cooperation of the promoters.

At this point, it is important to note that though there are a large number of similarities between credit granting and loan evaluation, there exist subtle distinctions specific to the Indian context. The primary objective of both is to 'maximise the firm's wealth', but, the latter lays more stress on socio-economic objectives. Thus, location preference (e.g. backward area development), promoter's track record (eg. entrepreneur development), type of industry (eg. small scale industry) and such government policy parameters become important, even though they may not be maximizing the lending firm's wealth. While credit granting procedures are fairly streamlined [17,18] literature in the case of loan evaluation is rather sparse.

A typical loan evaluation includes the following:

- Technical feasibility analysis
- Managerial competency analysis
- Commercial and financial analysis and
- Environmental and economic analysis.

It should be noted that the above mentioned analyses are by and large independent though the empirical data used may overlap. The various factors that [illegible]

consequently the decision making process [illegible]

form of a tree in Figure 1.

Some comments and explanations for the labels in the tree are in order here.

(i) The technical feasibility of the project involves scrutinizing all factors relating to :

a. Infrastructural needs : The variables involved in this analysis are -

- proximity to the source of raw materials and market
- availability of industrial infrastructure
  * reliable power supply,
  * water supply
  * effluent disposal facilities and
  * availability of spare parts.
- labour situation
- ancillary industries
- availability of government incentives
- other facilities (medical, transportation)
- other units in the area

b. Scope of Technology & Collaboration : The technology package broadly consists of -

- process know-how (specifications)
- operating know-how (procedures)
- basic plant design

- product application know-how
- special supplies, service of technicians & training

Collaboration agreements : Collaboration agreement factors include, apart from the above,

- problems with imported technology
- credibility of collaborators
- guarantees

c. Government Regulations

- Licensing rules
- Monopolistic Restriction Trade Practices, Foreign Exchange Regulations
- Industries forbidden for granting the loans (e.g. Tobacco industry in the Indian context)

d. Selection of Technology : After an initial short listing, the choice of technology would be based on several factors such as,

- capacity of the plant
- raw materials and other inputs
- product mix and market constraints
- source of technology
- reasonableness of technology fees.

In this branch of the tree, it is worthwhile observing that none of the variables is unique to a leaf. In other words, a variable at a node may influence aspects denoted by another node. Take the example of the project 'High-Tensile

Nuts and Bolts'. If powder metallurgy process (Selection of Technology Node) is favoured and some location is selected (Infrastructural Needs Node) then for the same product if the process is changed to, say, high alloy steel forging, then the same location may not be preferred in spite of same favourable factors

Thus a comprehensive analysis (Rules and Iterative Correction) of all the aspects present in this branch ought to be performed for arriving at a measure of this decision node.

(ii) Management Competency Analysis :

The various decision variables given at node 2, as leaves in Figure 1 are influenced by all the functional parameters given in Figure 2. The arcs here depict the influences. It may be noted that this is a bipartite complete graph [ 8 ].

(iii) Commercial and Financial Analysis :

This analysis is depicted in Figure 3. It consists of commercial and financial stages. In the commercial stage, a detailed study of the demand and supply pattern of the product is undertaken to determine its marketability and profitability. Various methods such as trend analysis and regression models for estimating the demand are employed which is then matched with the available supply of the particular product. This is done both for the 'company' and the 'industry'. The financial stage involves various computations using formulae and data reduction. The parameters and factors involved in this process are given in Figures 3 and 4.

(iv) Environmental and Economic Analysis :

The performance of a project is not only influenced by the financial factors, but in India, also by environmental factors, such as -

* Employment generation
* Domestic raw materials and other inputs' consumption
* Environmental effects as pollution, effluent disposal, energy efficiency.

Other economic factors considered by lending institutions includes calculation of the Economic Rate of Return (ERR : costs are revalued using the international price, currency conversion factors and the net flow of benefits and accruals are discounted), as well as Domestic Resource Cost and Effective Rate of Protection. Based on the policies and individual expertise, these are evaluated for the project.

## 3. A NEURAL NETWORK MODEL FOR LOAN EVALUATION

In the past there have been a number of Expert Systems in the area of finance that have been fairly successful [3,14]. More specifically, financial planning [5], risk assessment [12] and credit granting [2,17] have received considerable attention. It may be noted that these systems come under the generic category of 'classifiers'. Loan evaluation too falls in this category.

