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Integration of Balanced Scorecard and Three- stage Data Envelopment Analysis Approaches

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Abstract

The Balanced Scorecard (BSC) provides an outlook of an organization's general performance; it integrates financial perspective with other performance aspects, like learning and growth, internal processes, and customer perspectives. The momentous issue, in implementation of BSC, is the proper selection of measures. The main objective of this paper is to introduce a novel approach in an attempt to select the most appropriate measures by integrating BSC and three-stage Data Envelopment Analysis (DEA) model. To achieving this aim, the BSC's measures are utilized as input and output variables of DEA model and the most appropriate measures in each BSC's perspective are determined with interpretation of the efficiency variations in different stages. An experimental example containing six Iranian banks has been investigated to demonstrate the implementation of this approach. The results indicate that increased staff expertise (L2) and high speed services (P2), respectively in stage one and two are appropriate measures. Also, in this study, we cannot judge about the effect of customer satisfaction rate (C2), because the values of this measure are similar in different decision making units (DMUs). The proposed approach in the current paper helps managers to recognize appropriate measures for staff empowerment, internal process improvement, customer satisfaction increase, and organization's financial outcomes improvement.

Keywords

Appropriate measures, Balanced scorecard (BSC), Cause and effect relations, Iranian banks, Three- stage data envelopment analysis (DEA).

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Introduction

In today's competitive business environment, organizations should choose various approaches for their performance measurement systems instead of traditional performance measurement methods. Lucas (1997) believed that in an attempt to be successful in the current uncertain environment of business, organizations should decrease costs and lead time, as well as being more flexible in elimination of customer's individual demands. In many facets, the new performance system has greater advantages for organizations. Simmons (2000) and Chenhall (2005) signified the role and effect of performance indicators of this performance measurement system. They presented that this new performance measurement system attracts manager's interest to the longer-term results of their activities. Also, it encourages decision makers to employ effective strategies and informs them of the evaluation and progress of organizational performance. The new perspectives of performance measurement system contain both short-term and long-term activities. For example, an important feature of Balanced Scorecard (BSC), one of the new performance measurement systems, is the presentation of different performance measures in various perspectives, such as learning and growth, internal processes, and customer perspectives, to compensate for the restriction of focusing only on financial indicators (Kaplan & Norton, 1996; Görener, 2013). Summarily, exploiting of concurrency performance measurement systems such as BSC can lead to a series of better organizational outcomes (De Geuser et al., 2009). In addition, to comprehend the importance of the new performance measurement system, researchers underline the significance of the selection of its performance indicators. The gained information from these factors or measures provides a basis for firm's strategic procedure as well as highlights the fields that need the management attention. Neely and Bourne (2000) explained the reasons leading to failure of measurement initiatives. They mentioned two major reasons, poor design of measurement system and difficulty of implementation. Andrews, Boyne and Walker (2006) mentioned some business characteristics that can affect the choice of performance factors: Business strategies of companies, uncertainty of environment, and market status. Krishnan and Ravindran (2012) declared that market can affect the indicators. This factor demonstrates the organization's position to preserve its competitive edge.

Researchers have implemented different methods in order to choose key performance indicators. In some literature, indicators are selected based on the judgment of experts in related fields. The feasible procedures that may be employed to achieve experts' judgments include Delphi method or interview. Shafiee et al. (2014) utilized the BSC and data envelopment analysis (DEA) models to assess the performance of food supply chain. The supply chain management indicators were detected through literature review and experts' ideas. Azadeh et al. (2009) suggested a novel system in order to assess a gas refinery performance and management. After analyzing more than 61 logical indicators, they selected 19 appropriate indicators with experts' viewpoints in the gas refinery. Akbarian et al. (2015) combined balanced scorecard and data envelopment analysis technique to evaluate the perfornmance of national Iranian oil firm during the time. The BSC's factors were extracted based on the judgment of oil experts. Maadi et al. (2016) explored factors involved in building initial customer trust in online shopping when a customer wants to buy from a website for the first time. For the purpose of developing the model and recognition of its factors, data collection was performed by questionnaire distribution among 325 respondents. They proved the validity of this model with entropy factor analysis and confirmatory factor analysis. Tsai and Cheng (2012) analyzed the measures of e-commerce and internet marketing of elderly care products; They detected 29 indicators through Delphi method and questionnaire. Javadin et al. (2015) exploited the main indicators of Iranian banks by means of interview with banking executives and academic experts.

