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Inventory management using both quantitative and qualitative criteria in manufacturing system

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Abstract: The success parameters for any company are on time completion, within specific budget and with requisite performance. In particular an efficient and effective inventory management helps a firm maintaining competitive advantage, especially in a time of accelerating globalization. From this point of view several organizations employ the ABC analysis to have an efficient control on a large number of inventory items. With the increasing levels of integration in manufacturing and service systems conventional ABC analysis is limited because it accounts for only one criterion, mostly ‘‘annual dollar usage’’, for classifying inventory items. To alleviate this shortcoming, this paper proposes a modified version of ABC analysis and Cross Analysis based on Analytic Network Process, a multicriteria approach, that allows to consider several criteria all at once for the optimal choice of materials management.

1. INTRODUCTION

In an organization, even with small size, hundreds of items may be held in a warehouse. For organizations that maintain thousands of inventory items, it is unrealistic to provide equal consideration to each item. Inventory is one of the largest and most important assets of a manufacturing business. The management of inventory and how it can provide insight into the firm’s performance is a topic of interest to shareholders, investors, business owners, and the general public (De Felice, 2013). The main purpose of the inventory management practices in all production companies is to have the required items ready to be processed right on the required time with incurring minimum cost (Cakir and Canbolat, 2008). The most widely adopted technique in industrial inventory classification applications is still the ABC analysis that divides items into 3 classes, namely, A (very important), B (moderately) and C (least important), according to Pareto’s principle or the 80/20 rule. According to ABC Analysis inventory items can be classified in A, B, or C categories based on so-called annual dollar usage. Inventory items are arranged according to the descending order of their annual dollar usage. Class A items are relatively small in number, but account for the greatest amount of annual dollar usage. In contrast, class C items are relatively large in number, but make up a rather small amount of annual dollar usage. Items between classes A and C are categorized as class B. The classification obtained from ABC analysis is sometimes subject to further adjustments. For example, dollar usage of some stock-keeping units may not be significant, but their stock-out cost may be extremely high. ABC analysis is successful only when the inventory being classified is fairly homogeneous and the main difference among the items is in its annual use value. But, an organization of even moderate size has to control thousands of inventory items and they aren’t very homogeneous (Ramanathan, 2006). Different papers have mentioned that in addition to this criterion, such other criteria as ordering cost, criticality of part, lead time, commonality, obsolescence, reparability, number of requests, scarcity, durability, perish ability, reparability, demand distribution, stock ability are also needed for classification (Chen, Li, Kilgour, & Hipel, 2008; Ng, 2007; Partovi & Anandarajan, 2002; Zhou & Fan, 2007; Hadi- Vencheh, 2010; De Felice, 2012). Flores and Whybark (1987) developed a cross-tabulation matrix method for use in bi-criteria inventory classification; they found that the method becomes increasingly complicated when three or more criteria are involved in evaluations. In our opinion the ABC classification analysis is very simple to use and very useful but at the same time, for the reasons mentioned above, presents some weaknesses. To overcome the limitations of the traditional classification analysis, many researchers concentrated on incorporating multiple criteria judgments. In the present paper we propose a particular integration of Analytic Network Process (ANP) with ABC Analysis and cross-tabulation matrix. ANP is the successor of the popular Analytic Hierarchy Process (AHP) model, introduced by Thomas L. Saaty in the 1970s, and afterwards it gained widely acceptance of many researchers and practitioners. ANP provides a flexible and easily understood way of analyzing complicated problems (Saaty, 1980). The method has been used in several areas including supplier selection, performance evaluation, project management, inventory management, resource allocation, financial planning and credit scoring, portfolio management, budgeting decisions, etc (Sivestri et al., 2012). The aim of the present paper is to apply the ANP to inventory classification in order to include both quantitative and qualitative evaluation criteria and to propose the most suitable model for materials management applied to the considered industrial system. The organization of the paper is as follows: in the second section we discuss the research methodology, illustrate ANP method and give a brief explanation of it. We present our model and application and explain how the proposed model works, step by step. In the third section we present the case study. Finally, in the fourth section, we come to an end with our conclusions.

