CHAPTER 3

3. RESEARCH METHODOLGY

3.1. THEORETICAL FRAMEWORK FOR RESEARCH METHOD:

Research design for the study is exploratory and analytical.

Research data for large number of parameters gathered from literature review are less concrete concepts. So to group these large number of parameters into survey scale and then use it to calculate a total score or mean scale, 'Likert 5 Point Level' is opted which was 'Ordinal Data Type'. Out of many literatures studied, below literatures helped in deciding research method for the research study.

Between many controversies for use of parametric tests or non-parametric tests for ordinal data such as data from Likert scales, some literatures confirmed appropriateness of using parametric tests because these are more robust than nonparametric tests. That is, parametric tests tend to give "the right answer" even when statistical assumptions—such as a normal distribution of data—are violated, even to an extreme degree. Thus, parametric tests are sufficiently robust to yield largely unbiased answers that are acceptably close to "the truth" when analyzing Likert scale responses. To provide evidence that the components of the scale are sufficiently inter correlated and that the grouped items measure the underlying variable, experts suggested 'Cronbach Alpha' or 'Factor Analysis Technique'. (Sullivan 2013).

Also single-item questions pertaining to a construct are not reliable and should not be used in drawing conclusions. Hence multi-item scale is to be considered for reliability. (Gliem & Gliem 2013).

Method extensively used for Data analysis in Social Study research for examining patterns of inter-relationships, data reduction, instrument development, classification and description of data, data transformation, hypothesis testing, exploring relationships in new domains of interest, and mapping construct space is Factor Analysis. Factor analysis is useful for studies that involve a few or hundreds of variables, items from questionnaires, or a battery of tests which can be reduced to a smaller set, to get at an underlying concept, and to facilitate interpretations. It is easier to focus on some key factors rather than having to consider too many variables that may be trivial, and so factor analysis is useful for placing variables into meaningful categories. Many other uses of factor analysis include data transformation, hypothesis-testing, mapping, and scaling. (Rummel, 1970)

Scale development clearly involves a bit of art as well as a lot of science. Confirmatory factor analysis allows the researcher to quantitatively assess the quality of the factor structure providing further evidence of the construct validity of the new measure. It is still subject to the use of judgment, however, and thoroughly and clearly reporting confirmatory factor analyses is very important. Results should include at a minimum the chi square statistic, degrees of freedom, and the recommended goodness-of-fit indices used for each competing model. It may also be appropriate to report factor loadings and t values. (Hinkin, 1998)

(Briggs & Cheek, 1986) examined the usefulness of factor analysis in developing and evaluating personality scales that measure limited domain constructs and showed how factor analysis can be used to identify important conceptual distinctions.

Factor Analysis is used as multivariate statistical procedure to reduce large number of parameters into significant factors. Underlying dimensions are established. Reason to prefer 'Factor Analysis' is, "Factor analysis is a multivariate statistical procedure that has many uses, three of which will be briefly noted here. Firstly, factor analysis reduces a large number of variables into a smaller set of variables (also referred to as factors). Secondly, it establishes underlying dimensions between measured variables and latent constructs, thereby allowing the formation and refinement of theory. Thirdly, it provides construct validity evidence of self-reporting scales." (Williams, 2012)

A principal component analysis is concerned with explaining the variance-covariance structure of a set of variables through a few linear combinations of these variables. Its general objectives are (1) data reduction and (2) interpretation. Analysis of principal components often reveals relationships that were not previously suspected and thereby allows interpretations that would not ordinarily result. Analysis of principal components are more of a means to an end rather than an end in them, because they frequently serve as intermediate steps in much larger investigations. For example, principal components may be inputs to a multiple regression. (Johnson 2007)

This theoretical framework led in deciding most appropriate research method in finding large number of parameters listed from literature review to most relevant for Indian oil and gas industry is by 'Factor Analysis' with extraction method of 'Principal Component Analysis'.

References:

1. Bentler, P.M. & Chou, C. (1987). Practical issues in structural modeling. Sociological Methods and Research, 16, 78–117.
2. Briggs, S. R., & Cheek, J. (1986, March). The role of Factor Analysis in development and evaluation of personality scale. Wiley online library, 54(1), 106-148.
3. Gail M. Sullivan, A. R. (2013). Analyzing and Interpreting Data From Likert-Type Scales. J Grad Med Educ , 5(4): 541–542.
4. Gliem, J. & Gliem, R. (2003). Calculating, Interpreting, and Reporting Cronbach's Alpha Reliability Coefficient for Likert-Type Scales, Midwest Research to Practice Conference in Adult, Continuing, and Community Education, October 2003, pp. 82-88.
5. Hinkin, T. R. (1998). A Brief Tutorial on the Development of Measures for Use in Survey Questionnaires. Cornell University School of Hotel Administration.
6. Johnson, R. (2007). Applied Multivariate Statistical Analysis. NJ: Pearson Education, Inc.

