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CLUSTERING APPROACH FOR ORGANIZATIONAL EVALUATION PROJECT: INTEGRATING BSC AND DEA

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Abstract

In this paper a new comprehensive clustering method is introduced which integrates data envelopment analysis (DEA) into the balanced scorecard (BSC) for complex organizations. However, DEA is essentially applied to assess organizations from the best; BSC is not used for organizational comparison. The incapability of the DEA in the input and the output index definition is the major weakness of the method. Besides, combining BSC and DEA has another complexity which is the number of decision making units (DMUs) in comparison with the number of inputs and outputs as a major drawback of the integration. Nevertheless, this is not efficient in the suggested method, which makes it to be more hard-nosed. The method considers the most important strategic factors obtained from BSC as the input data for DEA and finally calculates the relative closeness (RC) of each DMU to the ideal one. Screening out the RC indexes and plotting the scree diagram may lead us to a comprehensive clustering method to achieve the reliable appropriate results for each establishment in each point, linked to their strategic design. Finally, the proposed method is practically tested and the results are illustrated in the following paragraphs.

Key words: *Balanced Scorecard, DEA, Ranking method, Clustering, Evaluating project, project management*

JEL code: D60

Introduction

Clustering is a branch of statistical analysis that enables the analyst to divide similar objects into the same bunches (Jain et al., 2000; Goudarzi, and Ansari, 2012). Clustering methods are, in general, classified into the five categories: (1) Hierarchical clustering (Hartigan, 1975; Po et al. 2009), (2) mixture-model clustering, (3) learning model clustering, (4) partition clustering (Po et al. 2009; Mooi and Sarstedt 2011) and (5) objective-function-based clustering (Goudarzi, and Ansari, 2012). Many algorithms are proposed to cluster data based on minimizing total dissimilarity (Po et al. 2009) such as hard C-means (HCM) (Hartigan, 1975; Ross, 2004), fuzzy C-means (FCM) (Ross, 2004) and possibilistic C-means (PCM) (Krishnapuram and Keller, 1993). Po et al. (2009) introduced a new clustering method based on data envelopment analysis (DEA) in CCR scheme and Goudarzi and Ansari (2012) used the BCC concept of DEA in their method. In this paper, we propose a new method based on the Wang and Luo (2006) for clustering sub-organizations of a complex organization. The method not only uses this model as a substructure of the method, but applies balanced scorecard (BSC)

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to introduce the outputs and rather the inputs to have a complete comprehensive method for organizational clustering.

Budget and resource assessment are taking place in the competitive environment (Bentes et al. 2011), particularly in large, complex organizations. Given the multidimensionality and the complexity of the concept, Chakravarthy (1986), Venkatraman and Ramanujam (1986), and Barney (2010) advise the use of multiple measures of organizational performance. One of the most well-known multi-dimensional assessment methods is the BSC method (Kaplan and Norton, 1996). The method is first introduced by Kaplan R., (1980) and by Johnson and Kaplan (1987). But its university based idiom was denoted by Kaplan and Norton (1992). Despite, it is not completely emphasized on balanced measurement and related factors in any publication of Kaplan and Norton; Cobbole and Lawrie (2002) highlighted it and finally, the strategy plan is used to complete the model (Niven, 2003). The model is based on four fundamental factors to find the relation between strategic goals and operational controls (Golpîra and Veysi, 2012). BSC eliminates information overload and forces the management team to illuminate the organizational strategy to a level of specificity at which its implementation can be tracked (Kaplan and Norton, 1992; Stewart, 2003), but the most important drawback of the BSC is its poorly identification of metrics (Stewart, 2003).

DEA introduced by Charnes and Cooper (1978), often evaluates the decision making units (DMUs) from the best possible relative efficiency (Wang and Luo, 2006). Entani et al. (2002) and Wang et al. (2007) acquire the model to look at both the optimistic and pessimistic points, until Wang and Luo (2006) propose their model based on the relative closeness (RC) index to the ideal DMU (IDMU). Desheng (2006) and Chen (2012) propose the corrective notes on the Wang and Luo (2006) model and its application but in the field of ranking. Golpîra, (2012a) applies this version of DEA for formulating the problem of project monitoring and achieve correct comprehensive project success measurement. He focuses on it only for ranking alternatives to achieve weight factors for activities in projects. Golpîra, (2012b) employs the same concept combined with the BSC model in order to assess the organizations. We use this approach not only for evaluating sub-organizations, but for clustering. Coelli et al. (2005) advocated 11 major drawbacks that one may encounter in conducting the DEA. He advised that the exclusion of an important input or output can result in biases which are emphasized by Chen et al. (2008). In other words, the main drawback of the DEA is its weakness on identifying Input and output factors. It is noteworthy that Banker et al. (2004) use the combination of DEA and BSC to evaluate the trade-offs among different performance indexes. Chen and Chen (2007) use it to assess the performance of a semiconductor industry. Chiang and Lin (2009) apply it to assess the performance in two distinct industries. Min et al. (2008) try it in Korean hotels and Macedo et al. (2009) apply it in banking. Amado et al. (2012) apply DEA to assess performance of DMUs in only one company. It is clear that the focus of these scholars is on the performance assessment; however, we use this combination to introduce a new powerful method for clustering. Besides, Cooper et al. (2000) proposed the generally accepted principle to ensure satisfactory discrimination of the DEA method which demands:

