CHAPTER-3

RESEARCH METHODOLOGY: TOOLS AND TECHNIQUES USED IN THIS RESEARCH

The main objective of this research work is to understand the SCR variables and risk management strategies in the context of a small-scale Indian manufacturing enterprise. This chapter presents different tools and techniques used to achieve the objective of this research. Interrelationship among the identified SCR variables was developed using Interpretive Structural Modelling (ISM). Analytical Hierarchy Process (AHP) is used for assessment and prioritization of SCR variables. Finally, the risk level of the firm is evaluated with the help of fuzzy logic and also identified the main obstacles of the SCRM. The ANP approach is used to evaluate and select a suitable risk management strategy. This chapter briefly presents these tools and techniques, which are used in the later chapters.

3.1 INTERPRETIVE STRUCTURAL MODELLING (ISM)

Interpretive structural modelling (ISM) is a structured technique, which is widely used in research to understand and establish interrelationships among various variables related to the research problem in various field of study such as social science, technology, education. This method is proposed by Warfield (1974) to understand and establish interrelation-ship among variables of complex problems. ISM is an interactive learning process whereby a set of different directly and indirectly related variables are structured into a comprehensive systemic model. The model so formed portrays the structure of a complex issues and a system of a field of study in a carefully designed pattern employing graphics as well as words (Faisal *et al.,* 2006b). ISM methodology has been used to analyse the criteria for vendor selection and to exhibit the relationship among these criteria and their levels

(Mandal and Deshmukh, 1994). This method converts the variables of a complex problem into Diagraph, which is used to understand the inter-relationship among variables. This diagraph is converted into the final 'interpretive structure model'. With this method, various variables can be compared and classified with the help of MICMAC analysis. The main objective of MICMAC analysis is to estimate the dependence and driving power of variables. ISM methodology is purely based on the judgment of experts and it shows the interrelationship among variables through these judgments (Digalwar and Giridhar, 2015). Through this approach, number of variables, which are directly associated with SCRM, as well as indirectly associated with SCRM, are identified. Figure 3.1 presents a modified flow diagram of ISM modelling. The main steps of the approach are also listed follows:

Step-1. Identification of relevant variables

Step-2. Establishing a contextual relationship among variables

Step-3. Constructing a structural self-interaction matrix (SSIM)

Step-4. Developing a reachability matrix and examine transitivity

Step-5. Level Partitioning of reachability matrix

Step-6. Development of conical matrix

Step-7. Development of Diagraph and Formation of ISM-based model

Step-8. Classification of variables on the basis of MICMAC analysis

Following sub-sections briefly describes these steps.

3.1.1 Identification of relevant variables

The first step is to identify the relevant the variables of research problem. These variables can be obtained either by primary sources (survey method, expert opinion, etc.) or by secondary sources (literature review, etc.). With the secondary sources, a comprehensive literature review from various academic database of reputed publishers can be used to identify these variables for this purpose. On the other side, few data can be obtained from primary sources by conducting a pilot study on the research problem. Group Discussion (GD), Delphi Method (DM), Nominal Group Technique (NGT) and Brain Storming (BS) are some approaches to identify such variables through primary sources.