Some studies have utilized other approaches to select key indices. Huang et al. (2011) utilized analytic hierarchy process (AHP) method in order to rank indicators and startegies of BSC model for a pharmaceutical firm. Farrokh et al. (2016) introduced a model to evaluate the base metals producing companies. They used fuzzy AHP to identify and determine financial facors' weights. In addition, VIKOR was implemented in order to rank the companies. Pan and Nguyen (2015) identified the key performance assessment criteria to obtain customer satisfaction by Decision Making And Trial Evaluation Laboratory (DEMATEL) technique in manufacturing firms. Ardekani et al. (2013) implemented fuzzy AHP-fuzzy VIKOR approach to find out the significance of each BSC's dimentons. They showed that financial index has the greatest significance, the second status belongs to customer perspective and the growth and learning, and internal process are respectively in third and fourth status.

Li et al. (2010) introduced a systematic and operational method based on the integration of BSC, AHP, and a minimal deviation-based method to rank customer demands for obtaining competitive and precedence information. Sohn et al. (2003) carried out a study on 219 Korean businesses from different sectors. They utilized AHP technique to compute measure weights pertaining to BSC's dimentions. Sadat et al. (2016) proposed fuzzy preferenced programing and fuzzy ratio system techniques to rank strategic objectives in BSC's model for ceramics company. Leung et al. (2006) introduced a model by integrating Analytic Network Process (ANP) technique, AHP technique, and BSC. Using this model, they specified the linkages among BSC's aspects and the weight of each perspective. Wu et al. (2009) integrated a fuzzy Multiple Criteria Decision Making (MCDM) approach and BSC model to assess the performance of bank. Twenty three evaluation indicators were obtained from the literature related to the bank's performance. The fuzzy AHP was implemented to compute the selected measures' relative weights. Sohrabi et al. (2015) used MCDM approach for detection of standardized factors and methods of performance evaluation. They implemented this approach in a real case to illustrate its capability. Shahverdi et al. (2011) introduced an approach based on MCDM and BSC in order to evaluate the performance of three banks. Having investigated the literature review and expert ideas, they selected twenty one indicators for evaluation. Alvandi et al. (2012) selected a collection of appropriate key performance indicators with respect to BSC model for SAPCO (Iranian vehicle suppliers), using MCDM method. Ebrahimi et al. (2016) identified five major indicators for measurement of customer relationship management in the bank and applied fuzzy Shannon entropy to calculate the relative importance of these indicators. In an effort to demonstrate the capplicability of the model, some branches of the bank were ranked based on their customer relationship performance. Falatoonitoosi et al. (2012) developed a strategic map with integrating BSC and MCDM-DEMATEL techniques to rank various business strategies of companies.

Although there are many studies about BSC model, which they have applied various methods in an effort to select BSC's indicators, none of these studies have utilized multi-stage DEA model. In this study, a novel approach is presented in order to select right indicators in balanced scorecard.

For this purpose, we use indicators of the BSC model as input and output variables of data envelopment analysis model and investigate the efficiency variations. Data envelopment analysis is a non-parametric method for measuring the decision-making unit's (DMU) efficiency. It has been implemented to assess the performance of various fields, such as, health care (Ghotbuee et al., 2012), financial institutions (Azadeh et al., 2009; Mostafa, 2009; Khaki et al., 2012; Ghafoorian Yavar Panah et al., 2014; Mirghafoori et al., 2014), hotel industry (Cheng et al., 2010; Shirouyehzad et al., 2014), education (Wu & Li, 2009).

This study is structured as follows: A brief explanation about the concept of cause and effect relationships is introduced in the following section. Then, a description of three-stage DEA method is presented. The proposed model is given in the next section. Afterward, an experimental example is presented and its results is then discussed. Finally, conclusion remarks are provided to present the contribution of the paper.

Balanced Scorecard

Balanced scorecard was first introduced by Kaplan and Norton (1992). This model can measure the organization's function from various aspects, financial and non-financial perspectives. Kaplan and Norton suggested that managers can consider their strategic measures as a set of causal relationships among BSC's aspects instead of performance factors in independent dimentions. They proposed a strategy map (Kaplan & Norton, 2004) to empower managers to perceive how performance in each dimension follows a hierarchical structure whereby improvements in learning and growth culminate in better internal process, enhancing the value propositions delivered to customers, leading to financial performance finally. Figure 1 shows these relationships among BSC's dimensions.