2. RESEARCH METHODOLOGY

2.1 The role of inventory management in the performance improvement and Analytic Network Process

Through examination of inventory practices and how they differ over time, it should become easier to judge the stability of a firm and the likelihood that it will perform well in future periods. Effective inventory management has played an important role in the success of supply chain management (Yu, 2011). From this point of view in today's timeliness production environment, it is extremely important for the decision makers to have access to the decision support tools in order to make rapid and accurate decisions. ANP is a problem-solving framework and a systematic procedure for representing the elements of any problem that breaks down a decision-making problem into several levels in such a way that they form a hierarchy with unidirectional hierarchical relationships between levels. The top level of the hierarchy is the main goal of the decision problem. The lower levels are the tangible and/or intangible criteria and subcriteria that contribute to the goal. The modeling process can be divided into different phases for the ease of understanding which are described as follows:

Phase 1. *Experts' team identification. Criteria, sub criteria and alternatives identification in order to define ANP Model.*

Phase 2. *Pairwise comparison and relative weight estimation.* Pairwise comparisons are obtained using a scale from 1 to 9,where 1is for equal importance, 3 for moderate importance, 5 for strong importance, 7 for very strong importance, and 9 for extreme importance. In addition, the even values 2, 4, 6, and 8 are used to reflect intermediate nuances in this scale. Let $A_1, A_2, \ldots, A_m$ denote the set of elements, while a_{ij} represents a quantified judgment on a pair of A_i, A_j. Through the 9-value scale for pairwise comparisons, this yields an m x m matrix A as follows:

$$A = a_{ij} = \begin{array}{c|cccc|} & A_1 & A_2 & \ldots & A_m \\ A_1 & 1 & a_{12} & \ldots & a_{1m} \\ A_2 & 1/a_{12} & 1 & \ldots & a_{2m} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ A_m & 1/a_{1m} & 1/a_{2m} & \ldots & 1 \end{array}$$

where $a_{ij} > 0$ (i, j = 1, 2,..,m), $a_{ii} = 1$(i = 1, 2,…,m), and $a_{ij} = 1/a_{ji}$ (1; 2;…,m). A is a positive reciprocal matrix. The result of the comparison is the so-called *dominance coefficient* a_{ij} that represents the relative importance of the component on row (i) over the component on column (j). If matrix w is a non-zero vector, there is a λ_{max} of $A_w = \lambda_{max} w$, which is the largest eigenvalue of matrix A. If matrix A is perfectly consistent, then $\lambda_{max} w = m$. We note that a_{ij} denotes the subjective judgment of decision-makers, who give comparison and appraisal, with the actual value (w_i/w_j) having a certain degree of variation. Therefore, $Ax = \lambda_{max} w$ cannot be set up. So the judgment matrix of the traditional ANP always needs to be revised for its consistency.

Phase 3. *Consistency index estimation*. Saaty (1990) proposed utilizing the consistency index (CI) to verify the consistency of the comparison matrix. The consistency index (CI) of the derived weights could then be calculated by: CI = $(\lambda_{max}-n)/ n-1$ where n represents the rank of the matrix. If CI is less than 0.10, satisfaction of judgments may be derived.

Phase 4. *Formation of the initial supermatrix.* Elements in ANP are the entities in the system that interact with each other. The determination of relative weights mentioned above is based on pairwise comparisons as in the standard AHP. The weights are then put into the supermatrix that represents the interrelationships of elements in the system.

The proposed ANP model consists of a control hierarchy and a network of connections between the clusters of alternatives, actors, and criteria. The strategic criteria were included into the model to rate Benefits (B), the good things that would result from taking the decision; Opportunities (O), the potentially good things that can result in the future from taking the decisions; Costs (C), the pains and disappointments that would result from taking the decision; and risks (R), the potential pains and disappointments that can result in the future from taking decisions. A synthesis of alternatives was finally obtained using rated BOCR. In Figure 1 is shown the research framework.

3. CASE STUDY DESCRIPTION

3.1 Problem delineation

A case study to demonstrate the proposed procedure is carried out based upon data on *automotive sector within a company that produces cars*. There are several reasons why the automobile manufacturing industry is worthy of being specifically studied. First, the capital-intensive nature of the industry, rapid changes in preferences and modifications resulting in obsolete inventory. Then price decline for products as they are replaced by newer and more appealing models, increases the likelihood and frequency of inventory write-downs for FIFO firms (Gokarn, 2010). In every industrial company, it is essential to obtain a correct logistic flow of materials, supported by a consistent flow of information (Silvestri *et al.,* 2011). Here below is shown ABC Analysis according sales and stocks (Table 1, Table 2). The analysis covers the period from January 2011 to January 2012. Since the amount of codes and products is huge, the data are clustered into different segments. The following tables are related to segment: mechanical components.

