Chapter 6

Risk Index Model for Portfolio Optimization using Rule Based Fuzzy Expert System

6.1 Introduction

The main aim of this chapter is to design a portfolio optimization technique for stock market investors. After the prediction of stocks, it’s very important for investors to decide, how much capital they want to invest in one stock. Modern portfolio theory (MPT) plays a very important role in portfolio construction for stock market investors in modern finance theory. The main assumption of MPT is, investors are risk averse i.e. if there are two portfolios with the same level of return, investors will choose the portfolio with lower risk. Therefore, an investor will take the chance to increase risk only if risk will be compensated by higher expected return. Expected return and risk on the portfolio are given as follows (Markowitz [73]):

- Portfolio return is weighted combination of the returns of the individual assets.

- Portfolio variance is the function of correlation \( \rho_{ij} \) of all asset pairs \((i, j)\).
  
  - Expected Return

\[
E(R_p) = \sum_i w_i E(R_i),
\]
where $R_p$ is the return on Portfolio, $w_i$ is the weighing factor of asset $i$ and $R_i$ is the return on asset $i$.

- Portfolio Variance

$$\sigma_p^2 = \sum_i w_i^2 \sigma_i^2 + \sum_{i \neq j} w_i w_j \sigma_i \sigma_j \rho_{ij},$$  \hspace{1cm} (6.1.1)

where $\rho_{ij}$ is the correlation coefficient between return on assets $i$ and $j$ and $\sigma$ represents the standard deviation of returns on an asset.

- Portfolio Risk

$$\sigma_p = \sqrt{\sigma_p^2}.$$  

The objective of this proposed model is to extend the MPT model in hybrid decision making expert system. The proposed portfolio model will help stock market dealers, investment managers and individual investors to take decisions by suggesting investment in a group of securities when strong chances of possible profit from these securities are available.

In order to generate a portfolio for stock investors, one way is to study the financial performance of the listed companies in the stock before investment. In this process, financial ratios are mostly undertaken as the evaluation criterion (Walter [89]). Since some financial ratios behave similar to each other, so consideration of all the financial ratios for the evaluation process would be inefficient and would make the system complex. To avoid this, financial ratios can be partitioned into clusters (Wang and Lee [90]). For the selection of more efficient financial ratios we have used a clustering technique proposed by Wang and Lee [90], based on these financial ratios we have designed a portfolio management technique for investors.

A large number of companies listed in a stock exchange, so they have to be ranked first and this can be done by using financial ratios. Efficient financial ratios are chosen by a clustering method and then a rule based fuzzy expert system developed to support investors and portfolio managers in their investment decisions. Finally, a linear programming model is developed for the construction of the portfolio. The proposed model has been evaluated using two data sets of BSE30. One data set
has been taken from recession period and one from growing market. Also, the
effectiveness of proposed portfolio model has been proved by comparing the results
with the benchmark index of BSE30. The flowchart of proposed model is given in
Figure 6.1.

6.2 New Portfolio Management System

Proposed expert system helps to evaluate stocks of BSE30, design a portfolio and
recommend it to the investors of BSE30 in accordance with their stock pay off and
preferences. We have evaluated the new technique using data set of BSE30. BSE30
is a free-float weighted Indian stock market index consisting of 30 financially sound
and well-established companies. These 30 companies represent different sectors and
are all actively traded stocks in the Indian economy. We have divided these com-
panies into eight sectors as shown in Table 6.1. The data has been taken for the
years 2008 (recession period) and 2012 (growing market period). By looking at the
historical data set of the years 2008 and 2012, we have designed a portfolio for the
years 2009 and 2013 respectively.

