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Measuring Uncertainty in Human Resources of Professional Academic Institutions Using Balanced Scorecards and Artificial Intelligence

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Abstract

Balanced Scorecard (BSC) is being used as one of the sound measures of non-financial performance in an organizational set up where the human resource plays a significant role at the operational level. Balanced scorecard can be incorporated as a strategy planner, which would be bi-focal in nature i.e. from organizational as well as from employee point of view. Although substantial development has been envisaged in the area of balanced scorecard related tools, a proper interface & blending with information technology, cognitive science and reasoning is yet to be achieved. There are several possibilities of uncertainty in information in the scorecard. Processing those uncertainties in the subsequent stages of a scorecard addresses the behaviour related issues in an organization.

This paper attempts to answer this blending in information technology and human resources and tries to implement balanced scorecard as a generic information technology enabled tool for an organization that intends to develop its human resources. The model derived in this research also proposes to filter the uncertainties, in the subsequent stages of balanced scorecard.

Keywords: Balanced Scorecard, Learning and Growth, Artificial Intelligence, Fuzzy Petri net, Professional Institutions, Decision Parameters.

1.0 Introduction

The Balanced Scorecard [1] is a new measure of performance and has been derived from strategy of the organization. It can be used as a future predictor of performance (both financial as well as non-financial), which encompasses the four quadrants of a scorecard i.e. financial, internal business process, external perspectives and learning and growth. It has a wide gamut of uses for communicating strategy in the organization, identifying and aligning strategic initiatives, reviewing strategy systems as well as generating feedback to improve upon the existing one.

As mentioned earlier the four metrics of Scorecard are as follows:

Financial metrics which measures the economic consequences of actions already taken in terms of

EVA (Economic Value Added) [2]. EVA can serve as a good indicator of financial performance. It (Economic Value Added) is the excess of returns (ROI-Return on Investment) over Cost of Capital.

In academics the Cost of Capital [2a] are the borrowed funds for development of infrastructure and the returns generated by way of fees, grants-in –aid etc (Figure 1).

Customer metrics defines the market position of the firm /organization and the perception it enjoys from the stakeholder point of view. It includes several generic measures of successful outcomes from a well-formulated and dexterously implemented strategy. In the customer perspective the customers are identified for a typical market segment in which the business intends to compete. For example in a mid sized business school charging fees of Rs. 4,00,000($8000) per annum the customers are typically students with family incomes ranging from Rs 5,00,000 ($10,000) and above having graduate level of education.

Internal Business metrics deals with the organizational excellence achieved by the company through its processes of knowledge sharing, transparency, knowledge management, and intellectual capital growth. In academics these may tantamount to value addition through intellectual capital growth. The above factors increase growth opportunities for the faculty members through open learning (as for example Experiential Learning, Sensitivity Training etc) as well as closed learning (indoor learning/classroom learning).

Lastly, the Learning andGrowth Metrics evaluates the academic institute on a new paradigm of excellence in terms of intellectual capital growth, a conducive atmosphere for research, publication by faculty members as well as through effective dissemination of knowledge that acts as throughput for the trainer (Teacher) as well as the trainee (Student). [4] [5] [6]

1.1 Scorecard in Application:

The Balanced Scorecard (BSC) equips the executives with a comprehensive framework by translating objectives into a coherent set of performance measures. It can make astounding improvements in critical areas like product, process and market development. The Scorecard presents the managers with four different perspectives to choose from. It harnesses the best of each metrics and helps the implementer (either in industry or in academics) to improve performance and act as a reference for past and future successes. It takes a paradigm shift from traditional measures and redefines an organization's vision, mission and strategy in a longer time frame . [7][8]

1.2 Limitations Encountered in this Approach

Balanced Scorecards, which has spread at lightning speed even by today's fast paced standards, failed over time to meet the expectations of their implementers. [3] Schneidermann further throws some light on the failure of Scorecards namely improper identification of variables, poorly defined metrics, negotiated goals and lack of linkage amongst non-financial and expected financial results. In academic institutions the limitations encountered are improper identification of EVA, poor development/false representation of intellectual capital index and non-linkage of research to industrial needs.