Table 1. ABC Analysis – Sales - mechanical components

Code	% Sales	% Cumulative	Ranking
XRC91	7,6%	7,6%	A
XRC94	6,3%	20,5%	
XRC74	2,9%	64,6%	
XRC90	2,1%	67,2%	
XRC12	1,4%	69,2%	
XRC79	1,4%	76,0%	

XRC97	1,2%	77,4%	
XRC99	1,0%	78,6%	
XRC900	0,9%	79,6%	
XRC740	0,8%	80,5%	B
XRC63	0,2%	81,3%	
XRC92	0,2%	93,6%	
XRC33	0,2%	93,8%	
XRC75	0,2%	94,1%	
XRC74000	0,2%	94,3%	
XRC68	0,2%	94,8%	
XRC77	0,2%	95,0%	
XRC990	0,2%	95,2%	C
XRC17	0,2%	95,3%	
XRC69	0,2%	95,5%	
…..	….	….	

Table 2. ABC Analysis- Stocks - mechanical components

Code	Cost warehouse	% Cumulative	Ranking
XRC63	38,430	7,6%	A
XRC94	37,539	20,5%	
XRC33	36,862	64,6%	
XRC74000	34,151	67,2%	
XRC740	29,617	69,2%	
XRC79	27,736	76,0%	
XRC99	25,729	77,4%	
XRC12	24,065	78,6%	
XRC68	20,539	79,6%	
XRC35	15,748	80,5%	B
XRC77	11,060	81,3%	
XRC990	10,629	93,6%	
XRC69	10,508	93,8%	
XRC97	9,235	94,1%	
XRC91	9,191	94,3%	
XRC17	8,975	94,8%	
XRC92	8,513	95,0%	
XRC900	8,234	95,2%	C
XRC74	7,907	95,3%	
XRC62	7,056	95,5%	
…..	….	….	

At this point, the approach followed required the application of Cross Analysis, which is a matrix that combines the results from the previous ABC analyses (Table 3).

Table 3. Cross Analysis - mechanical components

Code	Sales	Stocks
XRC91	A	B
XRC94	A	A
XRC74	A	C
XRC90	A	D
XRC12	A	A
XRC79	A	A
XRC97	A	B
XRC99	A	B
XRC900	A	C
XRC740	B	A
XRC63	B	A
XRC92	B	C
XRC33	B	A
XRC75	B	C
XRC74000	B	A
XRC68	C	A
XRC77	C	B
XRC990	C	A
XRC17	C	C
XRC69	C	B
…..	….	….

According to Figure 2 the cross analysis suggests JIT for all materials of the classes AA, AB, BA; for all materials of the class CA is suggested MRP; for all materials of the classes CB, CC, BB is suggested ROL/ROC, etc.

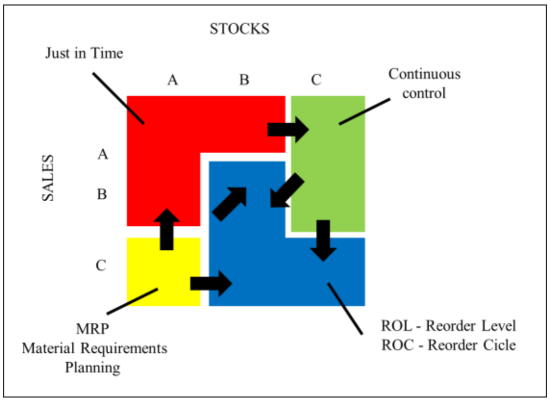

Fig. 2. Techniques of inventory management/classes

In general it is not enough to put into consideration only sales and stocks for Cross Analysis. In fact, many factors could be consider in order to decide the more suitable inventory management method (JIT, MRP, EOQ, ROC, ROL etc.). In particular, different "shape" factors/criteria such as:

- Value and cost;
- Weight and volume;
- Deterioration and damage risk;
- Quantity of units and packages;
- Transportability and physical state.

could suggest a different classification and management approach. Not only physical attributes, but also managerial aspects suggest the right choice of ordering and storage policy, such as:

- Production criticality;
- Turnover rate;
- Supplier reliability;
- Modularity;
- Obsolescence rate.