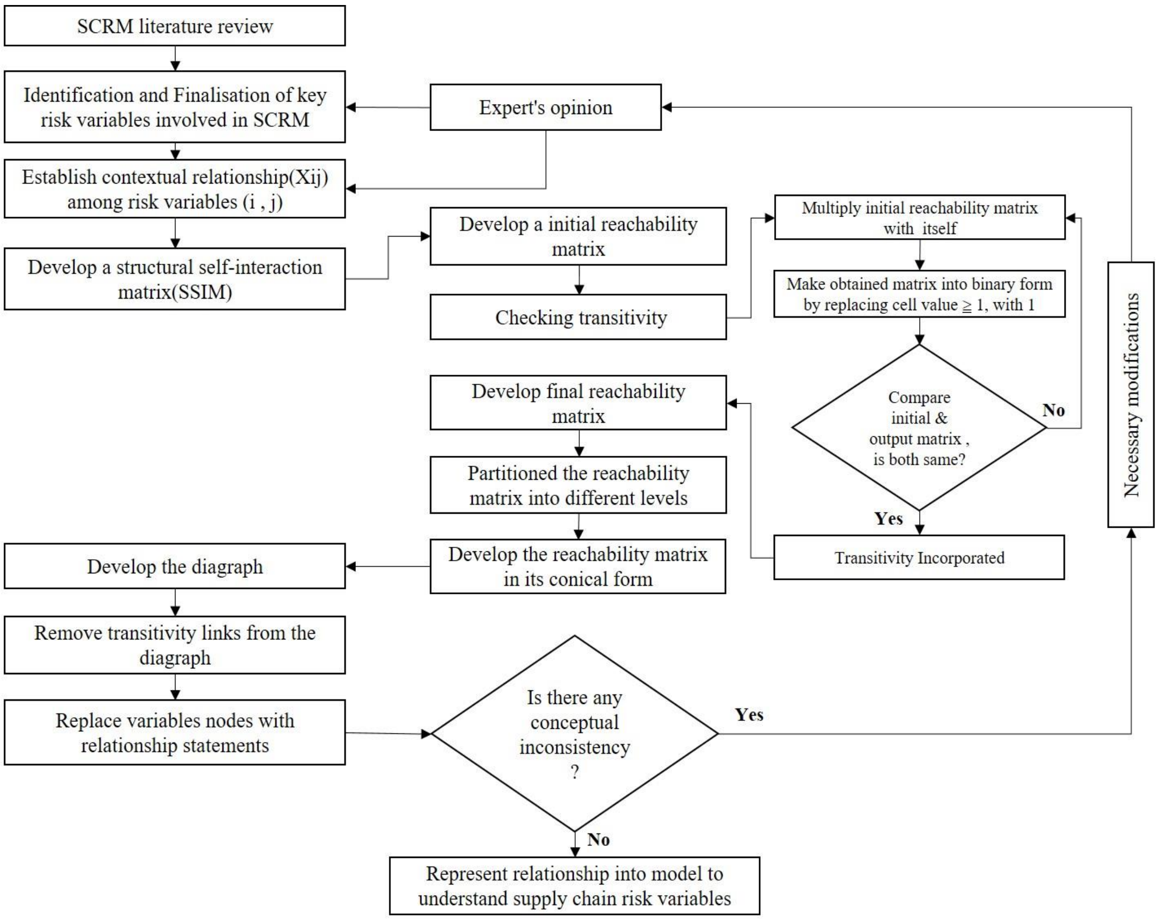

Figure 3.1: Modified flow diagram for ISM modelling (Ravi and Shankar, 2005)

3.1.2 Establishing a contextual relationship among variables

In this step, a contextual relationship among identified variables is to be established. Relations may be of several types like comparative, influential, neutral or temporal relations (Austin and Burns, 1985; Warfield, 1974). The influential contextual relationship between variables is represented as "lead to" type. This type of relationship implies that how one variable leads to another variable. Several management techniques like Delphi method, Brainstorming, Nominal Group Technique (NGT), etc. can be used to capture these relationship through the experts' opinions. This technique is purely based on the expert's opinion, so it is essential that experts have sufficient knowledge and practical experience in the same domain to avoid the biasness in contextual relationship (Digalwar and Giridhar, 2015). Four symbols are usually used to represent the direction of the relationship between any two variables (*i* and *j*):

- V: variable *i* will lead to variable *j* (relation from *i* to *j*, but not in both direction);
- A: variable *j* will lead to variable *i* (relation from *j* to *i*, but not in both direction);
- X: variable *i* and *j* will lead to each other (relation from *i* to *j* and *j* to *i*); and
- O: variables *i* and *j* will not lead to each other (No relationship).

These relations and symbols are used to prepare a structural self-interaction matrix.

3.1.3 Constructing a Structural Self Interaction Matrix (SSIM)

A matrix is developed using symbols and rules explained in the previous section known as Structural Self-Interaction Matrix (SSIM). This Matrix shows the pair-wise relationship among variables and help to prepare a reachability matrix.

3.1.4 Developing a reachability matrix and examine transitivity

In this step, conversion of SSIM into a binary matrix is done. This matrix is known as the initial reachability matrix. Rules for the conversion of V, A, X and O symbols into binary (0 and 1) are as follows;

- If the (*i, j*) cell value in the SSIM is V, then the (*i, j*) cell value in the reachability matrix becomes 1, and the (*j, i*) cell value becomes 0.
- If the (*i, j*) cell value in the SSIM is A, then the (*i, j*) cell value in the reachability matrix becomes 0, and the (*j, i*) cell value becomes 1.
- If the (*i, j*) cell value in the SSIM is X, then both the (*i, j*) and (*j, i*) cell values of the reachability matrix become 1.
- If the (*i, j*) cell value of the SSIM is O, then both the (*i, j)* and (*j, i*) cell values of the reachability matrix become 0.

This initial reachability matrix is used to check the transitivity, which is an important aspect of ISM methodology. Transitivity can be verified with the help of the method suggested by Malone (1975), which is further explained and used by many researchers (Faisal *et al.* 2006b, Pfohl *et al.* 2011, Ojha *et al.* 2014). The following steps describe the transitivity checking process.