1.3 Scope of the Research.

The foremost purpose of this research is to filter the vagueness, uncertainty measure, and to bring out several sets of inferences established through the scorecard. In this paper, we have used I.T. as a tool by blending it with a human resources domain to bring out a balanced measure of propositions and beliefs. Here an effort has been made towards generating a mathematical model to minimize the uncertainty and vagueness in empirical data and present it in a precise and comprehensive manner.

Figure 1: Schematic Diagram of EVA Creation

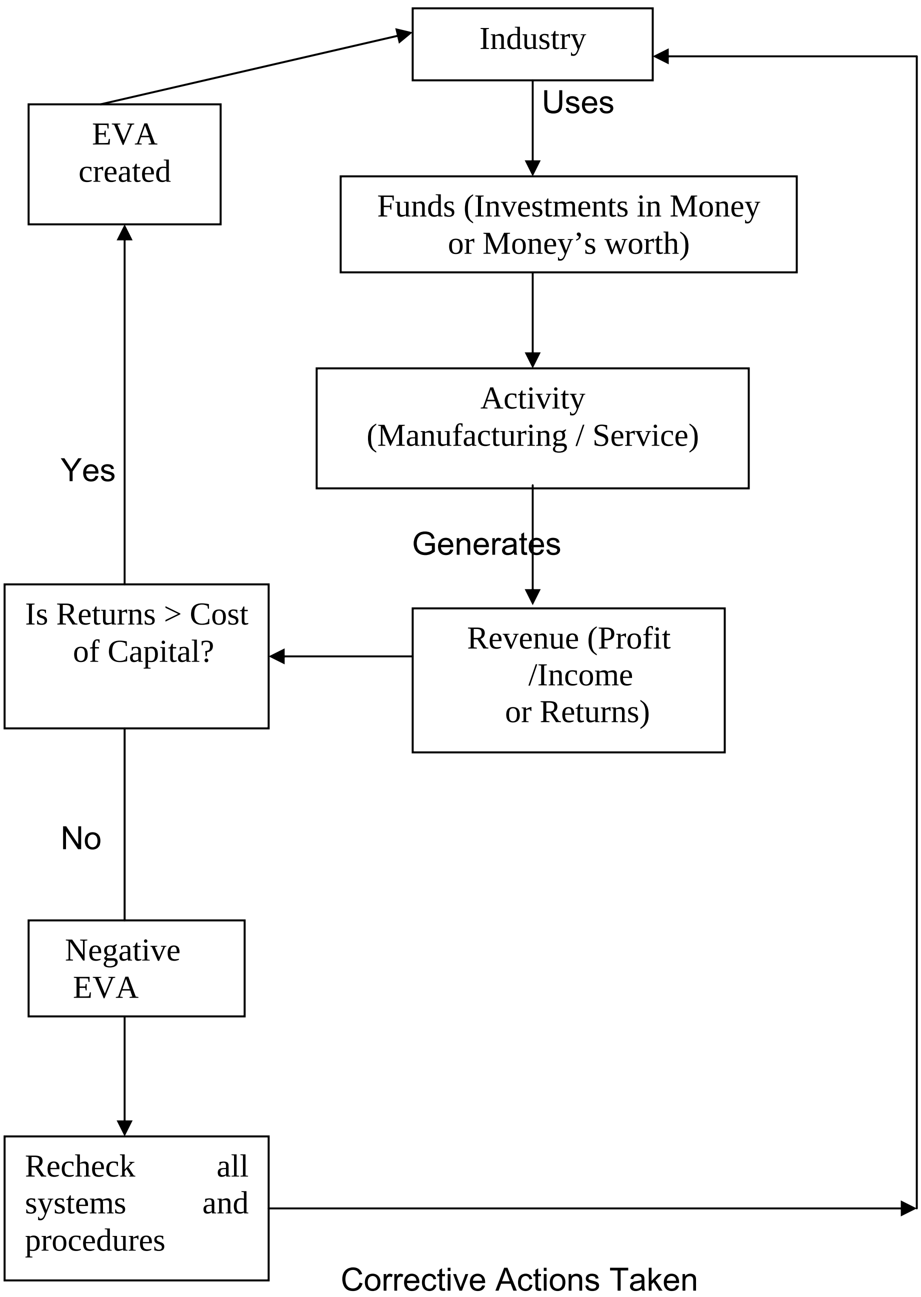
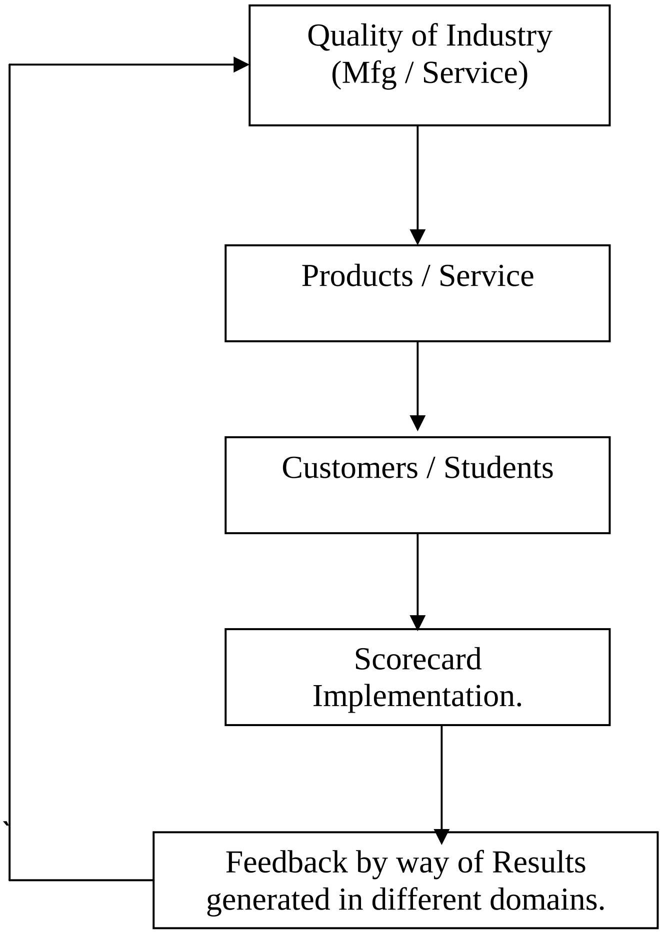