In general, more critical products relating to the above criteria, should be managed with more attention, obtaining the trade-off between benefits and costs. In the case study, considering a particular kind of component: *spare parts,* we had the need to value four factors: the *value of stock* in the warehouse (it provides information about which materials have a higher value and thus higher capital amounts); the *frequency of use* (defined as the ratio between the number of versions and models on which the material is used); the *material deterioration* (defined as loss of function in a specified time period) and the *risk of damage*. Changing the couple of criteria, we obtained 6 different combinations for Cross Analysis (see Figure 3). In Table 4 is shown synthesis for Cross Analysis considering the 4 added factors. As we can note when we consider all factors at the same time there is no univocal and specific choice for the management method.

Table 4. Cross Analysis

Code	Volume	Frequency	Deterioration	Damage
XRC91	B	B	A	B
XRC94	A	A	A	A
XRC74	C	B	A	A

XRC90	D	A	A	B
XRC12	A	A	A	A
XRC79	A	A	A	A
XRC97	B	A	A	A
XRC99	B	A	A	A
XRC900	C	A	A	A
XRC740	A	B	B	B
XRC63	A	B	B	B
XRC92	C	B	B	B
XRC33	A	C	B	C
XRC75	C	B	B	B
XRC74000	A	B	B	B
XRC68	A	C	B	C
XRC77	B	C	C	C
XRC990	A	C	C	B
XRC17	C	B	C	C
XRC69	B	C	C	B
…..	….	….	….	….

To overcome the limitations of Cross Analysis, we propose AHP/BORC Analysis (see Figure 4 and 5) in which the criteria are the 4 factors: *value of stock, frequency of use, material deterioration and risk of damage*. While the alternatives are: A1 (Just in Time); A2 (MRP); A3 (ROC/ROL) and A4 (Continuous control). In Table 5 are shown results and local priorities, defined according to phase 2 described in paragraph 2.1, while in Table 6 is shown the ranking for alternatives. As we can note the optimum solution is A2 (MRP) followed by the other.

Table 5. ANP/BOCR Results

Predictors	**Criteria**	**Subcriteria**	**Local Priorities**
Benefits 0.297	Service	Competitiveness	0.741
		On time delivery	0.183
		Process capability	0.075
Opportunities 0.338	Stability	Market share	0.229
		Customer satisfaction	0.432
		R&D expansion	0.336
Costs 0.268	Disadvantages	Human Resources	0.237
		Joint Venture	0.387
		Infrastructure	0.365
Risks 0.085	Corporation	Order delay	0.439
		BOM	0.198
		Lead Time	0.335

In the BOCR model, we used additive negative formula to synthesize the results because generally it is best for long-term results: bB+oO–cC–rR (b, o, c and r represent priorities while B, O, C and R are the vectors). In Table 6 is shown the best alternative (A2) for the managing of spare parts.

Table 6. ANP/BOCR Alternatives Ranking

Altern.	B	O	C	R	bB+oO-cC-rR
A1	0.586	0.449	1	0.574	0.145
A2	1	1	0.814	1	0.410
A3	0.404	0.514	0.513	0.269	0.214
A4	0.204	0.353	0.422	0.306	0.089

4. CONCLUSIONS

ABC-Cross Analysis suggests different materials management methods, depending on the particular criteria considered. In many case, it is a weaknesses. To overcome this limitation, in this paper we proposed a new integrated ANP/BOCR analysis, which allows you to consider simultaneously all the assessment criteria for the optimal choice of materials management.