- Initial reachability matrix multiplied with itself and the values ≥1 are replaced with 1 in the resultant matrix.
- Check this new resultant matrix, if this new matrix is same as the initial reachability matrix, final reachability matrix is obtained. If both are not the same, then repeat step one with the resultant matrix.
- Repeat this process until the final reachability matrix is obtained
- Compare the initial and final reachability matrix. If any cells value changes from 0 to 1 then it is marked as '1*' in the final reachability matrix, where 1* denotes transitivity reflecting new relationship surfaced up due to transitivity.

After incorporating transitivity analysis, final reachability matrix is obtained. This matrix is portioned for further analysis.

3.1.5 Level Partitioning of reachability matrix

The reachability and antecedent set for each variable are obtained from the final reachability matrix (Warfield, 1974, 1976). The reachability set (R_{si}) means the total number of variables, which may be affected by a particular variable (including itself), whereas the antecedent set (A_{si}) means the total number of variables which affect a specific variable (including itself). These reachability and antecedent set leads to the intersection sets (I_{si}), i.e., $I_{si} = R_{si} \cap A_{si}$; the common elements in both sets, which is derived for each element of the problem (Pfohl *et al.*, 2011).

On the basis of reachability, antecedent and intersection sets, the final reachability matrix is partitioned into different levels. For Level partitioning, any reachability set having mostly similar element to intersection set ($R_{si} = I_{si}$) is assigned as Level 1 and this level is placed at the top in the ISM hierarchy. Now Level 1 is identified, so it is eliminated from the table and the same process is repeated through iterations until the level of each variable is identified. These identified levels help in developing conical matrix.

3.1.6 Development of conical matrix

A conical matrix (lower triangular format) is developed by conglomeration of all variables in the same level across rows and columns of final Reachability Matrix (Chand *et al.*, 2015a). In the conical matrix all the variables having the same level are pooled together, i.e. top-level variable with most zeroes (0) in the upper diagonal of the matrix and lower level of variables most ones (1) in the lower half of the matrix. The conical matrix is achieved by rearranging variables based on their levels. It is used to develop the diagraph and final ISM model.

3.1.7 Development of Diagraph and Formation of ISM-based model

A diagraph is developed using a conical matrix and the information obtained from level partitioning of variables. All variables are represented by nodes. These nodes are connected with the help of arrows representing relationship/ hierarchy using information obtain thus for. Based on reachability matrix and expert opinion, transitivity links are also incorporated in the final diagraph. From the conical matrix, initial digraph is obtained and after removing indirect links, final digraph is developed. ISM model is basically a representation of pure hierarchical pattern of all variables and it is obtained from the final digraph. In this model, most driven/dependable variables are placed at the top-level position and similarly, level-II variables are placed below it and the process continues until the last level is positioned. This process ultimately results into the final ISM model. This final ISM model is followed by MICMAC analysis for classification of variables based on their dependence power and driving power.

3.1.8 Classification of variables on the basis of MICMAC analysis

Matriced' Impacts Cruoses Multiplication Applique a un Classement (MICMAC) analysis is widely used to understand and analyse the driving power and dependence power of the variables by segregating the variables (Venkatesh *et al.*, 2015). It divides all the variables into four clusters on the basis of their driving power and dependence power, i.e. (i) autonomous, (ii) dependent, (iii) linkage and (iv) independent variables. These clusters can be easily understood by plotting driving power against dependency on a dependency-driver diagram. These four clusters are explained as follows.

Cluster I: It consists of autonomous variables, which have both weak driving and dependence power. These variables are relatively disconnected from the system. These may have individual effect on SC or SCRM (Faisal *et al.*, 2006b; Venkatesh *et al.*, 2015).

Cluster II: It consists of dependent variables, which have weak driver power and strong dependence power.

Cluster III: It consists of linkage variables, which have both strong driving and also strong dependence power. These variables are unstable, i.e., any action on these variables will affect other variables and also feedback on themselves (Diabat *et al.*, 2012).

Cluster IV: It consists of independent variables, which have strong driving, but weak dependence power. These variables have extreme driving power, so these are also called critical variables.

In this research work, ISM is used to establish the interrelationship among the SCR variables.

These variables are required to be prioritize further to see the relative importance with each other. The prioritization can be done using methods like AHP, ANP, MOORA, etc.. In this work, AHP approach is used and the same is explained in the following section.