7. Rummel, R. J. (1970). Applied Factor Analysis. Evanston: Northwestern University Press, pp 617. Available at www.garfield.library.upenn.edu/classics1987/A1987H560200001.pdf
8. Williams, B. (2012). Exploratory Factor Analysis: A Five-Step Guide. Australasian Journal Of Paramedicine, 8(3).

3.2 **RESEARCH METHOD FOR OBJECTIVE 1:** Parameters (which are variables) are gathered from literature review and are grouped into project functions by taking views of 10 senior experts from Indian oil and gas sector. To analyze relevance of these parameters to Indian oil and gas contract award, primary data was collected by gathering feedback responses from respondents working in Indian oil and gas project functions like Finance, Technical, HSE, Risk Management, Human Resource Management, Marketing & Communication, Top Management, Legal & Branding, and Purchase Management & Procurement. Responses gathered for these parameters were based on impotence of each parameter to Indian oil and gas project performance using Likert Scale. Response '5' was scaled as 'Most Important' and response '1' was scaled as 'Least Important' to project performance. As it is Likert 5 point Scale so 'Measurement Level' of data wouldl fall under 'Ordinal'.

Factor Analysis was used to reduce large number variables to relatively smaller number of factor groups. To describe relationship among latent variable and observed variables and to find strength of association, Structural Equation Model (SEM) was used.

'Principal Component Analysis, PCA' was run to help investigating large number of relationships among these variables into a simpler way. PCA was selected as it is performed on an ordinary correlation matrix, complete with the correlations of each variable (parameter) with itself and it reproduces all information of variance, covariance associated with the set of variables. There are two conditions for PCA: a) There need to be relations between the variables and b) Larger the sample size, the more reliable the resulting factors usually are. There is no strong distributional assumption for PCA. Hence initially 'Descriptive Analysis' was run in software SPSS to check a) Is there a relation among variables of contract award b) To get correlation matrix to assess reliability and c) to compute basis for Factor Analysis. Calculating

Cronbach Alpha coefficient will help in knowing Internal Consistency of items. This is based upon the formula :

Cronbach Alpha Coefficient = rk /[1 + (k -1)r]

where k is the number of items considered

r is the mean of the inter-item correlations.

Alpha value equal to 0.8 is a reasonable goal with value < 0.8 is good and <0.9 is excellent.

PCA is based on correlations and the variables should be related to each other (in pairs) in a linear fashion and at least many of the variables should be correlated at a moderate level. Factor Analysis and PCA reproduce the correlation matrix which will not be sensible if correlation all over and all around are zero. Bartlett's test of sphericity addresses this assumption. Further 'Descriptive Statistics' was calculated to find factor solution with Scree plot and unrotated Component Matrix. Rotated component matrix provides loading for each component (parameter) on the factor and Component Plot gives visual representation of the loadings, plotted in space.

3.3 **RESEARCH METHOD FOR OBJECTIVE 2:** Similar method as carried out in Objective 1 was followed to reduce large Parameters (variables) for successful performance of a project. Parameters from literature review were grouped as per project function with 10 experts of Indian oil and gas industry. These parameters from these project functions were given for primary data collection for getting feedback responses from oil and gas project group persons like Projects, Operations Management, Costing departments, Quality Management, Project Management , HSE departments, Procurement and Subcontracting department and Stakeholders to carry out analysis for relevance to Indian oil and gas projects. Data collected using Likert 5 point scale with score of '5 for 'Most Important Parameter' and score of '1' for 'Least Important Parameter'.

Factor Analysis was carried out to reduce large number of parameters to relatively small number of factor groups. 'Descriptive Analysis' was run. Cronbach Alpha coefficient calculated to find internal consistency of data. Principal Component Analysis was used as method of extraction. PCA extracted initial factor solution and rotated factor solution which allotted loading to each project performance component (parameter).

3.4 RESEARCH METHOD FOR OBJECTIVE 3:

Factor solution has extracted factor loading to give weightage for each component.