<table>
<thead>
<tr>
<th>#</th>
<th>Sector</th>
<th>Companies in the Sector</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Computer and Telecom</td>
<td>Infosys, Wipro, TCS, Airtel</td>
</tr>
<tr>
<td>2</td>
<td>Bank and Finance</td>
<td>SBI, HDFC, ICICI</td>
</tr>
<tr>
<td>3</td>
<td>Auto</td>
<td>Hero Honda, M&amp;M, Bajaj, TATA Motors, Maruti Suzuki</td>
</tr>
<tr>
<td>4</td>
<td>Oil and Gas</td>
<td>ONGC, Relience Industry, GAIL</td>
</tr>
<tr>
<td>5</td>
<td>Personal care and</td>
<td>HUL, ITC, Cipla, Sun Pharma</td>
</tr>
<tr>
<td></td>
<td>Pharmaceutical</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Power and Steel</td>
<td>TATA Power, NTPC, Jindal Steel, TATA Steel</td>
</tr>
<tr>
<td>7</td>
<td>Metals and Mining</td>
<td>Coal India, Sterlite, Hindalco</td>
</tr>
<tr>
<td>8</td>
<td>Engineering and</td>
<td>DLF, L&amp;T, BHEL</td>
</tr>
<tr>
<td></td>
<td>Construction</td>
<td></td>
</tr>
</tbody>
</table>
6.2.1 Selection of Financial Ratios

To design a portfolio recommendation system, financial ratios can be used in the stock evaluation process. Since some financial ratios have same characteristics, so the selection of all the financial ratios for the evaluation process would be inadequate and would make the system complex. To avoid this, financial ratios can be partitioned into clusters [90]. In this study, for the selection of more efficient financial ratios, we have used a clustering technique proposed by Wang and Lee [90]. According to this technique, the ratios in one cluster will be similar in behavior, on the other hand, inter-cluster behavior will be different, which is described as follows:

Let, $Y_i = (y_{i1}, y_{i2}, ..., y_{ik}, ..., y_{in})$ be a set of $i$ financial ratios of $n$ companies. The similarity measure $r(Y_i, Y_j)$ between two financial ratios $Y_i$ and $Y_j$ is a fuzzy relation which is given by the following equation:

$$r(Y_i, Y_j) = \frac{1}{n-1} \sum_{k=1}^{n-1} \left(1 - \frac{|M_i(k, k+1) - M_j(k, k+1)|}{\|M\|}\right), \quad (6.2.1)$$

and

$$\|M\| = \max_{i,k}\{M_i(k, k+1)\} - \min_{i,k}\{M_i(k, k+1)\}, \quad (6.2.2)$$

where $0 \leq r(Y_i, Y_j) \leq 1$ i.e $Y_i$ is closer to $Y_j$ when $r(Y_i, Y_j)$ approaches 1 and $Y_i$ is away from $Y_j$ when it approaches 0 and $M_i(k, k+1)$ denotes the variation of company $k$ to $k+1$ defined as:

$$M_i(k, k+1) = \frac{y_{i,k+1} - y_{i,k}}{\sqrt{\sum_{t=1}^{n}(y_{it})^2}}. \quad (6.2.3)$$

Let, $R^\lambda = \{(Y_i, Y_j)|r(Y_i, Y_j) \geq \lambda\}$ be a fuzzy compatible relation and $0 \leq \lambda \leq 1$. Let, $C_m(\lambda)$ be the number of clusters partitioned by $R^\lambda$. When $\lambda = 0$, $R^\lambda$ partitions $m$ financial ratios into one cluster and when $\lambda = 1$, $R^\lambda$ partitions $m$ financial ratios into $m$ clusters. Value of $\lambda$ is calculated by a validation index (VI) which is defined as follows:

$$VI = \lambda - \frac{C_m(\lambda)}{m}, \quad (6.2.4)$$
where \( \lambda \) represents the intra-cluster and \( C_m(\lambda)/m \) represents the inter-cluster relation respectively. The best partition should have large value of intra-cluster relation and small value of inter-cluster relation. So from equation (6.2.4), a partition with highest value of validation index would be a good partition. After calculating the value of the validation index, the representative indicator (RI) is selected from each cluster by the following definitions:

**Definition 1.** Let, \( SP_i \) be a set of several financial ratios. Then \( Y_i \) is a candidate representative of \( SP_i \) as \( Y_i \in SP_i \) and \( RSP_i(Y_i) \geq RSP_i(Y_i) \), where \( RSP_i(Y_i) = \min_{y_k \in SP_i}\{r(Y_i, Y_k)\} \) and \( RSP_i(Y_i) = \min_{y_k \in SP_i}\{r(Y_j, Y_k)\} \).