3.2 ANALYTIC HIERARCHY PROCESS (AHP)

AHP is a Multi-Criteria Decision Making (MCDM) tool introduced by Saaty (1980). It is a structured technique used for solving complex decision-making problems. It is widely used by researchers to prioritize/to rank/to weigh alternatives by evaluating the criteria and sub-criteria from a given set (Mangla *et al.,* 2015). AHP can be used for quantitative as well as qualitative research. It has the capability to check the consistency of data. Hence, AHP methodology is preferred for prioritization the SCR variables in the present study. AHP converts the empirical data into the mathematical form. Many researchers have applied the AHP technique in the field of supply chain management, for evaluation of supplier, selection of plant location, selection of distribution channel, for assessment and prioritization of manufacturing flexibilities, and so on (Millet and Wedley, 2002; Schoenherr *et al.*, 2008; Sharma and Bhat, 2012; Samvedi *et al.*, 2013). Figure-3.2 shows the flow diagram of AHP. This methodology consists of seven steps, which are as follows.

Step-1. Determination of the problem, criteria, sub-criteria and alternatives

Step-2. Defining criteria, sub-criteria and alternatives

Step-3. Structuring the hierarchical model

Step-4. Pair-wise comparisons

Step-5. Determination of priority weights

Step-6. Checking the consistency of the judgments

Step-7. Synthesising the results

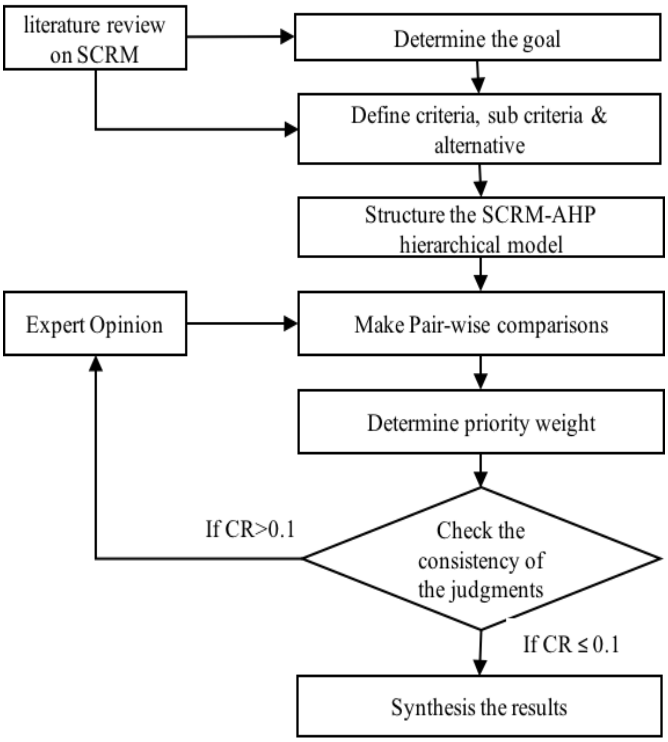

Figure 3.2 Flow diagram of AHP

3.2.1 Determination of the problem, criteria, sub-criteria and alternatives

AHP methodology starts with determining the goal or objective of the decision-making problem. This step also involves defining the criteria, sub-criteria (if any) and alternatives to achieve the desired goal. These elements are determined through the literature review and experts' opinion.