Component Index is calculated using formula:

$$\frac{\text{C. I. actual} - \text{C. I. min}}{\text{C.I. max} - \text{C. I. min}}$$

Where C.I. min and C. I.max are defined by stakeholders (Project Owners) as per objective of project at the beginning of the RFQ/Bid.

C. I. actual is the value scored by each bidder during evaluation of bids by owner/operator evaluation team.

Using component score and component Index value, Component Composite Index is constructed.

Each Factor is linear combination of its components and is represented by:

$$F_{ji} = \sum W_{kj} Z_{ik} \text{ where i is } (1\ldots.k.)$$

Where Fji is component score for jth factor with ith component

Wkj is weight of the component from factor analysis

Zik is value of component calculated as component Index

Each Factor will include components with component score more than 0.5, rest all are considered as not significant and hence not taken into Component Composite Index. Component Composite Index will be sum total of component scores of all components of a factor.

Once we have Component Composite Index for each Factor, a Composite Index, we named it as Contract Award Index (CAI) is constructed using Geometrical Mean :

$$\textbf{Composite Index} = \sqrt[n]{(I_1 \times I_2 \times I_3 \times I_4 \times \ldots\ldots I_n)}$$

Here Geometric Mean is calculated because for construction of the Index as mentioned above, (UNDP, 2010) method has been followed. Previously (UNDP, Human Development Report, 1990) used Arithmetic Mean method for Index construction but Geometric Mean method is an improvement over Arithmetic Mean as it normalizes each individual parameters or factors.

From UNDP, "The geometric mean is a particular case of the family of "general means." The attribute it averages can be income or any other cardinal variable. Its multiplicative form is easier to interpret in comparison to the other general means and the geometric mean satisfies several useful properties."

Similar way, with all factor of PP, Project Performance Index (PPI) is constructed using Geometric mean of all PP factor score.

In framing CAI, this CAI will be analyzed with PPI and both these indices will be used as progressive score of bidders and project performer. Geometric mean allows more accurately the average rate for processes with variable in time rate, hence geometric mean is preferred over arithmetic mean. Use of a geometric mean "normalizes" the ranges being averaged, so that no range dominates the weighting, and a given percentage change in any of the properties has the same effect on the geometric mean.

Scales (in ordinal data) and Indexes are important in researches as Scales measure level of intensity of the variable like agree , strongly agree, disagree , strongly disagree etc. and Index is compilation of score from various statements that represent attributes. Hence Indexes are very useful quantitative research for creating composite measure which summarizes responses of multiple itemized ranked statements. This provides data in research for participant's opinion on certain attributes.

General Linear Model was used to express relationship among dependent variables and independent variables by an equation with weights for each of the independent/predictor variables plus error terms.

Each Contract Award Factor is regressed against Project Performance Index. As this data set is calculated from Geometric Mean so assumption of normality is met.

Hypothesis for testing is

"Contract Award Factors do not affect Project Performance Index".

Multiple regressions were used to test null hypothesis.

$$Y = a + b_1X_1 {}^{+} b_2X_2 + b_3X_3 + \dots + b_tX_t + u$$

Similarly Contract Award Index is regressed on Project Performance Index.

Hypothesis proposition is

"CAI do not affect PPI".

Bivariate Regression was used to test this hypothesis.

$$Y = b_0 + bX + u$$

b_0-the slope, u-regression residual)

3.5 SOURCES OF DATA:

Primary data from various respondents from oil and gas companies is collected. Some secondary data is also used from different sources to collect additional data.

Primary Data: The primary data is collected from the representatives of:

- Oil and Gas owner/operator companies

- Consultants
- Contractor
- Sub-contractors

Secondary Data: The secondary data is collected from the following sources:

- Project Management Journal
- Oil and Gas websites
- Oil and Gas company websites
- Major contractors / sub-contractors websites in India
- Indian Oil and Gas Govt. /regulatory sites
- Other Research Journal / Research Papers / Articles/Forums

3.6 SAMPLING:

Sample size provides the basis for the estimation of sample error and impact on the ability of the model to be correctly estimated. Bentler suggests that in SEM the sample size requirements vary for measurement and structural models. (Bentler P. M., 1987) As with any statistical method, the critical question is how large a sample is needed?