It is useful to observe certain specific advantages that have stemmed from the neural approach to problem solving. Burke [7] recommends that neural approach to problems where there is large amount of data coupled with implicit dependencies and relationships and where appropriate learning procedures are available. Also, as compared to the conventional expert system approach, in the neural approach, the domain knowledge need not be formalized [11]. In loan evaluation, domain knowledge is 'fuzzy', as more Government regulations and individual expertise have to be combined. Also the availability of past data will make neural nets 'learn' more effectively in an unsupervised, self-organizing mode.

Before discussing the actual neural model, the following comments are in order.

- loan evaluation different from classification problems like bond rating, credit classification, and mortgage underwriting, in that, here the government's policies and expert's opinions are both taken into account. The resulting final decision need not be the 'best' from the finance theory's point of view.

- As shown in Fig 1, the main 'branches' of the decision tree are independent in analysis and the final variables for decision are very few. This, situation is ideal for an ES approach.

Thus, the suggested architecture is not a single network of neurons (units). There are cases in the manufacturing industry (eg. quality control) [19], where a combination of ES and neural networks has been suggested. Hence, it is proposed to have a separate neural network configuration or a simple ES configuration for each node of the decision tree, based on the merits of the situation.

### 3.1 The Neural Network Model

There is plenty of literature in the area of neural computing [4,9,13]. Artificial neural networks or neural networks consist of processing elements called 'units' that interact with each other using weighted connections. Each unit fires according to the following condition.

$$x_i w_{i,j} - y_j \geq T_j$$

| | | | |
|---|---|---|---|
| where | $y_j$ | : | output of $j^{th}$ unit |
| | $w_{i,j}$ | : | weight of the interconnection between the output of $i^{th}$ element in the previous layer and the $j^{th}$ unit in the current layer |
| | $x_i$ | : | output of $i^{th}$ unit in the previous layer connected as input to the $j^{th}$ unit. |
| | $T_j$ | : | The firing threshold of the $j^{th}$ unit. |

The network model that we propose for some of the loan evaluation problem's decision nodes, is a counter propagation network.

(i) Node 1.1.1 (Infrastructural needs Analysis) (of Fig.1)

<u>Basic Input Space</u>:

| | Variables | Values | Type |
|---|---|---|---|
| a) | Raw material & Market | Good<br>Okay<br>Bad | Continuous scale |
| b) | Industrial infrastructure | -do- | -do- |
| c) | Labour | -do- | -do- |
| d) | Ancillary industries | -do- | -do- |
| e) | Government incentives | Yes/No | Binary |
| f) | Other facilities | Good/Bad/OK | Continuous scale |
| g) | Other units in this area | -do- | -do- |

<u>Basic Output Space</u>

| | | |
|---|---|---|
| Variable | : | Basic infrastructural Needs (Node variable) |
| Value | : | Low/Medium/High |
| Mapping | : | Classification |
| Network Model | : | Counter propagation |

Counter propagation networks [7,9] are of a 'hybrid' type with a single hidden Kohonen's self-organising layer and a Grossberg's outstar output layer. It is hybrid in that while the hidden layer is trained with input vectors by

Kohmen's algorithm [9,13,16] in an 'unsupervised' way, the output layer is trained in a 'supervised' way, (the algorithm has a desired output to which it trains). The advantages of 'hybrid' or counter propagation networks are described elsewhere [7,9 ]. Fig 5 shows the full counter propagation network.

Here (in hybrid system), the first phase consists of training the Kohonen layer on the average of input values in an unsupervised/clustering way, as follows: [7,13]

1. Initialize weight vectors for the k output nodes to either small random values or small uniform values.
2. Present input vector, $\mathbf{x}$. Input $\mathbf{x}$ is multiplied by the weights on the conections from input nodes to each output node. Thus, the neural network finds

   $$\mathbf{x}^t\mathbf{w}(j)$$

   for each output node, j, which is its input. A

   competition ensues to determine the output node with the largest input. Denote the winning node, $j^*$
3. Update the weight vector for $j^*$ by the following learning rule, where $g$ is a learning rate and $0<g<1$:

   $$\mathbf{w}'(j^*) = \mathbf{w}(j^*) + \mathrm{PygPy}\{\mathbf{x} - \mathbf{w}(j^*)\}$$
4. Present next input vector.