**Definition 2.** Let, \( CSP_i \) be the set consisting of candidate representatives in the cluster \( SP_i \). Then \( Y_i \) is a representative, if \( Y_i \in CSP_i \) and \( ERSP_i(Y_i) \leq ERSP_i(Y_j) \), \( \forall Y_j \in CSP_i \),

where \( ERSP_i(Y_i) = \max_{y_k \in SP_i}\{r(Y_i, Y_k)\} \) and \( ERSP_i(Y_j) = \max_{y_k \in SP_i}\{r(Y_j, Y_k)\} \).

If the number of representative indicators in a cluster is greater than one, then any one of them can be chosen as the representative.

The behavior of a sector is explained by the behavior of companies listed in that sector, so here in this study, the financial ratios of each sector are calculated by taking the average of financial ratios of all the companies listed in that particular sector. Then we use a set of financial ratios of each sector for the selection of more efficient ratios. The financial ratios are grouped as, Investment Valuation, Profitability, Management Efficiency, Liquidity and Debt coverage (Table 6.2). For each group we calculate the clustering arrangement for different values of \( \lambda \) using equations (6.2.1) - (6.2.4) for the year 2009 shown in Table 6.3 - Table 6.6.

Now from each group, a clustering arrangement having the highest value of validation index is selected and a representative indicator is chosen with the help of Definition 1 and Definition 2 which is shown in Table 6.7. So we have Dividend per share \( (R_2) \), Earning per share \( (R_{10}) \), Interest cover \( (R_{13}) \), Debt equity \( (R_{14}) \) and Fixed asset turnover \( (R_{19}) \) as the representative indicators of all the ratios. These selected ratios are further used as input for the proposed expert system.

Similarly, we can select the efficient financial ratios for the year 2013.
<table>
<thead>
<tr>
<th>Type</th>
<th>Ratio</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Investment valuation</td>
<td>Face Value ($R_1$)</td>
<td>printed value of security</td>
</tr>
<tr>
<td></td>
<td>Dividend Per Share ($R_2$)</td>
<td>Dividends/Number of shares</td>
</tr>
<tr>
<td></td>
<td>Operating Profit Per Share ($R_3$)</td>
<td>Operating profit/Number of shares</td>
</tr>
<tr>
<td></td>
<td>Equity Capital ($R_4$)</td>
<td>Fixed Assets/Equity Capital</td>
</tr>
<tr>
<td>Profitability</td>
<td>Operating Profit Margin ($R_5$)</td>
<td>Operating Income/Revenue</td>
</tr>
<tr>
<td></td>
<td>Gross Profit Margin ($R_6$)</td>
<td>Gross profit/Revenue</td>
</tr>
<tr>
<td></td>
<td>Cash flow Margin ($R_7$)</td>
<td>Cash Flows from Operating Activities/Net sales</td>
</tr>
<tr>
<td></td>
<td>Net profit margin ($R_8$)</td>
<td>Net income / Sales revenue</td>
</tr>
<tr>
<td></td>
<td>Return On Capital Employed ($R_9$)</td>
<td>Net Operating Profit/Capital Employed</td>
</tr>
<tr>
<td></td>
<td>Earnings Per Share ($R_{10}$)</td>
<td>Net income-dividends on preferred stock/Average outstanding shares</td>
</tr>
<tr>
<td>Liquidity and Debt Coverage</td>
<td>Current Ratio ($R_{11}$)</td>
<td>Current assets/ Current liabilities</td>
</tr>
<tr>
<td></td>
<td>Quick Ratio ($R_{12}$)</td>
<td>Cash + Marketable Securities + Receivables/Current Liabilities</td>
</tr>
<tr>
<td></td>
<td>Interest Cover ($R_{13}$)</td>
<td>earnings before interest and taxes (EBIT)/Interest expenses</td>
</tr>
<tr>
<td></td>
<td>Debt/Equity ($R_{14}$)</td>
<td>Total liabilities/Owner’s equity</td>
</tr>
<tr>
<td></td>
<td>Fixed Charges Coverage ($R_{15}$)</td>
<td>EBIT + Lease Payments/Interest Expense + Lease Payments</td>
</tr>
<tr>
<td></td>
<td>Fixed charge coverage ratio-cash basis ($R_{16}$)</td>
<td>adjusted operating cash flow/fixed charges</td>
</tr>
<tr>
<td>Management Efficiency</td>
<td>Debtors Turnover ($R_{17}$)</td>
<td>Net Credit Sales / Average Trade Debtors</td>
</tr>
<tr>
<td></td>
<td>Investments Turnover ($R_{18}$)</td>
<td>Sales/long-term liabilities + stockholder’s equity</td>
</tr>
<tr>
<td></td>
<td>Fixed Assets Turnover ($R_{19}$)</td>
<td>Net Sales Average /Fixed Assets</td>
</tr>
<tr>
<td></td>
<td>Total Assets Turnover ($R_{20}$)</td>
<td>Net Sales Average /Total Assets</td>
</tr>
<tr>
<td></td>
<td>Asset Turnover ($R_{21}$)</td>
<td>Revenues/Total Assets</td>
</tr>
</tbody>
</table>
Table 6.3: Clustering arrangement of 2009 for different values of $\lambda$ for investment valuation