To test a measurement model, Flynn and Pearcy (2001) cited in (Williams, 2010), a rule of thumb of ten subjects per item in scale development is prudent. According to MacCallum, Widaman, Zhang, and Hong (1999), such rules of thumb can at times be misleading and often do not take into account many of the complex dynamics of a factor analysis. "They illustrated that when communalities are high (greater than .60) and each factor is defined by several items, sample sizes can actually be relatively small". Guadagnoli and Velicer found that solutions with correlation coefficients >.80 require smaller sample sizes, while Sapnas and Zeller point out that even 50 cases may be adequate for factor analysis. As can be seen, the suggested sample size required to complete a factor analysis of a group of items that participants have responded to, varies greatly. Factor Analysis should not be done with sample size less than 100 observations. It should be noted that an increase in sample size will decrease the level at which an item loading on a factor is significant.

Sample size calculation by (Bertlett J., 2001) (Singh A., 2014)

Necessary Sample Size = (Z-score) * StdDev*(1-StdDev) / (margin of error)

We chose a 95% confidence level, .5 standard deviation, and a margin of error (confidence interval) of +/- 5%.

Hence calculated sample size = ((1.96)x.5(.5))/(.05)

= (3.8416x.25)/.0025

= .9604/.0025

384.16

385 respondents

Using table :

Table 1. Sample Size for ±5% and ±10% Precision Levels where Confidence Level is 95% and P=0.5.

Size of Population	Sample Size (n) for precision (e) ±5%	±10%
500	222	83
1,000	286	91
2,000	333	95
3,000	353	97
4,000	364	98
5,000	370	98
7,000	378	99
9,000	383	99
10,000	385	99
15,000	390	99
20,000	392	100
25,000	394	100
50,000	397	100
100,000	398	100
>100,000	400	100

Table 3.1

Sampling technique used is non-probability, judgmental sampling. Respondents selected from Oil and Gas upstream Operators, Refinery, Pipeline operators, EPC Contractors, Engineering consultants, Large equipment manufacturers in India. Considering 30% response rate, more than 1200 respondents were picked up from 70 upstream, midstream, downstream companies. 42 parameters were gathered from literature review and secondary source of data. Again as thumb rule 10 responses per parameter, hence 420 completed responses were prudent for analysis. Responses were sent to more than 1200 personnel having experience in one or more of oil and gas functions as contract evaluation , material management , contract management and tendering, projects, technical management , engineering management, maintenance management and operations management functionality. Equal responses were taken from upstream, midstream and downstream players and respondents covering top management level, middle management level and lower management level in oil and gas companies. More than 50 questions on 'Contract Award' function and similar number of questions on project performance function were given to these 1200 personnel in oil and gas industry in India. Multi–item measures are used to measure various attributes of 'Contract Award' function and 'Project Performance' function because multi-item questionnaire has advantage of "Measurement error averages out when individual scores are summed to obtain a total score" (Gliem & Gliem, 2003). Five Point Likert Scale is used (scale 1-5, 1 being least important parameter and 5 being most important parameter) for gathering output of the descriptive data.

Output was gathered from various modes like online survey, link through social media, survey using hard copy and by direct interview. Questionnaire were provided in four sections , Section 1 to understand need for change in Current Contract Award Approach, Section 2 need for Project Performance Measure, Section 3 for important Parameters for Success of Project Performance, and Section 4 for Parameters to be considered during Contract Award Framework.

References:

1. Bentler, P.M. & Chou, C. (1987). Practical issues in structural modeling. Sociological Methods and Research, 16, 78–117.

2.Briggs, S. R., & Cheek, J. (1986, March). The role of Factor Analysis in development and evaluation of personality scale. Wiley online library, 54(1), 106-148.

3. Gail M. Sullivan, A. R. (2013). Analyzing and Interpreting Data From Likert-Type Scales. J Grad Med Educ , 5(4): 541–542.

4. Gliem, J. & Gliem, R. (2003). Calculating, Interpreting, and Reporting Cronbach's Alpha Reliability Coefficient for Likert-Type Scales, Midwest Research to Practice Conference in Adult, Continuing, and Community Education, October 2003, pp. 82-88.

5. Hinkin, T. R. (1998). A Brief Tutorial on the Development of Measures for Use in Survey Questionnaires. Cornell University School of Hotel Administration.

6. Johnson, R. (2007). Applied Multivariate Statistical Analysis. NJ: Pearson Education, Inc.

7. Rummel, R. J. (1970). Applied Factor Analysis. Evanston: Northwestern University Press, pp 617. Available at www.garfield.library.upenn.edu/classics1987/A1987H560200001.pdf

8. Williams, B. (2012). Exploratory Factor Analysis: A Five-Step Guide. Australasian Journal Of Paramedicine, 8(3).