$$n \geq \max\{m \times s, 3(m+s)\} \qquad (1)$$

where n is the number of DMUs, m and s are the number of inputs and outputs. However, such conditions may not met in many applications.

BSC literature shows that the strategy map of organizations should contains at least two or three indexes for each level of the factors which is consequently introduces at least 8 factors as the outputs. Optimistically, with considering only two inputs, the methods may contain more than 30 DMUs to make a clear satisfying result. This makes the traditional methods to be complex and impractical. It is the superiority of the proposed method that is not be limited by this principle and may be used for ranking and clustering the DMUs with any number of outputs or inputs. So, in this paper, a hybrid method is proposed that handle the advantages of BSC and DEA all together and encounter the disadvantage of the DEA by the relative advantages of the BSC and TOPSIS. In other words, The BSC method is used to determine two or three most important factors in any field of its four basic fundamental factors. The factors are then used as the input data for the DEA method to make ranking and clustering in any organizations with and number of sub-organizations.

Proposed method

Suppose n DMUs, each consumes m inputs, denoted by $x_{ij}(i=1,\dots,m, j=1,\dots,n)$, to produce outputs denoted by $y_{rj}(i=1,\dots,s, j=1,\dots,n)$. A virtual DMU which uses the least inputs, $x_i^{\min}(i=1,\dots,m)$, to produce the most outputs, $y_r^{\max}(r=1,\dots,s)$, and a DMU, which consume the most inputs, $x_i^{\max}(i=1,\dots,m)$, to generate the least outputs, $y_r^{\min}(r=1,\dots,s)$ can be defined as ideal decision making unit (IDMU) and anti ideal decision making unit (ADMU) respectively. To completing the model, the LP model shown in Equations (2) and (3) must be solved for all DMU$_s$ such as DMU$_0$ to calculate the $\theta^*_{j0}, \varphi^*_{j0}$, where $j0$ is the DMU under evaluation (denoted by DMU0), u_r, v_i are decision variables, ε is the non-Archimedean infinitesimal, θ^*_{IDMU} is the optimum efficiency of IDMU that may calculated by Equation (4) and φ^*_{ADMU} is the worst efficiency of the ADMU that may calculated by Equation (5). It is obvious that the relative closeness index of DMU0 to IDMU is defined by Equation (6). It is clear that the bigger the RC_{j0} value is the-better-the-performance of DMU$_0$.

$$
\begin{aligned}
Max \quad & \theta_{j0} = \sum_{r=1}^{s} u_r y_{rj0} \\
s.t. \quad & \sum_{i=1}^{m} v_i x_{ij0} = 1 \\
& \sum_{r=1}^{s} u_r y_j^{\max} - \sum_{i=1}^{m} v_i (\theta^*_{IDMU} x_i^{\min}) = 0 \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0 \quad j = 1, \dots, n \\
& u_r, v_i \ge \varepsilon \quad \forall r, i
\end{aligned}
\tag{2}
$$

$$\begin{aligned}
Min \quad & \phi_{j0} = \sum_{r=1}^{s} u_r y_{rj0} \\
s.t. \quad & \sum_{i=1}^{m} v_i x_{ij0} = 1 \\
& \sum_{r=1}^{s} u_r y_j^{\min} - \sum_{i=1}^{m} v_i (\phi_{IDMU}^{*} x_i^{\max}) = 0 \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0 \quad j = 1, \dots, n \\
& u_r, v_i \ge \varepsilon \quad \forall r, i
\end{aligned} \tag{3}$$

$$\begin{aligned}
Max \quad & \theta_{IDMU} = \sum_{r=1}^{s} u_r y_r^{\max} \\
s.t. \quad & \sum_{i=1}^{m} v_i x_i^{\min} = 1 \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0 \quad j = 1, \dots, n \\
& u_r, v_i \ge \varepsilon \quad \forall r, i
\end{aligned} \tag{4}$$