Figure 2 : Schematic Representation of Scorecard Implementation



2.1 What is Uncertainty in Information?

The lexical meaning of the term “Uncertainty” gives six clusters of meanings:-

1. Not certainly known: - Questionable, problematical.
2. Vague: not definite, or determined
3. Doubtful: Not having certain knowledge, not sure.
4. Ambiguous.
5. Not stable, varying, or not constant
6. Liable to change or vary: - Not dependable, or reliable.

Considering these broader aspects of uncertainty or vagueness, the parameters of Balanced Scorecard for different organization seem to be hazy or non- specific. Therefore knowledge representation about Balanced Scorecard can be modelled according to the uncertainty of information.

Classical measure of uncertainty as proposed by Hartley (1928) [9] was based solely on classical set theory. Another measure of uncertainty introduced by Shannon (1948) [10] is formulated in terms of probability theory. Both Hartley and Shannon introduced their measure for the purpose of measuring information in terms of uncertainty.

Recent works [11] [12][13] reveal that approximate reasoning tools are well compatible to handle uncertainty in information. The deliberate variations in the parameters of Balanced Scorecard, imperative to any organisation automatically inherits uncertainty according to the classification of services, categorisation of staff and their behavioural aspects, the combination of diversified inputs, as participating either like an agent or like an impact provider on the system. Regional inertia & socio-economic factors play a crucial role in fabricating the scorecard model as a generic one.

