# Chapter 3 Research Methodologies and Design of Study

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3. Research methodologies and design of study

Abstract
This chapter is divided into two sections, the first section deals with the introduction of methodologies and techniques applied in the research. The second section deals with study of problem. The study of various methods/techniques help to understand how these can be applied to current credit risk evaluation problem in hand. Second section describes the process of identification and formulation of the research problem. This chapter also discusses the foundation work done by earlier researchers and scope of the present research.

3.1 Research methodology

3.1.1 Expert systems Architecture
Expert systems are computer programmes that can reproduce the behaviour of human experts in specific problem domains. Expert systems represent an opportunity to assist users lacking expertise in a specific area to carry out complex tasks, promote efficient governance and enable sustainable decision-making in developing regions. Expert systems have enjoyed considerable success in many scientific and technological applications but their application in the field of management is relatively recent. The real life decision contexts represent a variety of complex situations and require the involvement of experts; decisions have to be made on the basis of incomplete or uncertain information as well-defined rules for action in a given context may not exist. Hence, the expert must rely on past experiences, heuristics (rules of thumb) and his/her knowledge in the specific subject. State-of-the-art computing technology facilitates automating some complex decision processes, allowing representation of human expertise on a machine.

The main elements of a rule-based system are facts, rules, and the engine that acts on them. The core of the architecture shown in Figure-6 consists of the working memory (fact base), the rule base (knowledge base) and the inference engine (rule engine). The working memory contains facts that are the smallest piece of information supported by the rule engine. The rule base contains rules in the form of if-then statements, which represent the knowledge provided by the user and/or an expert of the problem domain. The inference engine matches facts in the working memory against rules in the rule base, and it determines which rules are applicable according to the reasoning method adopted by the engine. The user interacts with the system through a user interface that may use menus, natural language or any other style of interaction. Almost all expert systems have an explanation system that allows the system to explain its reasoning to the user.
Some systems have a knowledge base editor, which helps updating and checking the knowledge base. The inference engine, the user interface, the explanation system and the knowledge base editor constitute the expert system shell. In contrast, the user, the fact base and the knowledge base, which are domain-specific knowledge, are not considered as part of this shell. The usage of expert system shells generally reduces the cost and time of development. Most modern rule engines can be seen as more or less specialized expert system shells, with features to support operation in specific environments or programming in specific domains.

Advantages of expert systems are as follows

- Provide rapid and informed decision-making
- Enable users to perform complex procedures
- Reduce time taken to perform complex calculations
- Combine collective knowledge of many experts
- Organize information and preserve knowledge
- Disseminate valuable and scarce expertise
- Maintain continuity and accuracy of decisions
- Provide transparency through audit trails
- Avoid training or acquiring human expertise
- Avoid problems associated with human errors
- Low overhead once initial set-up costs is outlaid
- Can easily reproduce solution
3.1.2 Jess (Java Expert System Shell)

Jess (Java Expert System Shell) is a fast and powerful rule engine for the Java platform, which supports the development of rule-based systems that can be tightly coupled to code written entirely in Java. Jess is also a powerful Java scripting environment, from which it is possible to create Java objects, call Java methods, and implement Java interfaces without compiling any Java code. The Jess rule engine does not contain any facts or rules until they are loaded, respectively, into the working memory and rule base. The working memory contains facts and for this reason it is also called a fact base. Facts are all pieces of information the Jess rule engine works with, and they can be used as both LHS and RHS of the rules. The Jess working memory is similar to a relational database, where facts are like rows of the database maintained with indexes to speed up searching in the working memory. The rule base contains all the rules that the engine knows. In rule-based systems, rules are sometimes stored as strings of text, but Jess holds a rule compiler for processing them into some format that the inference engine can manage more efficiently. Particularly, the Jess’s rule compiler builds a Rete Network, which is a complex and indexed data structure for speeding up rule processing.

The inference engine decides what rules to fire and when. It consists of the pattern matcher and the agenda. The pattern matcher decides which rules to activate based on the current contents of the working memory. A rule is activated when the pattern matcher finds facts that can satisfy the RHS of this rule. This is not a trivial task if we take into account that the working memory may contain thousands of facts and the rule base contains complicated rules with several premises and conclusions. In these cases, the pattern matcher might need to search through millions of combination of facts to find those combinations that satisfy rules. Fortunately, efficient ways exist to solve the problem, since a lot of research has focused on this area. The agenda stores the list of rules that could be potentially fired. The agenda consists of an ordered list of rules, whose RHS can be executed. The agenda has to decide which rules have the highest priority and should be fired first. This process is called conflict resolution strategy and usually it takes into account the specificity or complexity of each rule; the relative age of the LHS of each rule in the working memory.