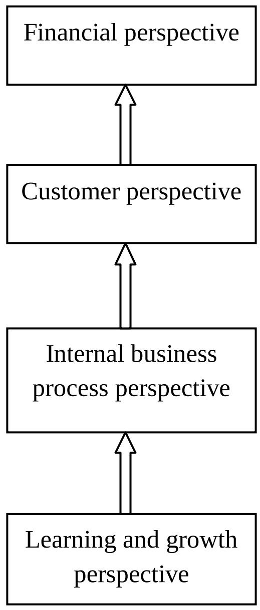


Fig. 1. The causal relationships among BSC's dimentions

Kaplan and Norton believed that the strategic relations among dimensions would permit managers to examine the strategies. As an illustration, investment in sale through internet (learning and growth) leads to quicker and more precise performance (internal process aspect). It can increase the share of market (customer aspect) and as a result, leads to more profit (financial aspect). If these intangible investments cannot culminate to better function financially, managers will be informed and it will be needed to depict a novel strategy map (Bento et al., 2013).

Liang and Hou (2007), in hotel industry, identified the linkage between customer and financial dimentions, but they could not detect relationships among learning and growth and financial indicators. Banker et al. (2000) studied whether customer satisfaction affects financial performance in hospitality. Ittner et al. (2003) expressed 75 percent of financial service firms neglect the causal relationships among the four BSC perspectives.

In view of the BSC's causal relationships, the classic DEA technique is not an appropriate quantitative one to measure the efficiency. Hence, we implement a cascade network DEA in this paper. Different researches have been done based on this network model. Readers can refer to Kao (2009) for more details.

Three-Stage DEA Model

Traditional DEA model considered the processes as black-boxes and used a single model to transform primary inputs to outputs (Färe & Grosskopf, 2000). In order to obtain advantageous information for performance improvement, the analysis should bekept off a black-box and the efficiency of decision-making sub-units should be investigated. Network DEA was first proposed by Färe and Grosskopf (2000). They opened the black-box and identified the source of inefficiency in different parts of organizational processes. In 2004, Lewis and Sexton (2004) presented a model applied to a set of sub-DMUs.

We know that BSC is a model that shows how each part of organizations can help to its success via a series of explicit causal relationship (Kaplan & Norton, 1996). Therefore, it can offer a suitable framework to arrange several interconnected DEA models.

Suppose a cascade system of h processes. X_{ij} and Y_{rj} are considered as input/ output factors, respectively. $Z_{pj}^{(t)}$ is defined as the *p-th* intermediate product, *P= 1, ..., q*, of process *t*, *t=1, ..., h-1*, for DMU_j. The intermediate products are outputs of process *t* and inputs of process *t+1*. Also, the intermediate products of the last process *h* are the system's output factors. Just for simplification, it is supposed that the number of intermediate products is the same for all processes although it can be different. This model has been shown in Figure 2.

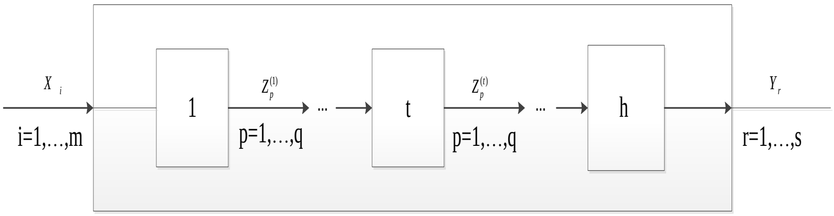


Fig. 2. Cascade system containing h stages

The efficiency of DMUj is calculated by the following equation.

$$E_k = \max \sum_{r=1}^{s} u_r Y_{rk}$$

s.t.

$$\sum_{i=1}^{m} v_i X_{ik} = 1$$

$$\sum_{r=1}^{s} u_r Y_{rj} - \sum_{i=1}^{m} v_i X_{ij} \leq 0$$

j=1,...,n

$$\sum_{p=1}^{q} w_p^{(1)} Z_{pj}^{(1)} - \sum_{i=1}^{m} v_i X_{ij} \leq 0$$

j=1,...,n

$$\sum_{p=1}^{q} w_p^{(t)} Z_{pj}^{(t)} - \sum_{p=1}^{q} w_p^{(t-1)} Z_{pj}^{(t-1)} \leq 0$$

j=1,...,n , t=2,...,h-1

$$\sum_{r=1}^{s} u_r Y_{rj} - \sum_{p=1}^{q} w_p^{(h-1)} Z_{pj}^{(h-1)} \leq 0$$

j=1,...,n

$\mathrm{u}_r, v_i, w_p^{(t)} \geq \varepsilon$

r=1,...,s , i=1,...,m

p=1,...,q , t=1,...,h-1 (1)