Thus, by 'cycling', the input vectors are clustered for firing the same Kohonen neuron. Also, by additionally adapting the neighbours of the $j^{th}$ node endows the network is endowed with an ability to preserve the topology of input population.

And in the second phase, the Grossberg layer is 'supervised' to get the desired output as follows

a) The 'top down' and 'bottom up' connection weights are established first. 'Vigilance' factor is kept between 0 and 1.

b) New input vector (from Kohonen layer) is applied and the matching scores (weighted sums) are computed.

c) The 'best matching exemplar' is chosen and if vigilance score for this <u>more</u> than the pre-set value, then the weights are recomputed using the Carpenter/Grossberg algorithm [13]. Otherwise, the 'best matching exemplar' is disabled and the matching scores are recomputed.

d) Step (b) is repeated.

Since the Grossberg layer's inputs are binary, and loan evaluation variables are continuous, introducing Kohonen's layer to output binary values is ideally suited here.

Thus, through the 'competitive learning' and 'adaptivity' a mapping of input clusters gets the desired output clusters. A look at the decision operation at Node 1.1.1 of loan evaluation will confirm this architecture. Also, the unique ability to generate a function (mapping of input vector to output vector) and its reverse makes the counter propagation network an ideal candidate (i.e. even if there is partial information like the absence of a particular variable the input would still map the input to desired output cluster).

Similar nodes: Nodes 1.4, 1.0, 2.0, 3.0 where typical clustering and classification of input to output is taking place. So, the topology of network is independently proposed for the respective nodes.

### 3.2 ES application nodes

As we mentioned earlier, the loan evaluation decision model is quite unique in that not all decision nodes are candidates for the neural approach. The following Nodes -

0.0 (Overall decision to grant a deny loan),

1.2 (Government's regulations),

1.3 (Collaboration agreements),

4.0 (Environmental and Economic Analysis),

4.1 (Environmental Analysis),

involve knowledge which is highly domain-dependent. Also, these nodes involve non-quantifiable, volatile, qualitative parameters. Depending on the government's policies and the market situation, rules are modified, deleted or added.

Nodes 3.1, 3.2 and 4.2 involve extensive data reduction (calculation of cash-flows and financial ratios from basic figures) and rule formulation based on reduced/inferred data.

At all these nodes, the application of neural nets would not only be cumbersome but also impractical in view of the undertainty of even the number of variables involved the rules may be modified, deleted or added. Thus, applying a conventional ES approach would be better for knowledge acquisition and maintenance.

## 4. Conclusions

In this paper we have analysed and disucssed the suitability of the Expert System - Neural Net approach to the loan evaluation Problem. We have also proposed a plausible architecture for this approach. It should be noted that this mixed-approach has several advantages. We mention a few.

(a) Each nodal network is small and independent thus facilitating higher efficiency,and easier training and maintainability.

(b) Partitioning the overall decision space helps in creating transparency. Consequently ,the confidence in the system improves.