<table>
<thead>
<tr>
<th>$\lambda$</th>
<th>$C_m(\lambda)$</th>
<th>Arrangement</th>
<th>validation index</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4</td>
<td>$R_1, R_2, R_3, R_4$</td>
<td>0</td>
</tr>
<tr>
<td>0.80</td>
<td>2</td>
<td>($R_1, R_2, R_3), R_4$</td>
<td>0.30</td>
</tr>
<tr>
<td>0.59</td>
<td>1</td>
<td>($R_1, R_2, R_3, R_4$)</td>
<td>0.42</td>
</tr>
</tbody>
</table>

Table 6.4: Clustering arrangement of 2009 different values of $\lambda$ for Profitability

<table>
<thead>
<tr>
<th>$\lambda$</th>
<th>$C_m(\lambda)$</th>
<th>Arrangement</th>
<th>validation index</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6</td>
<td>$R_5, R_6, R_7, R_8, R_9, R_{10}$</td>
<td>0</td>
</tr>
<tr>
<td>0.94</td>
<td>5</td>
<td>($R_7, R_8), R_5, R_6, R_9, R_{10}$</td>
<td>0.107</td>
</tr>
<tr>
<td>0.93</td>
<td>4</td>
<td>($R_5, R_6), (R_7, R_8), R_9, R_{10}$</td>
<td>0.263</td>
</tr>
<tr>
<td>0.83</td>
<td>3</td>
<td>($R_5, R_6), (R_7, R_8), (R_9, R_{10})$</td>
<td>0.33</td>
</tr>
<tr>
<td>0.80</td>
<td>2</td>
<td>($R_5, R_6), (R_7, R_8, R_9, R_{10}$)</td>
<td>0.467</td>
</tr>
<tr>
<td>0.67</td>
<td>1</td>
<td>($R_5, R_6, R_7, R_8, R_9, R_{10}$)</td>
<td>0.503</td>
</tr>
</tbody>
</table>

Table 6.5: Clustering arrangement of 2009 for different values of $\lambda$ for liquidity and debt coverage