$W_p^{(t)}$ is related to the *p*-th intermediate product of process *t*. If u_r^*, v_i^* and $w_p^{(t)^*}$ be considered as optimal multipliers, the efficiency of each process for DMU_k is computed as:

$$E_k^{(1)} = \sum_{p=1}^{q} w_p^{(1)*} Z_{pk}^{(1)} \Bigg/ \sum_{i=1}^{m} v_i^* X_{ik} \tag{2}$$

$$E_k^{(t)} = \sum_{p=1}^{q} w_p^{(t)*} Z_{pk}^{(t)} \Bigg/ \sum_{p=1}^{q} w_p^{(t-1)*} Z_{pk}^{(t-1)}$$

t=2,...,h-1 (3)

$$E_k^{(h)} = \sum_{r=1}^{s} u_r^* Y_{rk} \Bigg/ \sum_{p=1}^{q} w_p^{(h-1)*} Z_{pk}^{(h-1)} \tag{4}$$

$E_k^{(t)}$, $t = 1, \ldots, h$ equals to $\sum_{r=1}^{s} u_r^* Y_{rk} / \sum_{i=1}^{m} v_i^* x_{ik}$ that is the efficiency of system. We call a DMU efficient provided that all of its processes be efficient (Kao, 2009).

Proposed Approach

Determination of appropriate indicators in each BSC's perspective is the main objective of the current study followed by concurrent implementation of BSC and DEA technique. At first, two indicators are considered for each BSC model's perspective and regarding the causal linkages in BSC, these indices are implemented as input and output variables of three-stage DEA model. Hence, the measures of learning and growth perspective are utilized as inputs of stage one and outputs of this stage are the factors of internal process perspective. As mentioned in previous section, in our cascade three-stage DEA model, the output variables of each stage should be used as inputs of the next stage. Consequently, the output factors of stage one are employed as input factors of stage two and its outputs belong to customer perspective. The output variables of stage two are utilized as inputs of stage three. Ultimately, the indicators of financial perspective are applied as outputs of stage three. This three-stage DEA model with these inputs and outputs are assumed as a basic model; the efficiency of each stage is calculated by Equations (2), (3), and (4).

In the next step, we consider only one of two input indicators of stage one in basic model and calculate the efficiency of stage one for all DMUs. Then, another input variable of stage one is considered and the efficiency of stage one is computed again. Two calculated efficiency scores are compared to the efficiency score of stage one in the basic model. The efficiency variations equal to 0.1 or more are supposed to be meaningful and the variations less than 0.1 are considered intangible. The analysis of observed results helps us to determine which input is more appropriate variable for stage one. This procedure is repeated for stage two and stage three. Consequently, the most appropriate variable is specified for each stage.

Empirical Results

In accordance with the proposed framework in previous section, we investigate an experimental example in this section. In order to determine the measures of BSC’s perspectives and their numeral values, we use the information of six Iranian banks exploited from Najafi et al. (2011). In learning and growth perspective, the incentive fee (L1) and increased staff expertise (L2) are selected as measures. Advanced services (P1) and high-speed services (P2) are chosen for internal process dimension. The factors of customer aspect included customer satisfaction (C1) and customer attraction rate (C2). Ultimately, we selected profit margin (F1) and growth of asset value (F2) as the measures of financial perspective. These indicators have been showed in Table 1.

Table 1. Measures of BSC model

Perspective	Indicators	Description
L: Learning and growth	(L1) Incentive fee (L2) Increased staff expertise	– Variable payment commensurate with the level of employee's performance with the purpose of improving their performance – Increase skills, abilities, and experience
P: Internal process	(P1) Advanced services (P2) High-speed services	– Develop services corresponding new customer's requirements in order to increase customer satisfaction – Provide services in order to reduce process cycle time
C: Customer	(C1) Customer satisfaction (C2) Customer attraction rate	– All activities of organization in order to increase the satisfaction and loyalty of customers – Increase the number of new customers
F: Finance	(F1) Profit margin (F2) Growth of asset value	– After-tax profit to total operating income – Relative gross of organization's assets

These eight variables are important factors utilized in many studies. Table 2 shows other related studies which applied these indicators as measures of BSC's perspectives. Note that these inputs and outputs have been chosen to illustrate the details of implementation of our proposed approach and you can utilize any set of input and output variables and DMUs.