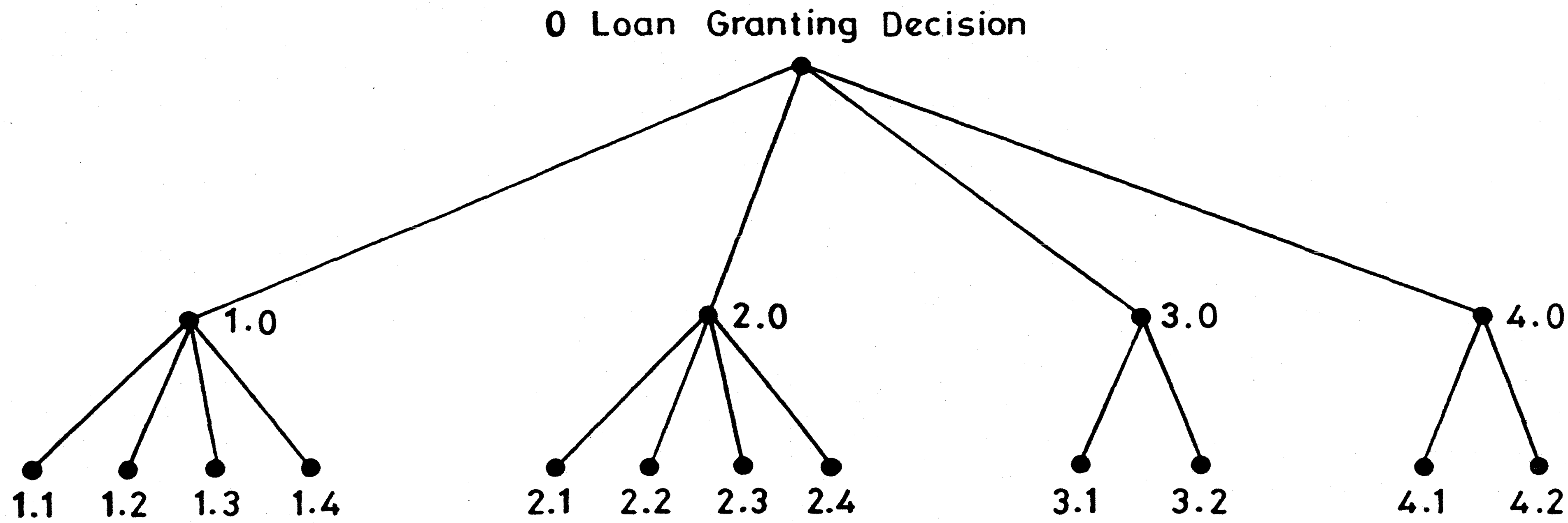
(c) Each nodal network, be it of the neural or expert model, permits the flexibility of having a measure on the agreement with other networks with regard to higher level decision making toward the root of the tree.

However, the following thinking of Eliot [6] warrants some examination!

> " ... Neural networks promise to probe the mind's mysteries, simultaneously opening research floodgates into the vast reaches of

mathematics and experimentation. ... Currently, scientists view neurons as single processing elements combining input signals by using differential equations. Even though neural networks can modify coefficients of these equations during neural activity, scientists still treat neurons as simple equation transfer functions. .... Opponents might mumble that having to understand the natural neuron leaves us with two unknowns : It's unknown what a neuron really is and does, and it's unknown how we should computationally construct such a thing. Proponents might counter that we know enough and that our experimentation could help bio/chem/phys workers - thus pushing all of us further forward. .... Can we reverse-enqineer the brain this way? Or, should we use a more symbolic approach? And, out of a symbolic (read that "traditional AI") - attack, can we discover underlying mechanics?"

Though much of what has been said is true, it should not be forgotten that 'science' itself has developed this way. From a black-box point of view we have partitioned the decision space of loan-evaluation analogous to the human approach. What is inside the black-box though debatable, as stated by Eliot, is nevertheless 'attemptable'.




1.0 Technical Feasibility-Analysis

1.1 Infrastructural Needs

1.2 Technology & Collaboration

1.3 Government Regulations

1.4 Selection of Technology

2.0 Management Competency-Analysis

2.1 Track Record

2.2 Leadership

2.3 Competency of team

2.4 Organizational Structure

3.0 Commercial & Financial Analysis

3.1 Commercial Analysis

3.2 Financial Analysis

4.0 Environmental & Economic Analysis

4.1 Environmental Analysis

4.2 Economic Analysis

Figure 1. Decision Tree for Loan Evaluation.