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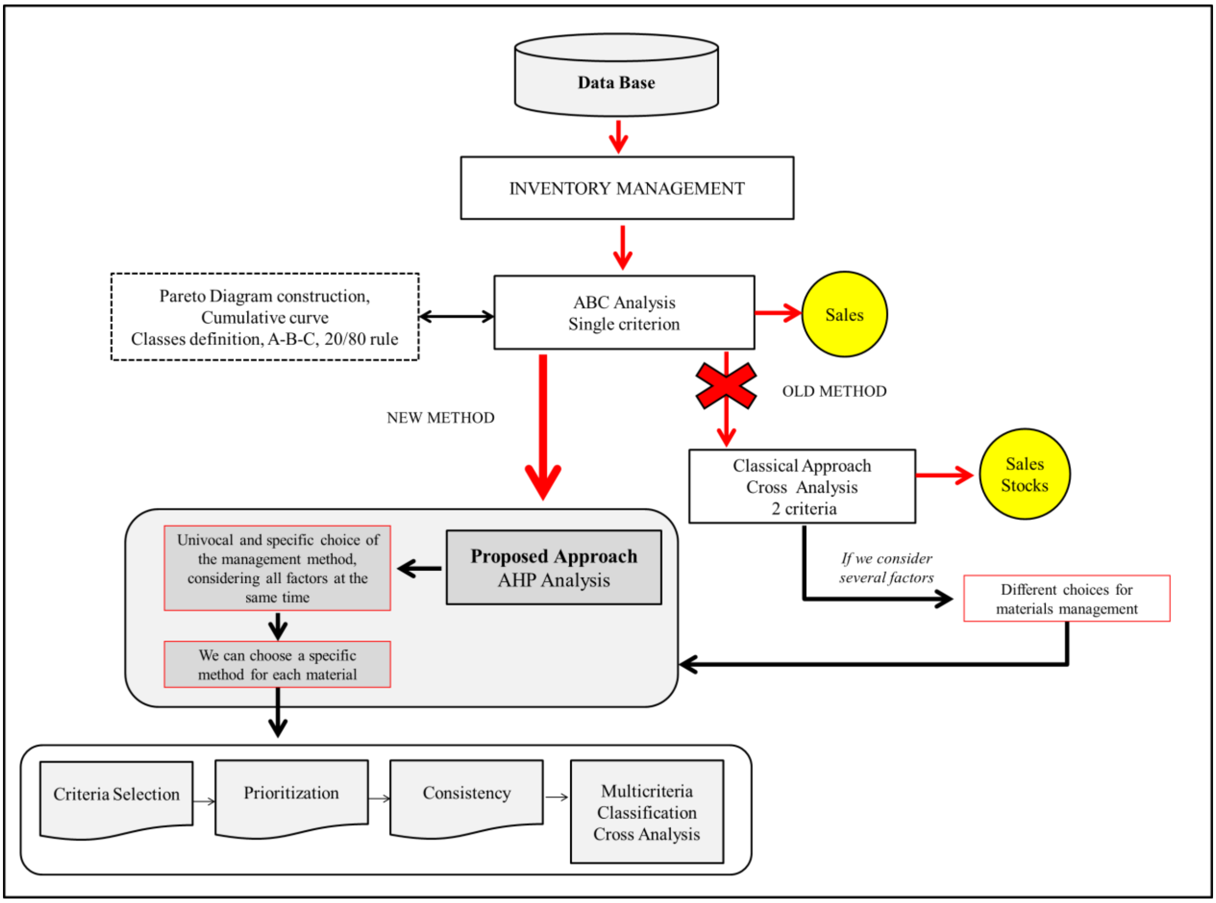