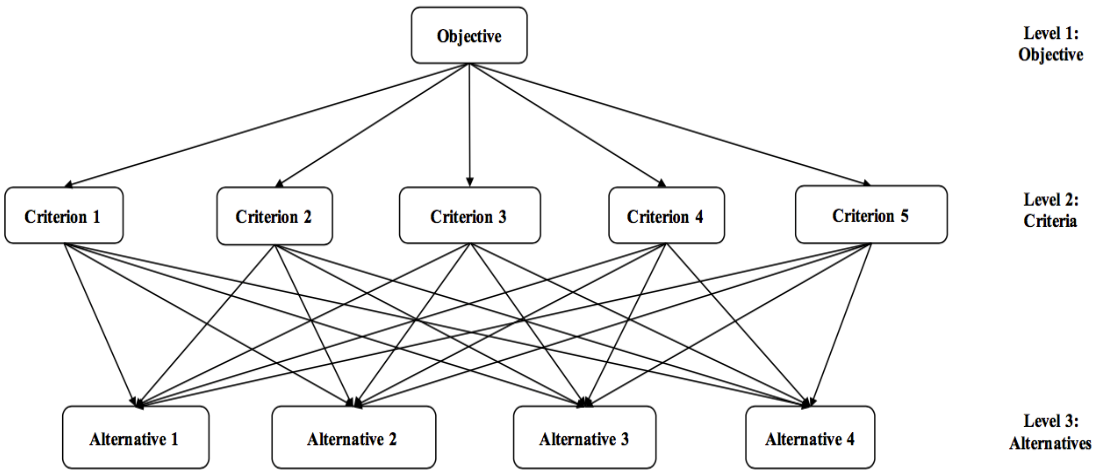

Figure 3.3: A basic hierarchy model of AHP

3.2.2 Structuring the hierarchical model

A hierarchical model is a graphical representation of the problem, which divides the problem into different sections be called as level. A three level hierarchical model is shown in Figure 3.3. This figure shows the objective of the problem placed at top level or level-1, selection criteria are placed at level-2 and the alternatives at the level-3 . Similar model can be developed with different levels depending upon the problem statement.

3.2.3 Pair-wise comparisons

After the formation of the hierarchical model, the next step is to collect the pair-wise comparisons of criteria with respect to goal and pair-wise comparisons of alternatives with respect to each of the criterion. A nine-point scale is used to collect pair-wise comparison of data as suggested by Saaty (1980). Table 3.1 shows the same. This scale shows how an element is dominant over another element. This data is collected from the expert's opinion. The pair-wise comparison matrix *(A*), as shown in equation 3.1 can be developed. The matrix has element a_{ij} represents the relative importance of the i^{th} factor with respect to the j^{th} factor.

$$Pair\text{-}wise\ Matrix\ (A) = [a_{ij}] = \begin{bmatrix} a_{11} & a_{12} & a_{1n} \\ a_{21} & a_{22} & a_{2n} \\ a_{m1} & a_{m2} & a_{mn} \end{bmatrix} \tag{3.1}$$

Table 3.1. Nine-point scale of relative importance (Saaty, 1980)

Numerical value	Verbal meaning for pair-wise comparison
1	Equally important
3	Moderately more important
5	Strongly more important
7	Very strongly more important
9	Extremely more important
2, 4, 6, 8	Intermediate value between the two adjacent judgment
Reciprocal	If the importance factor *i to j* $(a_{ij})=x$; then the importance factor *j* to *i* is Ryx = 1/Rxy

3.2.4 Determination of priority weights

After obtaining the pair-wise comparison data of criteria and alternatives, the next step is to calculate the priority weight of each risks and SCRM strategies. The steps to arrive at the Priority Weights are as follows.

i. Each element (a_{ij}) of pair-wise comparison matrix is divided by the sum of its corresponding column to obtain the normalised relative weight (x_{ij}) of that element, as shown in equation (3.2).

ii. Once the normalised relative weight of each element is obtained, the priority weight or priority vector (*W*) is obtained by averaging the corresponding row, as shown in equation (3.3).

$$Normalised\ Pair\text{-}wise\ Matrix\ (X) = \left[x_{ij}\right] = \left[\frac{a_{ij}}{\sum_{i=1}^{m} a_{ij}}\right] = \begin{bmatrix} x_{11} & x_{12} & x_{1n} \\ x_{21} & x_{22} & x_{2n} \\ x_{m1} & x_{m2} & x_{mn} \end{bmatrix} \quad (3.2)$$

$$Weighted\ Matrix\ (W) = \left[w_{ij}\right] = \left[\frac{\sum_{j=1}^{n} x_{ij}}{n}\right] = \begin{bmatrix} w_{11} \\ w_{21} \\ w_{m1} \end{bmatrix} \quad (3.3)$$

3.2.5 Checking the consistency of the judgments

The priority weights are derived from the pair-wise comparison based on the judgments of the experts, may be inconsistent. Therefore, a consistency test is required to ascertain the consistency of the data. Consistency Ratio (*CR*) index is widely used to evaluate the consistency of the pair-wise comparison data (Venkatesan and Kumanan, 2012),. Two steps to calculate the 'CR' value are explained as follows.

Step i. Calculate the consistency index (*CI*).

Consistency index can be calculated using equation (3.4), where '*n*' is the order of matrix and 'λ_{max}' is eigenvalue.

Step ii. Calculate the consistency ratio (*CR*).

CR is the ratio of the consistency index(*CI*) to the random index(*RI*), where the

Random Index (*RI*) can be obtained from the Table 3.2. Mathematical expression for CR calculation is shown in equation (3.5).

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{3.4}$$

$$CR = \frac{CI}{RI} \tag{3.5}$$

Table 3.2. Random index value (Saaty, 1980)

Order of matrix (*n*)	1	2	3	4	5	6	7	8	9	10
Random Index (*RI*)	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Using the above equations, consistency ratio of each pair-wise comparison matrix is obtained. The CR value equal to or less than 0.10 indicates that the pair-wise comparisons are consistent and acceptable. If CR value is greater than 0.1, it shows that the judgments are illogical or inconsistence. In that case, the pair-wise matrix is to be revised.