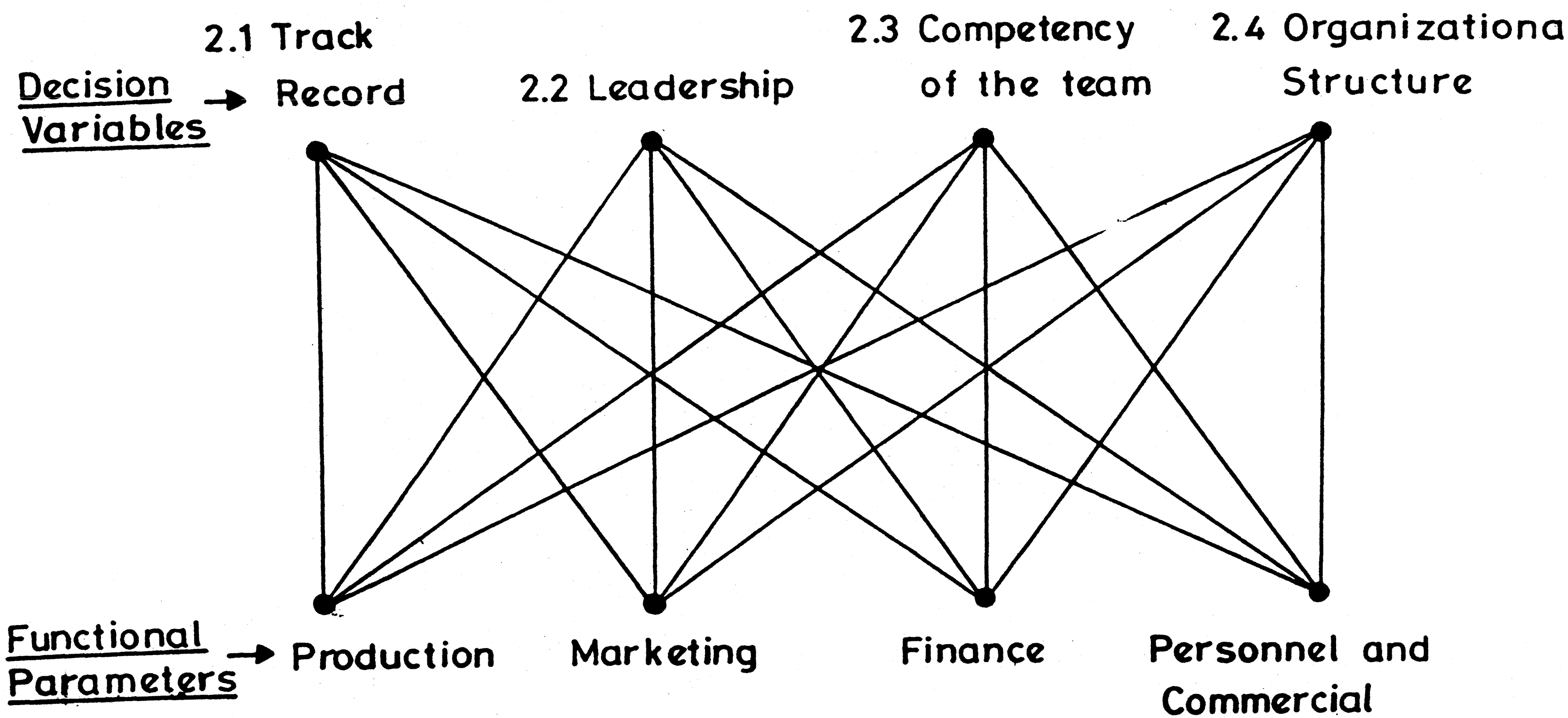



Figure 2: Functional Parameters for Management Competency Analysis.

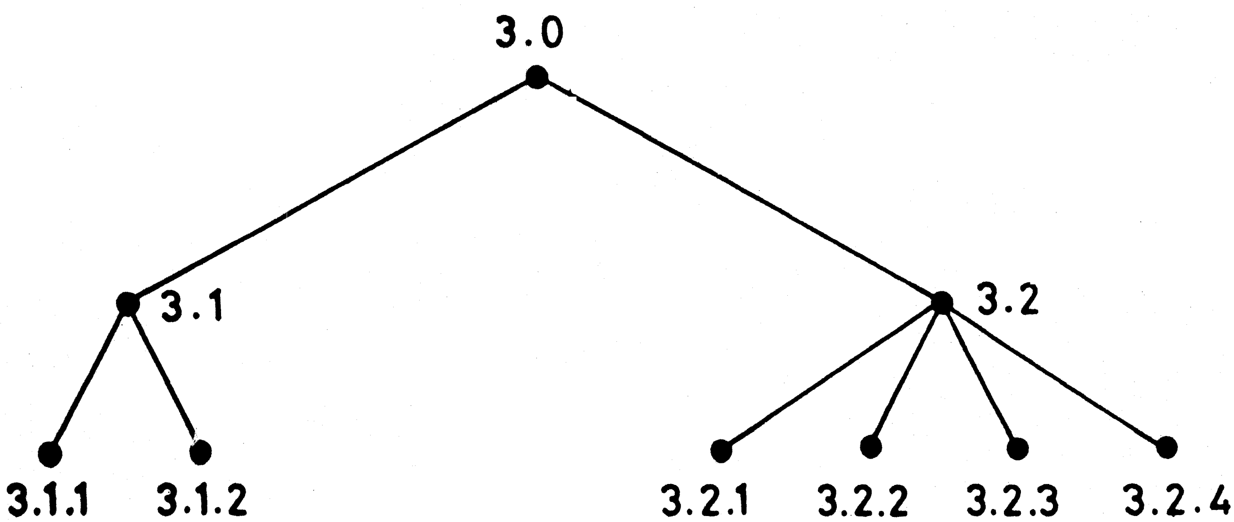



Figure 3. Decision Variables for Commercial and Financial Analysis.