Table 2. Previous studies implemented mentioned vaiables

Measure	Related Studies
Incentive fee	Aryanejad et al. (2011), Ghotbuee et al. (2012), Francioli & Cinquini (2014), Barnabè (2011)
Increased staff expertise	Khaki et al. (2012), Francioli & Cinquini, (2014), Barnabè (2011), Kong et al. (2012), Sofiyabadi et al. (2016), Yang et al. (2013)
Advanced services	Khaki et al. (2012), Valmohammadi & Sofiyabadi (2015)
High speed services	Aryanejad et al. (2011), Khaki et al. (2012), Ghotbuee et al. (2012), Sofiyabadi et al. (2016), Valmohammadi & Sofiyabadi (2015), de Oliveira & Cicolin (2016)
Customer satisfaction	Khaki et al. (2012), Ghotbuee et al. (2012), Francioli & Cinquini (2014), Barnabè (2011), Kong et al. (2012), Yang et al. (2013), Asosheh et al. (2010), Tsia & Cheng (2012), Guo et al. (2006), Pan & Nguyen (2015)
Customer attraction rate	Aryanejad et al. (2011), Khaki et al. (2012), Francioli & Cinquini (2014), Wu & Liao (2013)
Profit margin	Khaki et al. (2012), Wu & Liao (2013), Wang & Chien (2016)
Growth of asset value	Khaki et al. (2012), Wu & Liao (2013), Wang & Chien (2016), Shafiee et al. (2014), Azadeh et al. (2009)

At the next step, with respect to the causal relationships in BSC model, these indicators are utilized as input and output variables of three-stage DEA model. In stage one, ıncentive fee (L1) and increased staff expertise (L2) are input parameters chosen from the learning and growth perspective. Also, advanced services (P1) and high-speed services (P2) are supposed as the outputs of stage one. These factors are selected from internal process perspective. Note that the outputs of stage one are applied as input factors of stage two. The output parameters for stage two are customer satisfaction (C1) and customer attraction rate (C2). These indicators belong to customer perspective. Again, these parameters are assumed as the input factors of stage three and the outputs of this stage are the profit margin (F1) and growth of asset value (F2) adopted financial perspective. Table 3 summarize the numeral values of input/output variables.

Table 3. DEA input/output variables for different stages

DMU	Inputs of Stage 1		Inputs of Stage 2 (outputs of stage1)		Inputs of Stage 3 (outputs of stage 2)		Outputs of stage 3	
	L1	L2	P1	P2	C1	C2	F1	F2
1	23.03	12.11	91	3.13	3.25	22.91	17.42	4.81
2	18.72	11.96	57	3.41	3.21	25.08	12.98	7.16
3	18.50	12.08	8	3.25	3.41	29.0	47.59	7.00
4	5.30	12.07	37	3.32	3.12	34.50	18.9	1.40
5	17	11.96	34	3.25	3.43	21.80	20.13	1.23
6	3	13.66	10	3.35	3.74	13	10.28	1.02

After determination DEA model’s input/output variables, we make the basic model shown in Figure 3.

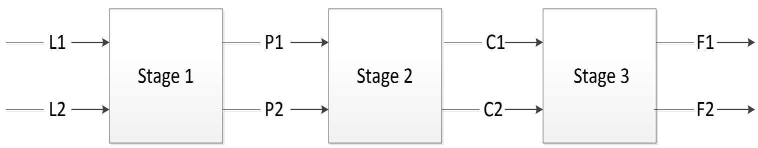


Fig. 3. The basic three-stage DEA model

Table 4 shows the calculated efficiency scores of this model using Equations (2), (3) and (4). At the following section, we investigate the effects of input factors on output factors. That is, we suppose that outputs are fixed and inputs are changed and the efficiency of that individual stage is calculated. The calculated efficiency is compared to the efficiency of the same stage in the basic model (Table 4). Efficiency variations equal to 0.1 or more are suuposed to be meaningful and variations less than 0.1 are neglected. The efficiency scores of DMUs have been obtained by GAMS Software.

Table 4. Efficiency scores of DEA model

	Stage 1	Stage 2	Stage 3
DMU1	1.000	0.972	0.798
DMU2	1.000	0.892	1.000
DMU3	0.945	1.000	1.000
DMU4	1.000	1.000	0.434
DMU5	0.957	0.980	0.563
DMU6	1.000	1.000	0.482

Efficiency variations of stage one by individual inputs.