3.1.3 FuzzyJess

Bob Orchard, the author of FuzzyJess, the Java-based, fuzzy logic API extension to Jess, and a veteran of many expert systems projects, discusses the state of artificial intelligence (AI), expert systems (ES), and the richness of possibilities for Java developers to utilize his tools for building fuzzy rule-based expert systems. FuzzyJ Toolkit is used to define fuzzy concepts and to create fuzzy rules in a Java setting. Much of the work is based on earlier experience with the FuzzyCLIPS.
3.1.4 Neuro-Fuzzy Systems

A neuro-fuzzy system is based on a fuzzy system which is trained by a learning algorithm derived from neural network theory to determine its parameters (fuzzy sets and fuzzy rules) by processing data samples. Modern neuro-fuzzy systems are usually represented as special multilayer feedforward neural networks like ANFIS, FuNe, Fuzzy RuleNet, GARIC, or NEFCLASS and NEFCON. However, fuzzifications of other neural network architectures are also considered, for example self-organizing feature maps. In those neuro-fuzzy networks, connection weights and propagation and activation functions differ from common neural networks. The (heuristical) learning procedure operates on local information, and causes only local modifications in the underlying fuzzy system.

A neuro-fuzzy system can be viewed as a 3-layer feedforward neural network. The first layer represents input variables, the middle (hidden) layer represents fuzzy rules and the third layer represents output variables. Fuzzy sets are encoded as (fuzzy) connection weights. It is not necessary to represent a fuzzy system like this to apply a learning algorithm to it. However, it can be convenient, because it represents the data flow of input processing and learning within the model. Sometimes a 5-layer architecture is used, where the fuzzy sets are represented in the units of the second and fourth layer. The learning procedure of a neuro-fuzzy system takes the semantical properties of the underlying fuzzy system into account. This results in constraints on the possible modifications applicable to the system parameters. The fuzzy rules encoded within the system represent vague samples, and can be viewed as prototypes of the training data. The following Figure-7 shows the structure of neuro fuzzy system.

![Figure-7 Structure of a NeuroFuzzy system.](image-url)

3.1.5 Genetic algorithms
Genetic algorithm is an optimization technique inspired by biological theories about evolution. It is a stochastic algorithm, starts with a population of candidate solutions, does not use gradient information. Crossover and mutation are two operations of GA (Genetic Algorithm) uses a fitness criterion to bias the evolution towards desired features. Mutations can be defined as they are responsible for the origin of new traits and therefore mutations are the source of all variations. Sudden, stable, discontinuous and inheritable variations which appear due to permanent change in the genotype of the organism. They are responsible for the origin of new traits and therefore mutations are the source of all variations.

**Algorithm canonical GA**

1. Generate random population.
2. Evaluation : Evaluate the fitness of each chromosome in the population.
3. Variation : Repeat the following steps
4. Selection : Select two parents according to their fitness
5. Crossover : Perform crossover according to crossover probability
6. Mutation : Mutate each offspring according to mutation probability
7. Acceptance : Add offspring to new population
8. If the end condition is not satisfied, go to step 2
9. Stop

**3.1.6 Evolutionary computing**

Evolutionary algorithms are soft computing techniques inspired by Charles Darwin’s “Survival of the fittest” theory. The general idea is to have a population of solution candidates (individuals) for the problem. A problem specified evaluation function is used to measure the fitness of each individual. The first population can be initialized with random parameters, but usually all other populations after that contain individuals that derive “good” parameter values from their parent populations. Different kinds of crossover, mutation and stochastic operations are performed when creating new populations. Evolutionary algorithms can be effective for finding global optimum of complex and non-continuous problems that are too difficult to solve using derivative-based methods. When using large and n-dimensional search space, evolutionary algorithm cannot always find the best possible solution in reasonable amount of time. However, solutions can still be “good enough” when compared to use of the brute force approach, which means the evaluation of all possible solutions. When the search space is large, brute force cannot be used because of so called combinatorical explosion that means too large a number of solution candidates to evaluate.
3.1.7 Knowledgebase Design

Knowledge intensive activities, products and services have increased substantially over the last decades calling for more systematic management of knowledge as resource or production factor. Knowledge assets are recognized as primary sources of competitive advantage. Consequently, Knowledge Management (KM) approaches focus on efficient deployment of these assets and support their creation, transfer and (re-)application in order to improve productivity of knowledge work. Knowledge management typically aims at increasing visibility of knowledge, codifying it and enhancing knowledge sharing in order to improve (re-)use of knowledge assets.