<table>
<thead>
<tr>
<th>$\lambda$</th>
<th>$C_m(\lambda)$</th>
<th>Arrangement</th>
<th>validation index</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6</td>
<td>$R_{11}, R_{12}, R_{13}, R_{14}, R_{15}, R_{16}$</td>
<td>0</td>
</tr>
<tr>
<td>0.99</td>
<td>5</td>
<td>($R_{15}, R_{16}), R_{11}, R_{12}, R_{13}, R_{14}$</td>
<td>0.157</td>
</tr>
<tr>
<td>0.97</td>
<td>4</td>
<td>($R_{13}, R_{15}, R_{16}), R_{11}, R_{12}, R_{14}$</td>
<td>0.303</td>
</tr>
<tr>
<td>0.92</td>
<td>3</td>
<td>($R_{13}, R_{15}, R_{16}), (R_{12}, R_{14}), R_{11}$</td>
<td>0.42</td>
</tr>
<tr>
<td>0.79</td>
<td>2</td>
<td>($R_{11}, R_{13}, R_{15}, R_{16}), (R_{12}, R_{14})$</td>
<td>0.46</td>
</tr>
<tr>
<td>0.54</td>
<td>1</td>
<td>($R_{11}, R_{12}, R_{13}, R_{14}, R_{15}, R_{16}$)</td>
<td>0.37</td>
</tr>
</tbody>
</table>
Table 6.6: Clustering arrangement of 2009 for different values of $\lambda$ for management efficiency

<table>
<thead>
<tr>
<th>$\lambda$</th>
<th>$C_m(\lambda)$</th>
<th>Arrangement</th>
<th>Validation index</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5</td>
<td>$R_{17}, R_{18}, R_{19}, R_{20}, R_{21}$</td>
<td>0</td>
</tr>
<tr>
<td>0.97</td>
<td>4</td>
<td>$(R_{20}, R_{21}), R_{17}, R_{18}, R_{19}$</td>
<td>0.17</td>
</tr>
<tr>
<td>0.88</td>
<td>3</td>
<td>$(R_{19}, R_{20}, R_{21}), R_{17}, R_{18}$</td>
<td>0.28</td>
</tr>
<tr>
<td>0.75</td>
<td>2</td>
<td>$(R_{18}, R_{19}, R_{20}, R_{21}), R_{17}$</td>
<td>0.35</td>
</tr>
<tr>
<td>0.54</td>
<td>1</td>
<td>$(R_{17}, R_{18}, R_{19}, R_{20}, R_{21})$</td>
<td>0.46</td>
</tr>
</tbody>
</table>

Table 6.7: Representative indicators for each group of financial ratios for 2009

<table>
<thead>
<tr>
<th>Type</th>
<th>Cluster</th>
<th>Ratios</th>
<th>RI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Investment valuation</td>
<td>1</td>
<td>$R_1, R_2, R_3, R_4$</td>
<td>$R_2$</td>
</tr>
<tr>
<td>Profitability</td>
<td>2</td>
<td>$R_5, R_6, R_7, R_8, R_9, R_{10}$</td>
<td>$R_{10}$</td>
</tr>
<tr>
<td>Liquidity and Debt coverage</td>
<td>3</td>
<td>$R_{11}, R_{13}, R_{15}, R_{16}$</td>
<td>$R_{13}$</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>$R_{12}, R_{14}$</td>
<td>$R_{14}$</td>
</tr>
<tr>
<td>Management efficiency</td>
<td>5</td>
<td>$R_{17}, R_{18}, R_{19}, R_{20}, R_{21}$</td>
<td>$R_{19}$</td>
</tr>
</tbody>
</table>

6.2.2 Rating of Stocks

After selecting the efficient financial ratios, we rank the stocks on the basis of selected financial ratios by using a fuzzy inference system (FIS). From the development of fuzzy set theory proposed by Zadeh [101], FIS has been studied as a crucial field in fuzzy logic. FIS can formulate human knowledge and reasoning process, which helps to find the logical results [58].