3.2.6 Synthesis the result

The last step of AHP methodology is to synthesis the model results such as relative weights of each criterion and each alternative with respect to each criterion and final relative weight of each criterion to achieve the objective of the research. On the basis of these relative weights, the ranking of each criterion and each alternative is obtained.

In this research work, seven SCR variables and their forty-two attributes were considered in relation to the case organisation. After the prioritization of these variables, it is important to learn about these SCR attributes which play vital role in SCRM. A fuzzy logic approach is used to identify these SCR attributes and to determine the risk-level of the supply chain of the case organisation.

3.3 FUZZY LOGIC APPROACH

Most of the conventional assessment tools are crisp and dichotomous such as true-or-false, yes-or-no. Whereas Fuzzy theory is different to the crisp system. This theory was introduced in 1965 by Lotfi A. Zadeh. Empirical researches are mainly dependent on the expert's opinion, which may be ambiguous and imprecise. Vagueness of estimation can be reduced by using the fuzzy logic approach. Fuzzy logic is a problem solving and data mining tool, which is comparatively superior and efficient to conventional methods (Lin *et al.,* 2006a). Since its inception, this methodology became popular among researchers for development of different models in different fields of study such as artificial intelligence, social science, technology and management science. Several types of fuzzy numbers are available such as, Trapezoidal, Triangular and Gaussian fuzzy number. In this research, triangular fuzzy numbers are used to evaluate the risk. Figure 3.4 illustrates the various steps of fuzzy logic approach, which are as follows.

Step-1. Development of conceptual model

Step-2. Define Linguistic scale

Step-3. Collection of data

Step-4. Calculate of Fuzzy Index

Step-5. Match fuzzy index with an appropriate linguistic level

Step-6. Determine fuzzy performance-importance index

3.3.1 Development of conceptual model

In the initial step, a comprehensive study of problem, which helps in dividing the complex problems into different levels to develop a conceptual model of the research problem, is conducted. The developed conceptual model of the problem must highlight different levels of variables, attributes of variables and sub-attributes based on internal and external environment of the research problem.

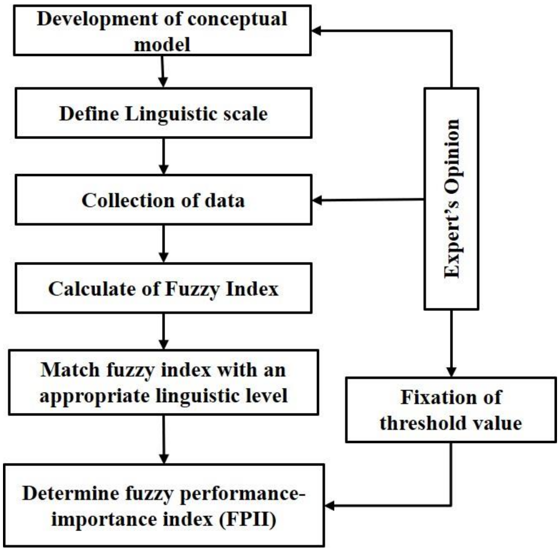

Figure 3.4 Flow diagram of fuzzy logic approach

3.3.2 Define Linguistic scale

Due to impreciseness and ambiguity of qualitative data, the determination of linguistic scale is an important aspect of an empirical research. Linguistic scale deals with conversion of qualitative data into quantitative data. In the literature, several linguistic scale have been proposed by the researchers (Lin *et al*., 2006b; Tseng and Lin, 2011; Vinodh *et al.* 2011). One such scale is shown in Table 3.3.

Table 3.3. Linguistic terms and fuzzy numbers (Lin *et al.*, 2006b)

Performance ratings		Importance weights	
Linguistic variable	**Fuzzy Number**	**Linguistic variable**	**Fuzzy Number**
Worst (W)	(0, 0.5, 1.5)	Very low(VL)	(0, 0.05, 0.15)
Very poor (VP)	(1, 2, 3)	Low (L)	(0.1, 0.2, 0.3)
Poor (P)	(2, 3.5, 5)	Fairly low (FL)	(0.2, 0.35, 0.5)
Fair (F)	(3, 5, 7)	Medium (M)	(0.3, 0.5, 0.7)
Good (G)	(5, 6.5, 8)	Fairly high (FH)	(0.5, 0.65, 0.8)
Very good (VG)	(7, 8, 9)	High (H)	(0.7, 0.8, 0.9)
Excellent (E)	(8.5,9.5, 10)	Very high (VH)	(0.85, 0.95, 1.0)

3.3.3 Collection of data

After determination of linguistic scale, the next step is to assess the performance ratings and importance weights of each element of conceptual model. This primary data is collected from the expert's opinion in the form of linguistic variables and converted these linguistic variables into fuzzy numbers, as listed in Table 3.3.