A rule statement is a logical statement that is built in to capture and implement business process logic. A business rule is the familiar, generic connotation that describes a well-defined business process. Such processes provide a way to define the operations, definitions and constraints applied to organizational procedures in a way that allows the organization to achieve organization. Banks that are able to make better risk management and business decisions are more likely to remain profitable, and accurate data supports more informed decision making. As outlined in Basel II, the internal ratings-based (IRB) approach requires banks to meet historical data requirements for estimating probability of default (PD), exposure at default (EAD), and loss given default (LGD), a condition that is difficult to fulfill without substantial histories of loss data.

A Knowledge Based System (KBS) is a computer program that encapsulates expertise, elicited from experts in the form of business concepts and the relationships between them. The expertise was compiled over almost a decade by bankers and credit. The system is implemented in proprietary expert systems experts from a variety of institutions language called Syntel™. The basic component of the Syntel™ language is called a node. Nodes represent business concepts and a particular knowledge base's network architecture describes how these concepts relate to each other for Management quality Figure-7.

![Figure-8 Management Quality Knowledge Representation](image-url)
3.1.8 Role of credit rating agencies

The Indian credit rating industry has evolved over a period of time. Indian credit rating industry mainly comprises of CRISIL, ICRA, CARE, ONICRA, FITCH & SMERA. CRISIL is the largest credit rating agency in India, with a market share of greater than 60%. It is a full service rating agency offering its services in manufacturing, service, financial and SME sectors. SMERA is the rating agency exclusively established for rating of SMEs.

Small and Medium Enterprises Rating Agency (SMERA)

SMERA a joint initiative by SIDBI, Dun & Bradstreet Information Services India Private Limited (D&B) and several leading banks in the country. SMERA is the country's first rating agency that focuses primarily on the Indian MSME segment. SMERA has completed 7000 ratings.

CRISIL

CRISIL is the largest credit rating agency in India. It was established in 1987. The world’s largest rating agency Standard & Poor's now holds majority stake in CRISIL. Till date it has rated more than 5178 SMEs across India and has issued more than 10,000 SME ratings.

CARE Ratings

Incorporated in 1993, Credit Analysis and Research Limited (CARE) is a credit rating, research and advisory committee promoted by Industrial Development Bank of India (IDBI), Canara Bank, Unit Trust of India (UTI) and other financial and lending institutions. CARE has completed over 7,564 rating assignments since its inception in 1993.

ONICRA Credit Rating Agency

ONICRA was established in 1993 by Mr. Sonu Mirchandani as a rating agency. It analyzes data and provides rating solutions for Individuals and Small and Medium Enterprises (SMEs). ONICRA has an extensive experience in operating a wide range of business processes in areas such as Finance, Accounting, Back-end Management, Application Processing, Analytics, and Customer Relations. It has rated more than 2500 SMEs.

Fitch Ratings

Fitch Ratings is a global rating agency committed to providing the world's credit markets with independent and prospective credit opinions, research and data. Fitch Ratings is headquartered in New York and London and is part of the Fitch Group.
ICRA
ICRA was established in 1991 by leading Indian financial institutions and commercial banks. International credit rating agency, Moodys, is the largest shareholder. ICRA has a dedicated team of professionals for the MSME sector and has developed a linear scale for MSME sector which makes the benchmarking with peers easier. Sovereign credit ratings estimate the future ability and willingness of the sovereign governments to service their commercial and financial obligations in full and on time. The process of evaluating the nations and assigning ratings is a business involving various international rating agencies. Governments seek the credit ratings so as to improve their access to the international capital markets.