A rule-based fuzzy expert system is proposed using the stock evaluation knowledge of experts. Since the knowledge from experts is always in linguistics terms, so the inputs and outputs have to be given in linguistic terms. Here we have five financial ratios for each of the 30 companies, which are used as inputs for the proposed system. The proposed system estimates the stocks by using the inputs and produce the output rating (which varies from 0 to 100) for each stock with the help of fuzzy
We have used Mamdani inference system for the stock rating process [72]. Inputs of proposed system are crisp, however Mamdani system works with fuzzy inputs and generates fuzzy outputs. So to fuzzify the inputs, we obtained the infimum (\(inf\)) and supremum (\(sup\)) value of input data set. For the output, we have selected 0 as the \(inf\) value and 100 as the \(sup\) value. After choosing \(inf\) and \(sup\) value for input and output, median and data range are calculated which are given as follows:

\[
\text{data range} = [inf, sup], \\
\text{median} = \frac{sup - inf}{2}. 
\]

(6.2.5)  \hspace{1cm} (6.2.6)

For the fuzzification process, trapezoidal membership function is used. Inputs and outputs are formulated in terms of their linguistic values: Low, Medium, and High. The equation of trapezoidal membership function is given as:

\[
f(t) = \begin{cases} \
\frac{t-a}{b-a}, & \text{if } a \leq t \leq b \\\n1, & \text{if } b \leq t \leq c \\
\frac{t-d}{c-d}, & \text{if } c \leq t \leq d \\
0, & \text{otherwise},
\end{cases}
\]

where \(a\), \(b\), \(c\) and \(d\) are the parameters of the trapezoidal membership function. We assumed the value of parameters as follows:

\[
a = \text{inf}, \\
b = \frac{\text{median} - \text{inf}}{2}, \\
c = \frac{\text{sup} - \text{median}}{2}, \\
d = \text{sup}.
\]

After fuzzifying the inputs and outputs, a rule-based expert system has been developed. This expert system determines qualitatively, how the different instances of input factors (Dividend per share (\(R_2\)), Earning per share (\(R_{10}\)), Interest cover
(R_{13}), Debt equity (R_{14}) and Fixed asset turnover (R_{19})) are related to output. This fuzzy expert system consists of 93 fuzzy 'if-then' rules. For instance:

- If dividend per share is low and earning per share is high and interest cover is high and Debt equity is low and fixed asset turnover is high then stock rating is medium.

- If dividend per share is high and earning per share is high and interest cover is high and debt equity is high and fixed asset turnover is high then stock rating is high.

- If dividend per share is low and earning per share is low and interest cover is low then stock rating is low.

The outputs given by Mamdani inference system are in terms of fuzzy, so outputs have to be defuzzified first. There are numerous techniques which can be used for defuzzification. Here, we have used Center of Gravity (COG) method for the defuzzification process, which is a well-balanced and consistent approach [66] given as:

$$t^* = \frac{\int f(t) * t dt}{\int f(t) dt}, \tag{6.2.7}$$

where $t^*$ is the value obtained after defuzzification.

### 6.2.3 Construction of Portfolio

According to the risk profile and preferences of investors, a portfolio is constructed by using linear programming technique. The recommended portfolio uses stock ratings from subsection 6.2.2 and the risk levels of the stock.

The objective of portfolio management system is to maximize the total weighted
stock ratings. The LPP formulation of the proposed system is given as follows:

\[
\text{Max } Z = \sum_{l=1}^{p} w_l s_l, \quad (6.2.8)
\]

Subject to \[
\sum_{l=1}^{p} w_l = 1, \quad (6.2.9)
\]

\[0 \leq w_l \leq 0.2, \quad (6.2.10)\]

\[
\sum_{l=\text{PS}}^{p} w_l \geq \text{LBW}. \quad (6.2.11)
\]

Where \(w_l\) is the stock weight in the recommended portfolio, \(s_l\) is the stock rating specified in subsection 6.2.2 and \(p\) is the number of stocks in the portfolio.

Constraint (6.2.9) assures that all the capital of investors should be invested.