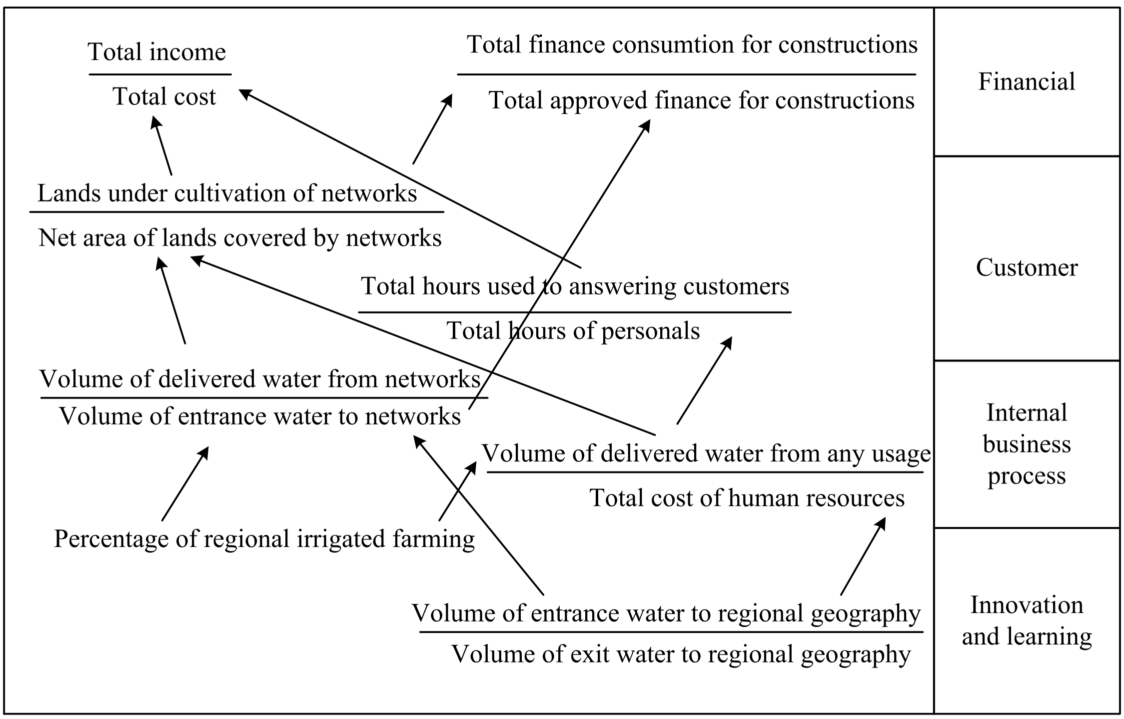
$$\begin{aligned}
Min \quad & \phi_{ADMU} = \sum_{r=1}^{s} u_r y_r^{\min} \\
s.t. \quad & \sum_{i=1}^{m} v_i x_i^{\max} = 1 \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0 \quad j = 1, \dots, n \\
& u_r, v_i \ge \varepsilon \quad \forall r, i
\end{aligned} \tag{5}$$

$$RC_{j0} = \frac{\varphi_{j0}^{*} - \varphi_{ADMU}^{*}}{(\varphi_{j0}^{*} - \varphi_{ADMU}^{*}) + (\theta_{IDMU}^{*} - \theta_{j0}^{*})} \tag{6}$$

The RC indexes are sorted in descending order and plotted in the way which is similar to the scree plot in the hierarchical clustering method. In this diagram, the sharp increase in RC illustrates a new cluster in DMU_S. As per validating the method, it is successfully installed in 10 sub organization of Kermanshah Regional Water Organization Company which is illustrated in the last section.

Empirical study

The data for this study are taken in from the Kermanshah Regional Water Organization, Iran. The data included 53 creditable performance indexes that factor analysing in SPSS software classifies them into four levels of factors. Data are classified as: (1) 10 financial indexes, (2) 7 internal business process indexes, (3) 7 customer Indexes, (4) 24 innovation and learning indexes. Indexes are given to experts to give a privilege to them according to organizational predefined strategies. Consequently, "five point Likert" and "factor analysis" methods are used to prove the classification. Then the most important indexes in each four levels are chosen. After linking the factors in BSC procedure, the strategic map is given as shown in Fig. 1. These indexes are used as the outputs for the DEA method. Seven inputs which are strongly related to these outputs are also selected and the real data are collected from the 10 sub-organization of the Kermanshah Water Regional Organization which are illustrated in Table 1. Finally, DEA is used to rank these sub-organizations using factors which are indicated on the strategy map. The results are illustrated in Table 2.