| | |
|---|---|
| 3 0 | Commercial and Financial Analysis |
| 3.1 | Commercial Analysis |
| 3.1.1 | Demand and Supply Analysis |
| 3.1.2 | Profitability Analysis |
| 3.2 | Financial Analysis |
| 3.2.1 | Determine Cost of Project |

- Land and Site
- Buildings
- Plant and Machinery
- Special Training
- Miscellaneous Fixed Assets
- Preliminary and Capital Issue
- Pre-operative Expenses
- Contingency
- Provision for Working Capital Margin

| | |
|---|---|
| 3.2.2 | Sources of Funds and Means of Finance |
| 3.2.3 | Break-even Analysis |
| 3.2.4 | Ratio Analysis and Projected Balance Sheet |

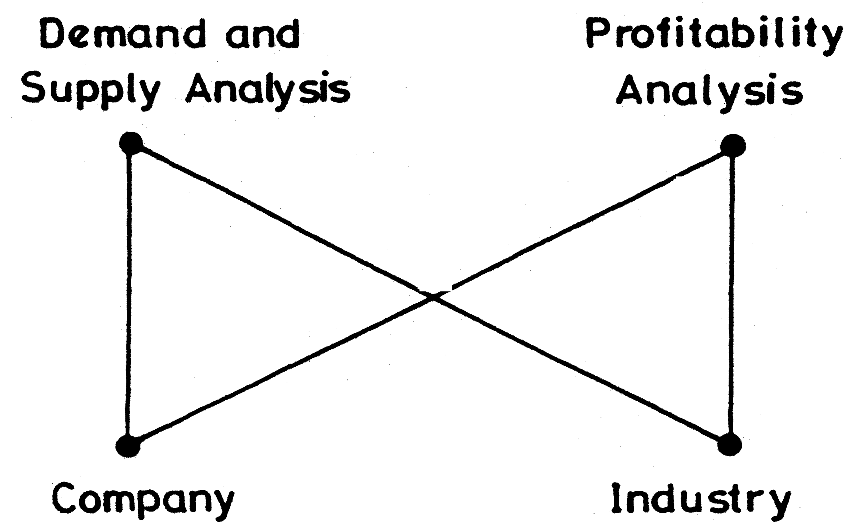



Figure 4: Commercial Analysis.

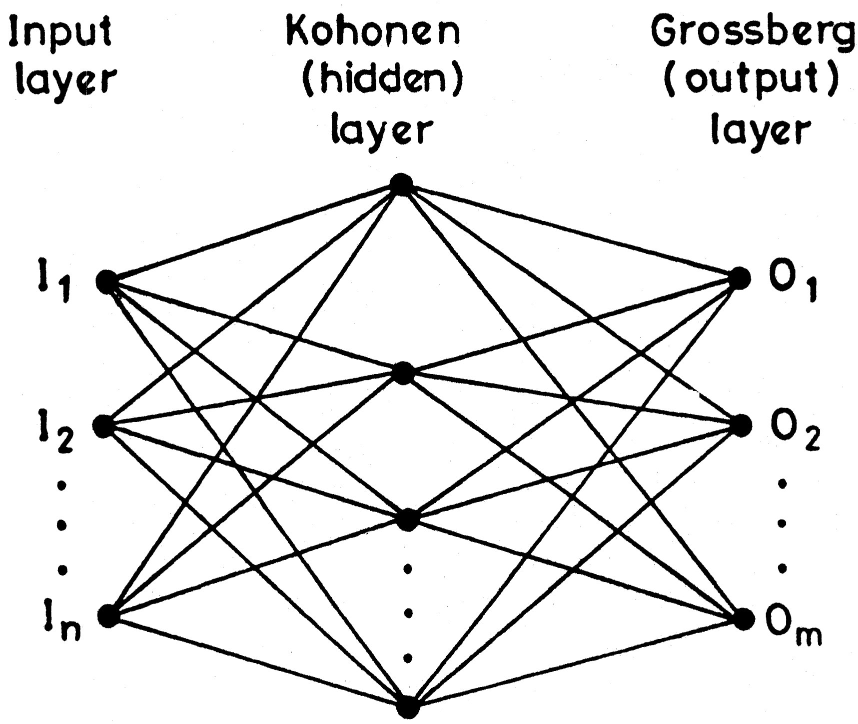



Figure 5. Self-organising Counter-propagation network.