Constraint (6.2.10) limits the amount of capital invested in one stock i.e. the investment amount should not be more than 20% in one stock. Investors can set this limit according to their preference.

Constraint (6.2.11) gives the risk profile of investors. For the stocks with the systematic risk \(\beta\) less than one, constraint (6.2.11) sets lower bound on the total weight (LBW) of stocks. Where PS is the set of those stocks whose \(\beta\) value is less than one and the value of LBW is specified according to the risk profile of investors. Where LBW represents the lower bound of the stocks having the \(\beta\) value less than one. The value of LBW should be set high for risk-avoiding investors and low for risk-loving investors.

6.3 Results and Discussion

In this section, experimental results of the proposed system for portfolio planning are presented. The performance of the proposed rule based fuzzy expert system is evaluated for different data sets.

The efficient financial ratios are selected by using equations (6.2.1) - (6.2.4). For the year 2009, we have dividend per share \(R_2\), earning per share \(R_{10}\), interest cover \(R_{13}\), debt equity \(R_{14}\) and fixed asset turnover \(R_{19}\) as most effective ratios, which is shown in Table 6.7. Similarly, after calculation for the year 2013, we get dividend per share \(R_2\), operating profit margin \(R_5\), cash flow margin \(R_7\),
current ratio \( (R_{11}) \), investment turnover \( (R_{18}) \) as the most efficient ratios.

We have designed the portfolio for different risk profile investors, i.e. for the risk-loving and risk-avoiding investors. We have set the value of constraint (6.2.10) between 0 and 0.2, that is the amount of capital invested should not be more than 20\% in one stock.

The risk profile of investors is defined in the constraint (6.2.11). The risk profile of investors affects the portfolio construction stage directly in this proposed system. The value of LBW should be higher for the risk-avoiding and low for the risk-loving investors. So here in our study, we have set 0.75 and 0.25 as the value for risk-avoiding and risk-loving investors respectively.

The stocks and their corresponding weights selected by the proposed system are given in Table 6.8 and Table 6.9 for the year 2009 and 2013 respectively. We tested our results with the Sensex (benchmark index of BSE30) by taking the monthly returns for the period of Jan 1, 2009 to Dec 31, 2009 and Jan 1, 2013 to Dec 31, 2013 of both the portfolios. The return pattern of the proposed portfolio is almost coinciding with the Sensex for the year 2013 as shown in Figure 6.2, which proves the effectiveness of the proposed portfolios. But from Figure 6.3, it is observed that returns for the year 2009 (recession period) are deviating from Sensex. The economy had been in trouble because of the recession in the year 2009. So for investors, it had become very difficult to capture the ongoing market fluctuations during recession years. During the growing market (i.e. 2013) relative returns from our portfolios show trend similar to the Sensex index.

We have also compared the returns of proposed portfolios with three existing portfolio techniques [76], for the same BSE30 data set of the year 2013. The weight distribution of different stocks of proposed portfolio and the existing portfolios are given in Table 6.9 and Table 6.10 respectively for the year 2013. Finally, from the Figure 6.4, one can observe that proposed portfolio gives relatively better returns compared to the existing portfolios [76]. Hence the proposed portfolio technique will be a good choice for investors.
Table 6.8: Stock weights recommended by proposed expert system for the year 2009

<table>
<thead>
<tr>
<th># of Stock</th>
<th>Risk-avoiding Companies</th>
<th>weigh</th>
<th>Risk-loving companies</th>
<th>weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Bajaj Auto</td>
<td>0.05</td>
<td>Bajaj Auto</td>
<td>0.2</td>
</tr>
<tr>
<td>2</td>
<td>HUL</td>
<td>0.03</td>
<td>Infoysis</td>
<td>0.2</td>
</tr>
<tr>
<td>3</td>
<td>ICICI</td>
<td>0.07</td>
<td>TCS</td>
<td>0.2</td>
</tr>
<tr>
<td>4</td>
<td>Infosys</td>
<td>0.1</td>
<td>SBI</td>
<td>0.2</td>
</tr>
<tr>
<td>5</td>
<td>Maruti Suzuki</td>
<td>0.15</td>
<td>Hero Honda</td>
<td>0.2</td>
</tr>
<tr>
<td>6</td>
<td>Hero Honda</td>
<td>0.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>TCS</td>
<td>0.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>SBI</td>
<td>0.2</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 6.9: Stock weights recommended by proposed expert system for the year 2013