The implementation of Balanced Scorecard in different service sectors (academics, healthcare etc) suffers from a great deal of uncertainty while assessing the required parameters.

The modelling of balanced scorecard is highly dependent on empirical data (liable to change for different agents in any point of time), which is substantially gathered through questionnaire sessions. It is evident that the cognitive processes of the participant's influences the data and reflects plenty of variation. Thus presence of vagueness in the information is inevitable. This project proposes a mathematical model and filtering mechanism, so that the uncertain data can be made more definite, which in turn will be propagated through the core model of Balanced Scorecard for proper evaluation.

2.0 How to tackle it with help of Artificial Intelligence (AI) Model?

Recent research findings broadly exhibit many fold paradigms to ensure uncertainty measures with the help of Artificial Intelligence and Information Technology (I.T) related tools . [11] [12] [13] the various algorithms have been deployed successfully for weighing the performance of individuals, and organizations.

A new mathematical modeling technique known as soft computing is showing promise in modeling complex system, which is typically chaotic and uncertain in nature like Neural Networks, Fuzzy Logic, Met heuristic, Genetic Algorithms etc. In this research project some prominent AI tools are also used [13a] [13b] . Either they were broadly used for validation of rules and parameters in multiple agent environment or application, or they are successfully applied to find a definite relation among parameters and their utility in commercial applications. This paper also incorporates linguistic based fuzzy techniques, for evaluating perfect parameters for bsc implementation.

3.0 Balanced Scorecard: Proposed Model

For years the development of approximate reasoning based models have been characterized by capturing and extrapolating uncertainty inherent to the system. In this particular project several classical methodologies to handle uncertainties have been tried; but somehow, the work did not accomplish the convergence of expected goals. However, parameter upliftment through Balanced Scorecard has been achieved and the system is supposed to take a shape, completely data centric, without the emphasis on the representation on uncertain set derived from the original data set of customers (students).

Therefore a hybrid model has been adopted combining fuzzy logic and Petri net, leading to FPN (Fuzzy Petri net). Instead of using pure IT or Computer Science jargon this report describes such a model, in a language that is familiar to HR practitioners.

Chen, Ke and Chang (1990) used to a fuzzy Petri net model to represent fuzzy rule based system. Fuzzy reasoning algorithms can also be used to determine whether or not an antecedent consequence relationship exists from one proposition, called starting place to another proposition called goal place. Based on FPN (Fuzzy Petri net) model, this research paper proposes to incorporate this model for deciding several levels of inferences, as established through balanced scorecard.

As we know, balanced scorecard is a balanced measure for given beliefs and propositions. Therefore, a need is felt for proper defuzzyfication model, which has been duly taken care of in this project.

3.1 Notation & backgrounds:

According to the notation adopted in Chen, Ke & Chang (1990) [14], a generalized fuzzy

Petri net structure can be defined & tupple: FPN= [P, T, D, I, O, F, α, β]

where p={p1, p2, p3, ……….pn} denotes the set of places.

T= {t1, t2, t3………………..,tn} denotes set of transitions

D= {d 1, d 2, d 3… d n} denotes a set proposition

$p \cap t \cap d = \acute{\emptyset}$, $|p| = |d|$, I(O);