I - Input vector

O - Output vector

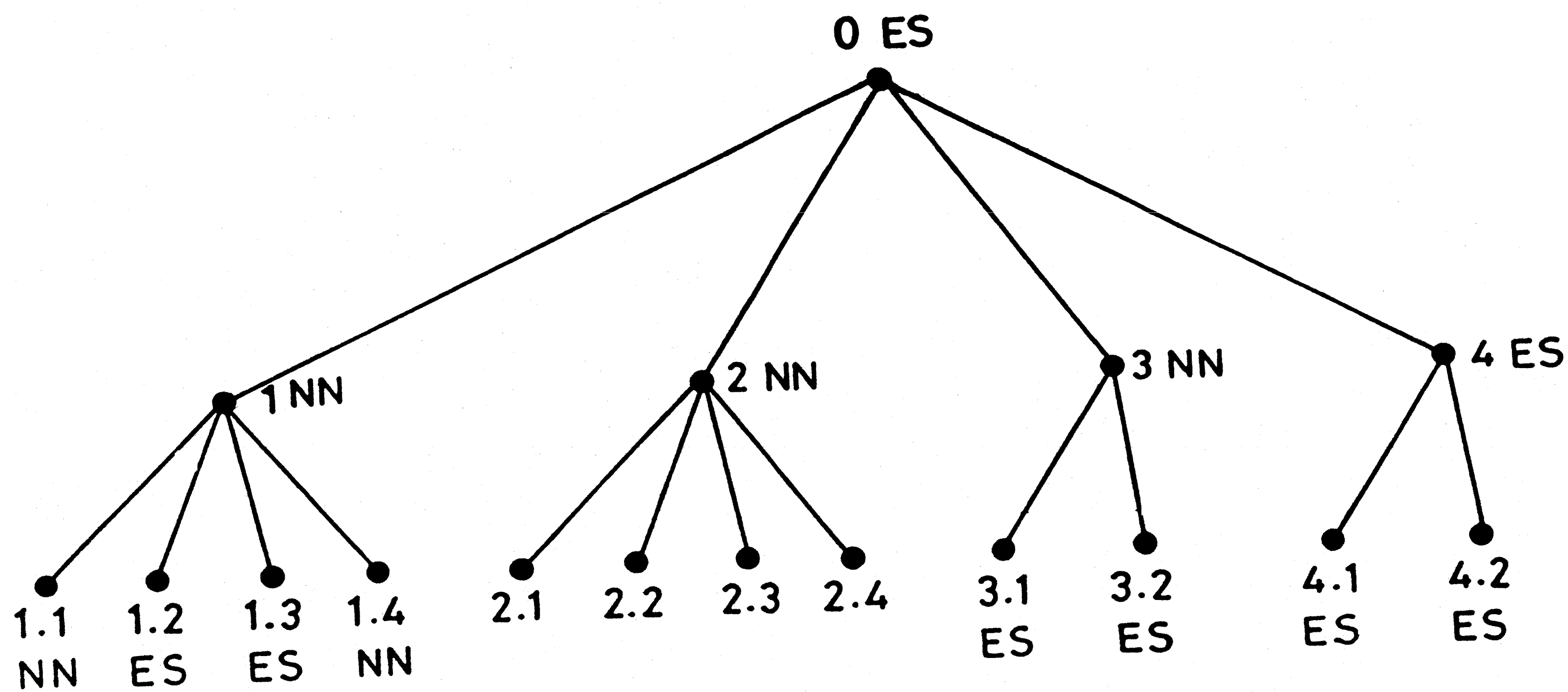



Figure 6. Mixed Network Architecture for Loan Evaluation model.

NN : Neural Net

ES : Expert System

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