Credit Ratings are
- An opinion on probability of default on the rated obligation
- Forward looking
- Specific to the obligation being rated

But they are not
- A comment on the issuer's general performance
- An indication of the potential price of the issuers' bonds or equity shares
- Indicative of the suitability of the issue to the investor
- A recommendation to buy/sell/hold a particular security
- A statutory or non-statutory audit of the issuer
- An opinion on the associates, affiliates, or group companies, or the promoters, directors, or officers of the issuer

3.2 Design of the Study
The literature on MSME loans evaluation is rare, but there are many articles on personal loans evaluation. This paper presents a hybrid soft computing evolutionary neuro-fuzzy technique. MSME clients approach the banks and financial institutions for credit to conduct their operations. The credit rating executives gather information about the clients in order to take an informed decision about client creditworthiness and the prospects of repayment. The algorithm for credit risk evaluation of the client is shown in the flow chart Figure-8 below.
3.2.1 Identification of client type based on investment
MSME client is identification is carried out based on the investment as shown in Table-4 of MSME definition by Govt. of India MSMED act.

3.2.2 Identification of client type based on business
Identification of the client category is the first step in credit risk evaluation.

The MSME client’s business categories are classified as shown in Table – 4 below

Table-4 MSME client business categories

<table>
<thead>
<tr>
<th>Sl. No.</th>
<th>Client Category</th>
<th>Sl. No.</th>
<th>Client Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.0</td>
<td>MSME Manufacturing sector</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.1</td>
<td>Micro enterprise - Manufacturing</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.2</td>
<td>Small enterprise - Manufacturing</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.3</td>
<td>Medium enterprise - Manufacturing</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2.0</td>
<td>MSME Service sector</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2.1</td>
<td>Micro enterprise - Service</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2.2</td>
<td>Small enterprise - Service</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2.3</td>
<td>Medium enterprise - Service</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.0</td>
<td>MSME - Trading sector</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.1</td>
<td>Micro enterprise - Trading</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.2</td>
<td>Small enterprise - Trading</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.3</td>
<td>Medium enterprise - Trading</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

3.2.3 Identification of client type based on Govt. policy
The Government releases its industrial policies of rebates, subsidies, exports promotions time to time and implements them through banks and financial institutions. The government has classified industries and business sectors as follows

- Priority sector - Agro, food based drugs etc.
- Normal sector - Mobile canteen, travel, soaps, oil etc.
- Restricted sector - Fruit juice, mineral water, resorts, floriculture etc.
- Prohibited sector - Vanaspati, malt extraction, ice plant and acid plant.

The credit granting decision period is decided after a close scrutiny of the factors such as the estimated project cost, cost ceiling, type of industry such as IT related or transport sector. The loan amount to be granted varies from the type of organization such as proprietary, partnership, corporate body or cooperative. The collateral security is computed as the percentage of loan amount and it normally varies from 50% to 200% sector wise depending upon the purpose of loan. The promoter’s contribution is decided upon the kind of region, whether rural or urban, private or government sponsored schemes such as National Equity Fund scheme (NEF) or Mahila Udyam Nidhi (MUN) ranging from 20% to 22.5% with only 10% for government schemes.

3.2.4 Identification of client type based on credit portfolio
Lenders identify the client based on business portfolio of the client. Credit budgets are allocated based portfolio risk analysis. The various types of risks, which banks face in the credit domain, do not necessarily reside in a single transaction. It is odd that even today most credit risk analysis is based on a transaction rather than portfolio.
3.2.5 Identification of client type based on legal status of business
Credit risk executives identify the client based on legal status of business. Business registration certificates will give the client legal status such as Public Ltd, Private Ltd., Proprietary, Partnership etc.

3.2.6 Identification of major risk categories
Client category identification will help us in identification of major risk parameters to determine the client credit worthiness. The major risk parameters and their significance in decision making various from one client category to other.

1. Management risk
2. Business risk
3. Industry risk
4. Technical feasibility risk
5. Finance risk
6. Political risk
7. Environmental risk
8. Foreign currency/ exchange rate risk
9. Resources risk
10. Market risk
11. Legal/regulatory risk

3.2.7 The lending decision - participating institution model
Researchers conducted interviews with credit rating executives, studied lending policy guidelines, risk evaluation documentation pertaining to underwriting process and identified the key dimensions employed by the bank when assessing small business loan applicants.