Source: author's construction based on (Golpîra and Veysi, 2012)

Fig. 1. **Strategy map of Kermanshah Regional Water Organization**

What is indicated in column five (RC) of Table 2 shows the difference of the sub-organizations. So managers not only can clearly recognize the differences between their organizations to others, but also the related distances can show the intensity of these differences. This information helps the manager to have a better view to perceive the position of his/her organization and enhance an ability to compare it with other similar ones in terms of the organizational strategic goals that may be changed and updated over its life cycle. This ranking is based on the other similar organizations that make it possible and acceptable for any others.

Table 1

Inputs and outputs data for 10 sub-organization of Kermanshah Water Regional Organization

	DMU	X_1	X_2	X_3	X_4	X_5	X_6	X_7	
1	DMU_1	46963	54	990	169934.1	75357	273600	16	
2	DMU_2	37570.4	9	99	118953.87	52749.9	164160	16	
3	DMU_3	16437.05	12.6	264	101960.46	45214.2	68400	14	
4	DMU_4	16437.05	32.4	330	33986.82	33910.65	54720	14	
5	DMU_5	18785.2	7.92	231	254901.15	22607.1	76608	14	
6	DMU_6	28177.8	6.48	198	169934.1	33910.65	109440	16	
7	DMU_7	37570.4	14.04	264	339868.2	15071.4	191520	16	
8	DMU_8	11740.75	16.74	330	254901.15	36171.36	54720	14	
9	DMU_9	7044.45	13.68	429	169934.1	37678.5	41040	12	
10	DMU_{10}	14088.9	13.14	165	84967.05	16578.54	27360	14	
	Max	46963	54	990	339868.2	75357	273600	16	
	Min	7044.45	6.48	99	33986.82	15071.4	27360	12	
	DMU	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6	Y_7	Y_8
1	DMU_1	3	0.148148148	0.007595767	9.185965736	0.34	0.508632244	0.86	16
2	DMU_2	0.75	0.333333333	0.005086451	6.450145506	0.2	0.537696944	0.56	16
3	DMU_3	0.4	0.047619048	0.00356536	9.505477587	0.23	0.406905795	0.57	14
4	DMU_4	0.333333333	0.032716049	0.00604561	2.376369397	0.19	0.565146938	0.39	14
5	DMU_5	0.514705882	0.116161616	0.0042048	7.311905836	0.26	0.339088163	0.56	14
6	DMU_6	0.384615385	0.114197531	0.002351071	4.558749455	0.39	0.429511673	0.67	16
7	DMU_7	0.133333333	0.196581197	0.006103741	10.04864774	0.23	1.449601895	0.56	16
8	DMU_8	0.609756098	0.05734767	0.006076614	9.820710263	0.19	0.635790305	0.48	14
9	DMU_9	0.928571429	0.097953216	0.00795747	3.830045914	0.18	0.345869926	0.56	12
10	DMU_{10}	0.304878049	0.04718417	0.004702141	4.616946257	0.25	0.439273302	0.45	14
	Max	3	0.333333333	0.00795747	10.04864774	0.39	1.449601895	0.86	16
	Min	0.133333333	0.032716049	0.002351071	2.376369397	0.18	0.339088163	0.39	12

Source: author's calculations based on Fig. 1 on the Kermanshah Water Organization real data