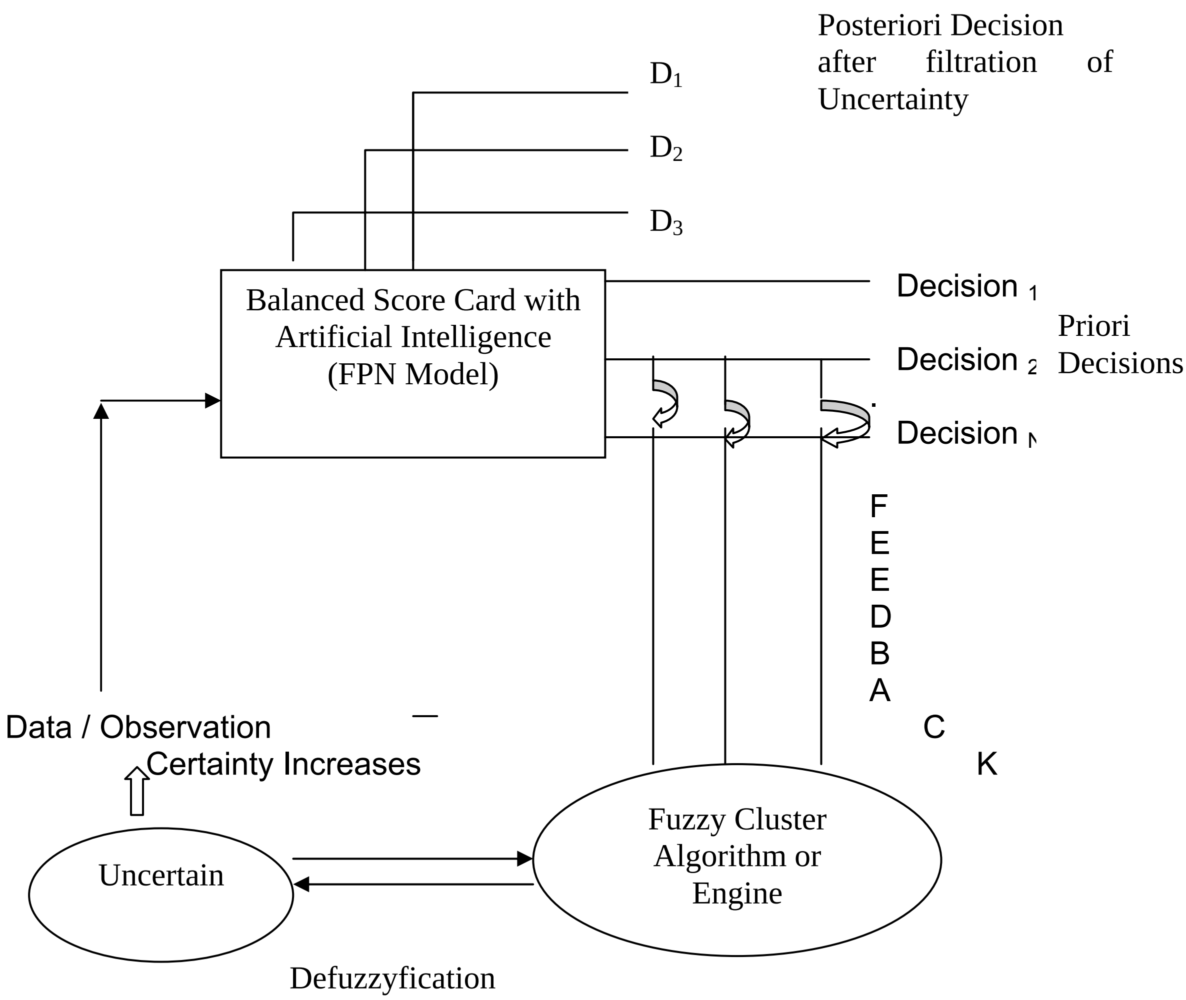
T→Pα is the input, output function, f: T → [0, 1]. Assigns a certainty value to each α: P→ [0, 1], assign a certainty value to each place and β: P→ D is an injective mapping between the preposition and place level for each node.

By using a FPN a fuzzy production rule can be modeled and furthermore it can be expressed as a fuzzy relation between two propositions.