- Repayment capacity - accounts for 35% of the credit decision and comprises the evaluation of financial parameters such as current, quick and debt/service ratio and an assessment of the borrower’s credit history
- Financial position - accounts for 20% of the credit decision and comprises the evaluation short and long term repayment capacity backed by financial statements, representative of an adequate financial condition
- Character - accounts for 10% of the credit decision and comprises personal factors of the borrower such as honesty, propensity to meet with obligations, disposition, availability and cooperation with bank officials and managerial experience
- Business and industry conditions - accounts for 10% of the credit decision and comprises the evaluation of physical conditions of the business and industry conditions
- Collateral - accounts for 25 percent of the credit decision and comprises the evaluation of identifiable and accessible assets, whose net value covers the loan principal, interests and escrow

3.2.8 Characteristic features of good credit rating system
- A strong credit rating system minimizes the risks being taken, while holding the commercial loan and helps the lending officials to identify, monitor, and mitigate these risks in a better way
A good risk-rating system is a significant asset to the bank, which helps in proper documentation, comprehension and an objective evaluation.

An effective risk-rating system can act as an early-warning system that cautions the management about impending risks. It also boosts the talent and efficiency of the staff and ensures the financial health of the banks.

A Blend of objective and subjective elements of credit ratings can prove useful in the assessment of risk ratings.

### 3.2.9 Credit risk models
- Credit spread risk
- Downgrade risk (credit rating)
- Default risk (default probability)
- Recovery rate risk (recovery rate)
- Exposure at default (loss given default)
- Portfolio diversification (correlation risk)
- Historical Probabilities vs Risk-Neutral Probabilities

### 3.2.10 Credit rating standards
Credit ratings are the primary indicator of a financial institution’s commercial credit exposure based on assessments of the borrower creditworthiness and the severity of the estimated loss. These ratings shape and reflect the nature of commercial lending decisions made from loan inception until loan pay-off. A strong credit rating process will make clear the risks being taken while holding the commercial loan and help lending officials better identify, monitor, and mitigate the risks. Commercial credit rating systems are used for a variety of purposes, such as determining loan approval requirements, identifying problem loans, performing portfolio management and loan monitoring, pricing loans, and supporting the loan loss reserve calculations. In short, risk rating systems are generally an important element of a safe and sound member business lending program. Table-5 shows standard credit ratings.

Table–5  Standard credit ratings
3.2.11 Credit risk evaluation process
The study of documents, personal interaction with experts and questionnaire techniques are used in determining the weights for each of the risk parameters (linguistic variables). The weights are assigned to each of these linguistic variables. These risk parameters are organized in to hierarchical levels called credit rating framework. The credit rating frameworks are designed for trading, manufacturing and service sectors. The algorithm used in credit risk evaluation process resemble credit rating executive thought processes.

3.2.12 Problem formulation - Credit risk evaluation
The repayment period is decided after a close scrutiny of the factors such as the estimated project cost, cost ceiling, type of industry such as IT related or transport sector. The loan amount to be granted varies from the type of organization such as proprietary, partnership, corporate body or cooperative. The collateral security is computed as the percentage of loan amount and it normally varies from 50% to 200% sector wise depending upon the purpose of
loan. The promoter’s contribution is decided upon the kind of region, whether rural or urban, private or government sponsored schemes such as National Equity Fund scheme (NEF) or Mahila Udyam Nidhi (MUN) ranging from 20% to 22.5% whereas only 10% for government schemes. Table: 6 Risk categories, weights. This is the system of credit ratings Standard & Poor’s applies to bonds. Ratings can be modified with + or – signs, so a AA– is a higher rating than an A+ rating. With such modifications, BBB– is the lowest investment grade rating. Other credit rating systems are similar. Source: Standard & Poor’s.

Lists of problem loan early-warning signals are worth noting as supplements to the loan-structuring approach, based on practical experience

1. The company lacks an overall strategic plan, or plan is not followed
2. Internal reporting is weak, particularly for financial statements
3. Personnel turnover is high in key positions
4. Reputation in the industry or market is falling
5. Vendors have tightened their credit terms
6. Maintenance of machinery and the premises appears to be neglected
7. Change in external accountant or the financial reports arrive later and later
8. Other creditors take additional collateral (monitor UCC filings)
9. Non-compliance with loan agreement covenants (if applicable) occurs
10. Checking accounts are overdrawn
11. The borrower is generally evasive

3.2.13 Research Study Centres

- State Bank of India Zonal Office, Hubli
- SBI Commercial Branch, Belgaum
- Canara Bank, Bagalkot
- Karnataka State Finance Corporation, Bagalkot
- Software Technology Entrepreure Park, Bagalkot
- Rural Development Foundation, Bagalkot

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7. Resource Persons in Conferences Attended