<table>
<thead>
<tr>
<th># of Stock</th>
<th>Risk-avoiding Companies</th>
<th>weigh</th>
<th>Risk-loving companies</th>
<th>weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>DLF</td>
<td>0.04</td>
<td>Bharti airtel</td>
<td>0.2</td>
</tr>
<tr>
<td>2</td>
<td>Bharti airtel</td>
<td>0.1</td>
<td>HDFC</td>
<td>0.2</td>
</tr>
<tr>
<td>3</td>
<td>TCS</td>
<td>0.08</td>
<td>TCS</td>
<td>0.15</td>
</tr>
<tr>
<td>4</td>
<td>Wipro</td>
<td>0.05</td>
<td>Coal India</td>
<td>0.2</td>
</tr>
<tr>
<td>5</td>
<td>HDFC</td>
<td>0.07</td>
<td>Cipla</td>
<td>0.05</td>
</tr>
<tr>
<td>6</td>
<td>Cipla</td>
<td>0.0.6</td>
<td>TATA Steel</td>
<td>0.2</td>
</tr>
<tr>
<td>7</td>
<td>Sun Pharma</td>
<td>0.12</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Coal India</td>
<td>0.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>NTPC</td>
<td>0.06</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>TATA Steel</td>
<td>0.18</td>
<td></td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>GAIL</td>
<td>0.04</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 6.10: Portfolios suggested from the existing literature [76], for the year 2013

<table>
<thead>
<tr>
<th># of Stock</th>
<th>Portfolio 1 (K-means)</th>
<th>Portfolio 2 (SOM)</th>
<th>Portfolio 3 (FCM)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Companies</td>
<td>weight</td>
<td>companies</td>
</tr>
<tr>
<td>1</td>
<td>Bharti Airtel</td>
<td>0.42</td>
<td>SBI</td>
</tr>
<tr>
<td>2</td>
<td>TATA Steel</td>
<td>0.29</td>
<td>Infosys</td>
</tr>
<tr>
<td>3</td>
<td>DLF</td>
<td>0.10</td>
<td>GAIL</td>
</tr>
<tr>
<td>4</td>
<td>Hindalco</td>
<td>0.04</td>
<td>Hindalco</td>
</tr>
<tr>
<td>5</td>
<td>Maruti Suzuki</td>
<td>0.15</td>
<td>DLF</td>
</tr>
</tbody>
</table>

6.4 Conclusion

This chapter presented a new technique for portfolio designing using rule-based fuzzy expert systems for the BSE30 index. Critical factors i.e., financial ratios were selected by using a clustering technique, then fuzzy inference system was used to rank the stocks according to their performance in Sensex. Then according to the preferences of investors, a linear programming model was developed to design a portfolio. This expert system could be applied in real-life situations because the fuzzy inference system uses fuzzy inputs and dynamically calculates the range of data. Besides, the proposed expert system could be easily modified according to the specific preferences of investors and their risk profiles.

The proposed expert system was evaluated using the data of BSE30, an Indian stock market index and results were tested with the benchmark index of BSE30 called Sensex. Also, results were compared with an exiting portfolio technique and the results revealed that proposed expert system performs relatively better than the existing technique in the period of evaluation and it would give a flexible and technically balanced portfolio for investors.
Figure 6.1: Process flow diagram of the proposed model
Figure 6.2: Proposed expert system returns with respect to Sensex for the year 2013

Figure 6.3: Proposed expert system returns with respect to Sensex for the year 2009
Figure 6.4: Comparison of proposed portfolios with existing portfolio techniques for the year 2013