Ri: if Dj then Dk (Cf= μi) certainty factor

Where Dj and Dk are proposition and μ i [0, 1] is the degree of truth of the rule representing the belief in the proposed rule. Again the detailed definition and discussion can be found in Chen, Ke & Chang (1990). [15]

Proposed Model



Decision Parameters

Value addition $\rightarrow$ **P_1**

Quality of teaching $\rightarrow$ **P_2**

Extracurricular $\rightarrow$ **P_3**

Ambition fulfillment $\rightarrow$ **P_4**

r_1 (Results) {Tupples of R_1 embedded in the model}

R_1

r_2 (Placements)

R_3 (Market Share declines)

R_2

R_4 (Negative Placements)

- P 1 occurs very seldom in student with result R 1.
- P 1 often occurs in student with result R 2 but seldom confirms the presence of R 2.
- P 2 always occurs with result R 1 and always confirms the presence of R 1.
- P 2 never occurs with result R 2 and obviously its presence never confirms result R 2.
- P 3 very often occurs with R 2 and often confirms the presence of R 2.
- P 3 seldom occurs with students for results R 1.
- P 4 is completely variable for R 1& R 2 .

Let us assume that we are given a student who exhibits/pivots to the parameters, P 1, P 2, P 3, and P 4; at the level of importance given by the following vectors:

$$X = \begin{pmatrix} P_1 & P_2 & P_3 & P_4 \\ 0.1 & 0.7 & 0.4 & 0.6 \end{pmatrix}$$

Let $\mu_x(P_i)$ **ε [0,1]** denote the grade of the membership in the fuzzy set characterizing student 'x' and defined on the set P = {P_1, P_2, P_3, P_4} which indicates importance level of the perimeter 'P_i' for the student.
We must determine an inference mechanism for this student among **three (3) possible inferences D_1, D_2 and D_3.** Each of these inferences is described by a matrix giving the upper and lower bounds of the normal range of importance of each of the parameters that can be expected in a student.

The decision D_1, D_2 and D_3 are described in this way by matrices:

$$D_1 = \begin{array}{c} \\ \text{lower} \\ \text{upper} \end{array} \begin{pmatrix} P_1 & P_2 & P_3 & P_4 \\ 0 & 0.6 & 0.5 & 0 \\ 0.2 & 1 & 0.7 & 0 \end{pmatrix}$$

$$D_2 = \begin{array}{cc} & \begin{array}{cccc} P_1 & P_2 & P_3 & P_4 \end{array} \\ \begin{array}{c} \text{lower} \\ \text{upper} \end{array} & \begin{pmatrix} 0 & 0.9 & 0.3 & 0.2 \\ 0 & 1 & 1 & 0.4 \end{pmatrix} \end{array}$$

$$D_3 = \begin{array}{cc} & \begin{array}{cccc} P_1 & P_2 & P_3 & P_4 \end{array} \\ \begin{array}{c} \text{lower} \\ \text{upper} \end{array} & \begin{pmatrix} 0 & 0 & 0.7 & 0 \\ 0.3 & 0 & 0.9 & 0 \end{pmatrix} \end{array}$$

Let μ_{djl} **(P_i) ε [0,1]** denote the lower bound of the parameter 'i' for decision 'j' and let μ_{dju} **(P_i) ε [0,1]** denote the upper bound of the fuzzy parameter 'i' for the decision.

We further define a fuzzy relation W on the set of parameters and decisions that specifies the pertinence or importance of parameter 'p' in the confirmation of decision 'D'. The relation 'W' of these weights of relevance is given by:

$$W = \begin{array}{c c} & \begin{array}{ccc} D_1 & D_2 & D_3 \end{array} \\ \begin{array}{c} P_1 \\ P_2 \\ P_3 \\ P_4 \end{array} & \begin{pmatrix} 0.4 & 0.8 & 1 \\ 0.5 & 0.6 & 0.3 \\ 0.7 & 0.1 & 0.9 \\ 0.9 & 0.6 & 0.3 \end{pmatrix} \end{array}$$