Fig. 1. Research Framework

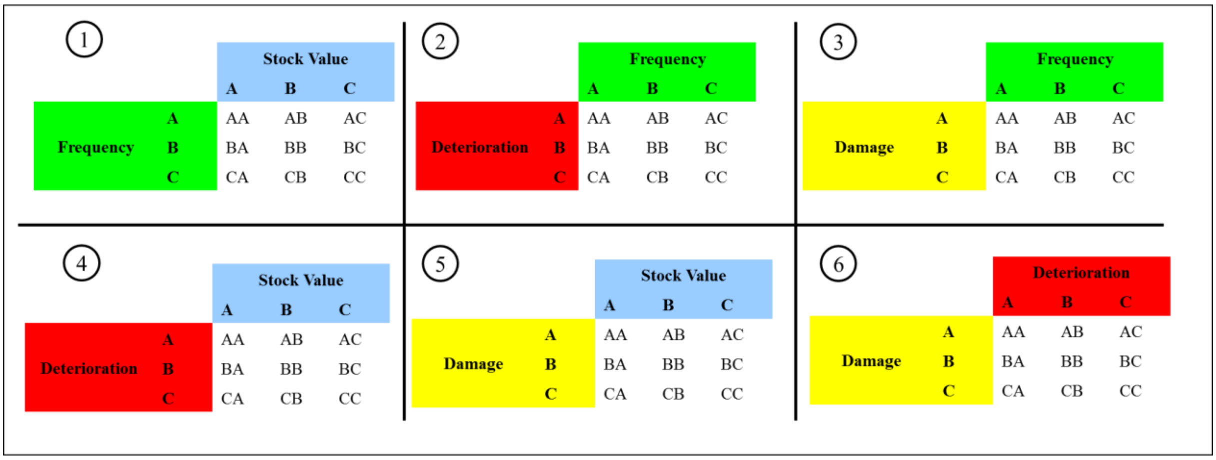

Fig. 3. Cross Analysis combinations

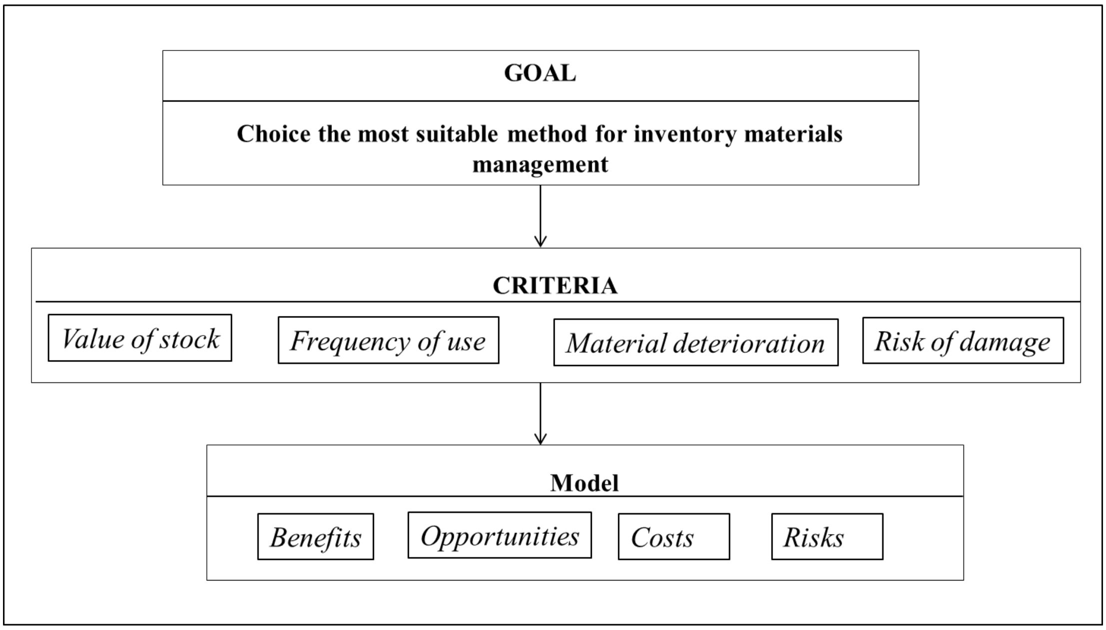

Fig. 4. ANP/BOCR Model

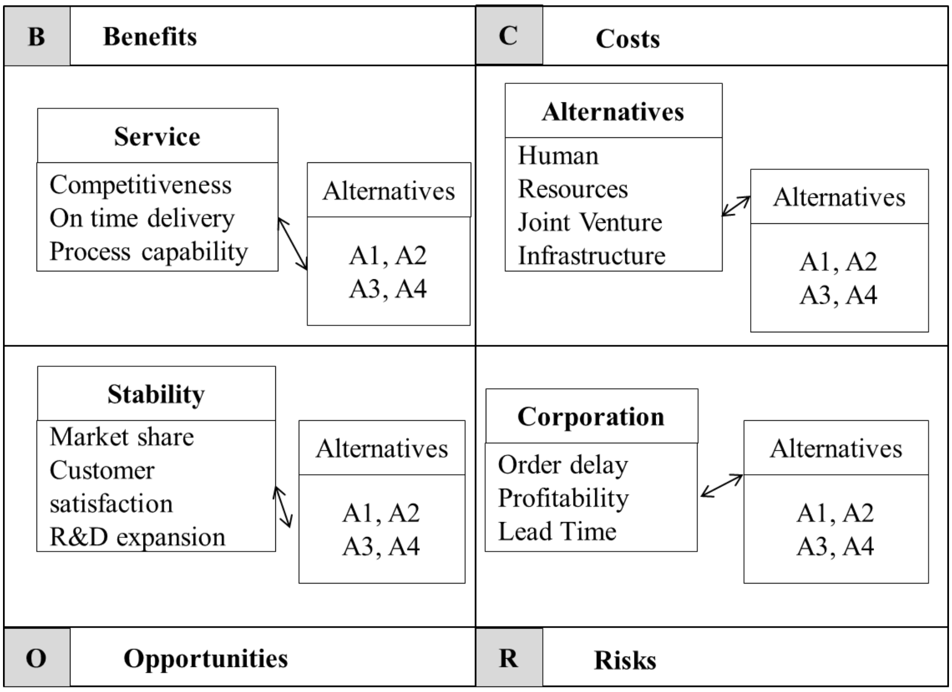

Fig. 5. ANP/BOCR Model details