3.3.4 Calculation of Fuzzy Index

The primary data is collected from multiple experts. Therefore, aggregation is data is essential step before calculation of fuzzy index. To aggregate the data, several methods are available in the literature such as arithmetic mean, median, and mode (Lin *et al.,* 2006a). From the past studies, arithmetic mean is most preferable method among researchers. Therefore, the same method is used in the present research to aggregate the opinion collected from 'n' number of expert's. The computation of average performance ratings (R_{ij}), importance weights (W_{ij}) of sub-variables and importance weights (W_i) are carried using the following equations (Lin *et al.*, 2006a; Vinodh *et al.*, 2013).

$$R_{ij} = \frac{R_{ij1}+R_{ij2}+\cdots....+R_{ijn}}{n} \tag{3.6}$$

$$W_{ij} = \frac{W_{ij1}+W_{ij2}+\cdots....+W_{ijn}}{n} \tag{3.7}$$

$$W_{i} = \frac{W_{i1}+W_{i2}+\cdots....+W_{in}}{n} \tag{3.8}$$

where,

R_{ij}= Performance rating of j^{th} attribute in i^{th} variable,

W_{ij}=importance weight of j^{th} attribute in i^{th} variable;W_i=importance weight of i^{th} variable,

R_{ijk} = Performance rating of j^{th} attribute in i^{th} variable given by k^{th} expert.

W_{ijk} = importance weight of j^{th} attribute in i^{th} variable given by k^{th} expert.

After getting the average performance ratings (R_{ij}) and importance weights(W_{ij}), Fuzzy index is calculated from the lowest level to the highest level of the model; from sub-attributes to main variables. Fuzzy index consolidates the fuzzy weights and fuzzy ratings of all the variables, attributes and sub attributes. The variable index (V_i) and the overall fuzzy index (FI) of the research problem are calculated using the following equations (Lin *et al.*, 2006a; Vinodh *et al.*, 2013).

$$V_i = \frac{\sum_{j=1}^{n}(W_{ij} \times R_{ij})}{\sum_{j=1}^{n} W_{ij}} \quad (3.9)$$

$$FI = \frac{\sum_{i=1}^{n}(W_i \times V_i)}{\sum_{j=1}^{n} W_{ij}} \quad (3.10)$$

where,

R_i= Performance rating of i^{th} variable,

W_i=importance weight of i^{th} variable;

3.3.5 Match Fuzzy Index with an appropriate linguistic level

After obtaining the fuzzy index, it can be matched with the linguistic labels.. In the literature, several methods are available to match the fuzzy index with linguistic terms such as successive approximation, piecewise decomposition and Euclidean distance (Lin *et al.*, 2006a). In the past researches, Euclidean distance method is recognised as most intuitive method of perceiving proximity for human being (Guesgen and Albrecht, 2000). The same method is used in the present research. The Euclidean distance $d(FI,\ L_i)$ from the fuzzy index to linguistic label is calculated by using equation 3.11 (Lin *et al.*, 2006a; Vinodh *et al.*, 2013), where $U_{Li}(x)$ and $U_{FI}(x)$ represent the membership functions of the linguistic label *and FI*, respectively.

$$d(FI,\ L_i) = \left\{\sum_{x \in p}(U_{FI}(x)) - U_{Li}(x))^2\right\}^{1/2} \quad (3.11)$$

3.3.6 Determine Fuzzy Performance-Importance Index

Fuzzy logic approach is not only limited to evaluate the objective, its variables and sub-variables; but also determines the main obstacles to achieve the objective of the research. To identify these obstacles, fuzzy performance-importance index (FPII) of each variable and sub-variable is calculated by using the following equation (Lin *et al.*, 2006a; Vinodh *et al*., 2013).

$$FPII = W_i' \times R_i \tag{3.12}$$

where,

$$W_i' = [(1,1,1) - W_i] \tag{3.13}$$

Thus, FPII is calculated for each sub-variable. As FPII is obtained in the form of fuzzy numbers, it is required to convert this index into real number in order to get the ranking of each sub-variable. To get the ranking of each sub-variable, Vinodh *et al.* (2013) implemented the centroid method for membership function (a, b, c). This technique is simple and easy for conversion of fuzzy numbers into real numbers, so the same is used in this research. The ranking score is calculated by using the following equation.

$$Ranking\ Score = \frac{a + 4b + c}{6} \tag{3.14}$$

where,
a, *b* and *c* denote the lower, middle and upper values triangular fuzzy numbers.