Let μ_w **(S_i, dj)** denote the weight of parameter P_i for decision D_j. In order to investigate the feedback of student 'x' we use a clustering technique to determine which investigating cluster (as specified by matrices D_1, D_2 and D_3) **the student is most affine to**. This clustering is performed by computing a similarity measure between the student's parameter and those typical/responsible of each of decision D_j.To compute this similarity, we use a distance measure based on Minkowski distance that is modified by one model. It is given by:

$$D_p\,(d_j, x) = \Big[\sum_{i\,\varepsilon\,A_j} \left|\mu_w(p_i,d_j)(\mu_{djl}(P_i) - \mu_x(P_i))\right|^Z + \sum_{i\,\varepsilon\,B_j} \left|\mu_w(p_i,d_j)(\mu_{dju}(P_i) - \mu_x(P_i))\right|^Z\Big]^{1/Z}$$

..................**Equation 1**

$A_j = \{ i \mid \mu_s(P_i) < \mu_{djl}(P_i),\ 1 \leq i \leq m\}$
$B_j = \{ i \mid \mu_x(P_i) > \mu_{dju}(P_i),\ 1 \leq i \leq m\}$
Where, 'm' = Total number of parameters.
Here, Z = 2 for the distant measure using equation (1). We calculate the similarity between students and the decision D_1, D_2 and D_3 as follows:

$D_2\,(d_1, x) = [|(0.7)\,(0.5 - 0.1)|^2 + |(0.9)\,(0 - 0.6)|^2]^{½} = 0.54$

$D_2\,(d_2, x) = [|(0.6)(0.9 - 0.7)|^2 + |(0.8)(0 - 0.1)|^2 + |(0.6)(0.4 - 0.6)|^2]^{½} =$

0.190

$D_2\,(d_3, x) = [|(0.9)(0.7 - 0.4)|^2 + |(0.3)(0 - 0.7)|^2 + |(0.3)(0 - 0.6)|^2]^{½} =$

0.39

The most likely decision for Balanced Scorecard is the one for which similarity measure attains the minimum value. In this student's parameters are most similar to those typical factors arrived through decision D_2.

4.0 Balanced Scorecard: Analysis & Results

In this work, for implementing the scorecard, we have taken four modeling parameters of decisions, mentioned earlier, and by applying fuzzy clustering algorithms and FPN (Fuzzy Petri nets) we would thus, like to infer following level of decisions achieved through different methods for clustering the uncertain information incorporated through fuzzy logic. One group of common methods uses some form of distance measure to determine the similarity between observed attributes of data from the students and present them in existing responsible and diagnostic clusters. Here D_1 (decision1) matrix directly impresses the result (d_1) with placement, whereas D_2 (decision2) matrix indicates the result (d_2) declination of market share of the particular institutes with negative placements. Similarly D_3 (decision3) matrix indicates the repercussions (d_3) for extracurricular activities and ambition fulfillment of the students, which once again impresses the decision D_2 for market share & placement. From the analysis we found Decision D_2 against d_1=0.54; again Decision D_2 against d_2 =0.19 and Decision D_3 against d_3=0.39. Therefore, the most likely decision for the balanced scorecard is the one for which similarity measure attains the minimum value. Hence our set of decisions achieved through the balanced scorecard may vary with students' parameters; but can be defuzzyified with the abovementioned parameters to give a comprehensive and definite result.