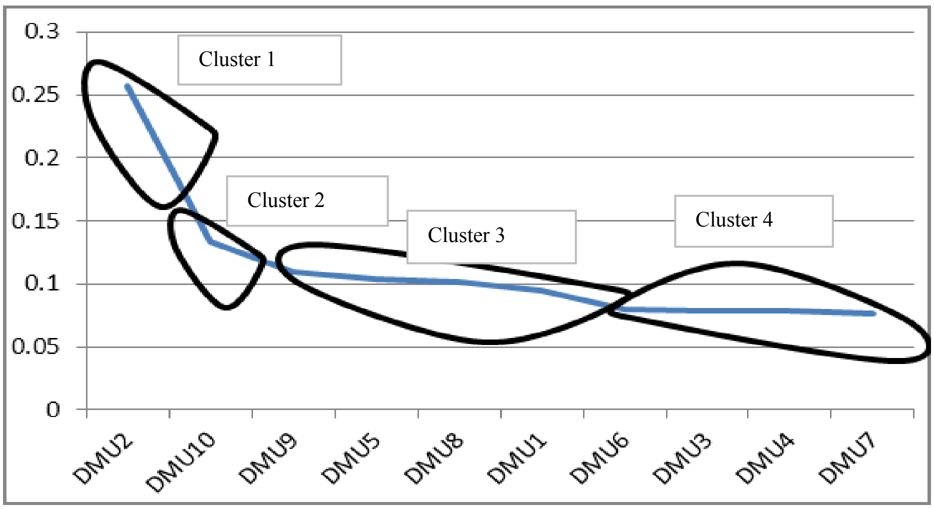
Table 2

DEA Results

	DMU	φ*(ADMU)	Θ*(IDMU)	RC	rank
1	DMU_1	1.16903	1	0.0953237213371733	6
2	DMU_2	3.573291	0.95	0.256965674488989	1
3	DMU_3	1	0.6497418	0.0786201569817434	8
4	DMU_4	1	0.5973795	0.0782527880957957	9
5	DMU_5	1.308757	0.7616327	0.104458622564129	4
6	DMU_6	1.018273	0.5963	0.0797457146743756	7
7	DMU_7	1	0.4182025	0.0770212647288676	10
8	DMU_8	1.257319	0.8997455	0.101623935288267	5
9	DMU_9	1.346556	1	0.109727723753503	3
10	DMU_{10}	1.647861	1	0.133152584206886	2
11	IDMU	-	10.92647	-	-
12	ADMU	0.1231	-	-	-
$\varepsilon = 1\times 10^{-6}$					

Source: author's calculations based on Table 1

As per completing the proposed clustering procedure the scree diagram is plotted in Fig. 2. One can see that the diagram has sharp increasing shape in some points which produces 4 partitions. The clustering is graphically obvious but the hierarchical clustering method is used to define the number of clusters and this number of clustering is used as the input of the hard C-means method to have a clear predefined valid clustering. This process is done by using SPSS software which its results are shown in Table 3. The results show that the optimal number of clusters is 4 clusters which are used to have final clustering by using hard C-means method. The results are shown in Table 4, Table 5 and Table 6. The results are clearly emphasizing on what is achieved in the proposed method.



Source: author's construction based on Table 1

Fig. 2. **Final clustering results**

Table 3

Hierarchical clustering results

Stage	Cluster Combined		Coefficients	Stage Cluster First Appears		Next Stage
	Cluster 1	Cluster 2		Cluster 1	Cluster 2	
1	8	9	0.000	0	0	2
2	7	8	0.000	0	1	3
3	7	10	0.000	2	0	7
4	4	5	0.000	0	0	5
5	3	4	0.000	0	4	6
6	3	6	0.000	5	0	7
*7	3	7	0.001	6	3	8
8	2	3	0.002	0	7	9
9	1	2	0.026	0	8	0

Source: author's calculations based on Table 1

Table 4

Hard C-means cluster membership

Case Number	VAR00001	Cluster	Distance
1	DMU2	1	0.000
2	DMU10	2	0.000
3	DMU9	3	0.007
4	DMU5	3	0.002
5	DMU8	3	0.001
6	DMU1	3	0.007
7	DMU6	4	0.001
8	DMU3	4	0.000
9	DMU4	4	0.000
10	DMU7	4	0.001

Source: author's calculations based on Fig. 2 and Table 3

Table 5

Hard C-means final clustering centers results

	Cluster			
	1	2	3	4
VAR00002	0.256966	0.133153	0.102784	0.078410

Source: author's calculations based on Fig. 2 and Table 3

Table 6

ANOVA results

	Cluster		Error		F	Sig.
	Mean Square	df	Mean Square	df		
VAR00002	0.009	3	0.000	6	470.700	0.000

Source: author's calculations based on Fig. 2 and Table 3

Conclusion

This study introduces a new comprehensive clustering system based on DEA and BSC methods. The basic BSC is used to define the important factors in organizational performance which leads the system having valid and strategic-based measurement factors. These factors are used as the outputs of the DEA method and trying the relative inputs with no limitations. The Wang and Luo (2006) DEA method is subsequently used to define the RC indexes for all of the DMUs and finally the DMUs are graphically classified by using the scree plot and focusing upon sharpness of the diagram. The results are exactly and clearly validated by using two well-known traditional clustering methods. The salient superiority of the system is its ability to encounter with clustering problems without any limitation of number of inputs/outputs or the number of DMUs. The other superiority of the system is its comprehensiveness and practical characteristics. The simple graphical process is the other advantage of the method that makes it understandable and acceptable in addition to its capability to be used as the ranking, benchmarking and clustering method synchronously. The numerical results are clearly validating the method and make it practical.

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