The ranking score of each sub-variable is obtained and compared with a threshold value to identify the main obstacles. This threshold value is set through expert opinion. Sub-attributes with a rating score lower than the threshold value are identified as the barrier to research objective. Using the set threshold value, twenty SCR attributes of seven SCR variables have been identified for the case organisation. For each identified SCR attribute of SCR viable, an appropriate risk management strategy is to be identified under SCRM.

For this purpose, Analytic Network Process (ANP) technique is used and explain in the following section.

3.4 ANALYTICAL NETWORK PROCESS (ANP)

MCDM (Multiple Criteria Decision Making) techniques are often used to decision making, when there are several conflicting criteria. Several (MCDM) approaches are available in the literature. Analytical Network Process (ANP) is one of them to find out the best alternative among set of alternatives. Saaty (1996) developed ANP technique to solve the multi criteria decision-making problems. He Explained AHP as special case of ANP, a more general approach. This considers the elements of problem as a network and prioritize the alternatives. ANP is widely used by researchers for a complex problem with multiple elements having multidirectional relationship. This approach not only consider the interdependencies within a cluster of element, but also consider the outer dependencies and feedback among the different elements of clusters. In this research, the ANP is used for evaluation and selection risk management strategies. Figure 3.5 illustrates the various steps of ANP approach, which are as follows.

Step-1. Define the problem

Step-2. Construct the network model

Step-3. Collect the data

Step-4. Solve the model using the Super Decisions software

Step-5. Result analysis

3.4.1 Define the problem

Like the AHP, ANP process starts with determining the goal or objective of the decision-making problem. Further, it involves defining the criteria, sub-criteria and alternative to achieve the desired goal. These elements are determined through the literature review and expert’s opinion.

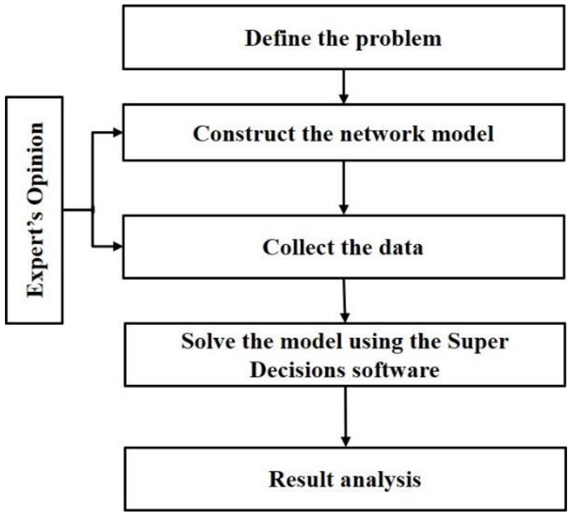

Figure 3.5 Flow diagram of ANP approach using Super Decision Software

3.4.2 Construct the network model

In this step, the research problem is divided into different sections through cluster identification and nodes creation. First, clusters are created consisting of criteria and alternatives of the problem. Next, the different nodes of each clusters are created. For example, all alternatives are considered to create as nodes within the alternative cluster. After creating, all the clusters and their nodes, the next step is to create the connections/relationship among the clusters and nodes. Thus, the network model of the problem is constructed for further analysis.

3.4.3 Collecting the data

After construction of network model, pairwise data of each cluster and node is collected. A nine-point scale is used to collect pair-wise comparison data as suggested by Saaty (1980), which is same as shown in Table 3.1. This scale explains the relative importance between two elements of the model and shows how one element is important with respect to another element.

3.4.4 Solve the model using the Super Decisions software

Super Decisions software was developed by Saaty (2003). To solve the present research problem, Version 3.2 of Super Decisions software is used. With the help of clusters, nodes and arrows, the network model is designed in this software. Two type of arrows is used to show the connection between two elements: one-directional and two-directional. One-directional arrow represents the dependency of one element on another, while two-directional arrow represents the two-way interdependency between the two elements of the network.

3.4.5 Result analysis

This step is to synthesis the network model results, which are directly obtained from the Super Decision software. This software provides the priority weight of each criteria with respect to each alternative. With normalized weight of each criteria is provided by the software, ranking of each alternative is obtained. These tools and technique are used.

1. to establish interrelationship amongst SCR variables,
2. to assess and prioritize the SCR variables,
3. to evaluate the risk level and select the risk management strategy

Next chapters describe the implementation of these tools and technique for the case organisation.