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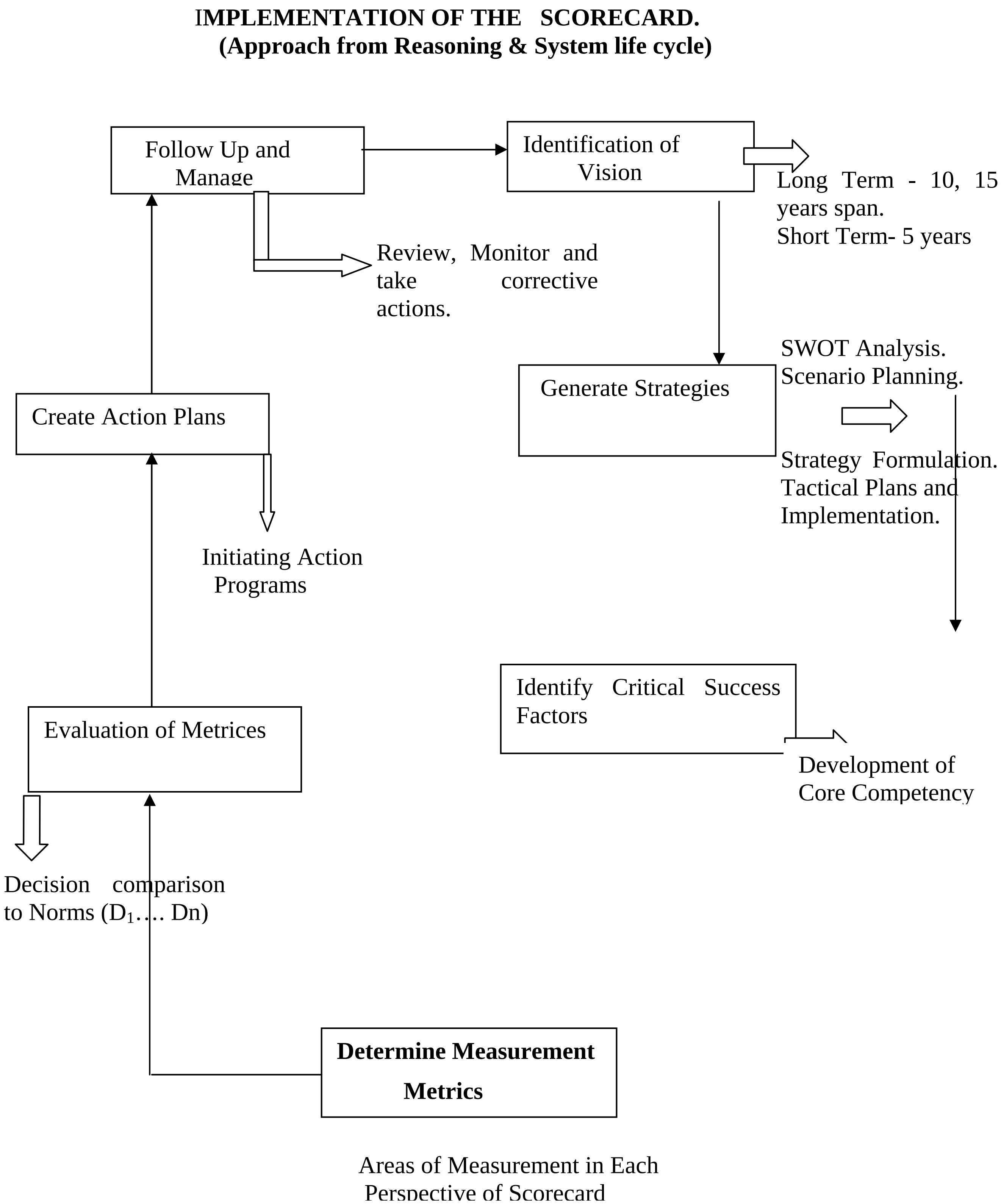
Annexure 1


IMPLEMENTATION OF THE SCORECARD.
(Approach from Reasoning & System life cycle)
Follow Up and Manage
Identification of Vision
Long Term - 10, 15 years span.
Short Term- 5 years
Review, Monitor and take corrective actions.
Generate Strategies
SWOT Analysis.
Scenario Planning.
Strategy Formulation.
Tactical Plans and Implementation.
Create Action Plans
Initiating Action Programs
Identify Critical Success Factors
Development of Core Competency
Evaluation of Metrices
Decision comparison to Norms (D1…. Dn)
Determine Measurement Metrics
Areas of Measurement in Each Perspective of Scorecard