To examine the efficiency variations of stage one, two states are assumed. At first, only the incentive fee (L1) component is used as input and the efficiency is calculated. The model of this assumption has been shown in Figure 4a. Second, only increased staff expertise (L2) measure is supposed as the input and the efficiency is computed again (Fig. 4b).

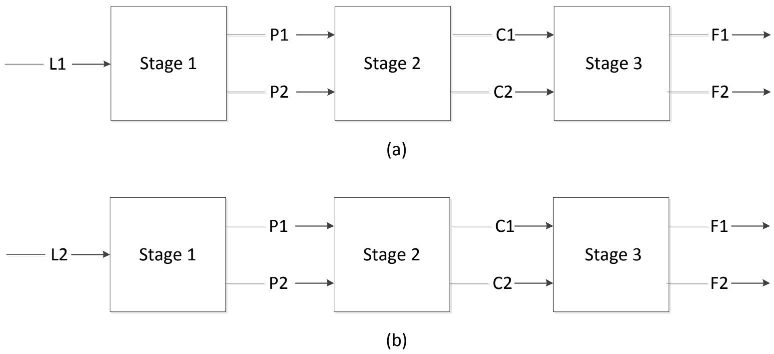


Fig. 4a. Three-stage DEA model based on (L1) input
Fig. 4b. Three-stage DEA model based on (L2) input

The calculated efficiency of stage one for each DMU has been presented in Table 5a and Table 5b. These efficiency scores are compared to the efficiency of stage one in the basic model.

Table 5a. Efficiency of stage one, input: (L1) or (L1, L2)

	Stage 1 (L1,L2)	Stage 1(L1)
DMU1	1.000	0.566
DMU2	1.000	0.436
DMU3	0.945	0.157
DMU4	1.000	1.000
DMU5	0.957	0.294
DMU6	1.000	1.000

Table 5b. Efficiency of stage one, input: (L2) or (L1, L2)

	Stage 1 (L1,L2)	Stage 1(L2)
DMU1	1.000	1.000
DMU2	1.000	1.000
DMU3	0.945	0.944
DMU4	1.000	0.965
DMU5	0.957	0.953
DMU6	1.000	0.860

As shown in Table 5a, the efficiency variations are significant when only the incentive fee (L1) is supposed as the input. On the other hand, Table 5b shows that the efficiency changes are not tangible except in DMU 6. A good explaination for significant efficiency variation in DMU 6 is the extremely small value of incentive fee (L1) relative to other DMUs leading to a big difference when it is added to increased staff expertise (L2).

Efficiency variations of stage two by individual inputs

Similar to stage one, in an attempt to investigate the changes of efficiency in stage two, two states are supposed. At first, advanced services (P1) measure is used as the input and the efficiency is calculated (Fig. 5a). Second, high-speed services (P2) measure is used as the input and the efficiency is computed again (Fig. 5b).

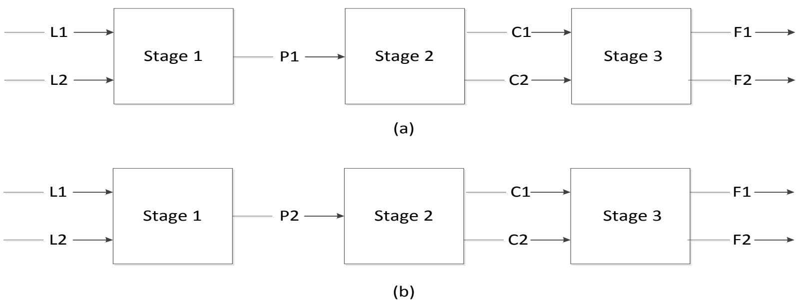


Fig. 5a. Three- stage DEA model based on (P1) input
Fig. 5b. Three- stage DEA model based on (P2) input

The computed efficiency of stage two for each DMU is given in Table 6a and 6b. These efficiency scores should be compared to the efficiency of stage two in the basic model.

Table 6a. Efficiency of stage two, input: (P1) or (P1, P2)

	Stage 2 (P1,P2)	Stage 2 (P1)
DMU1	0.972	0.084
DMU2	0.892	0.132
DMU3	1.000	1.000
DMU4	1.000	0.257
DMU5	0.980	0.237
DMU6	1.000	0.877

Table 6b. Efficiency of stage two, input: (P2) or (P1, P2)

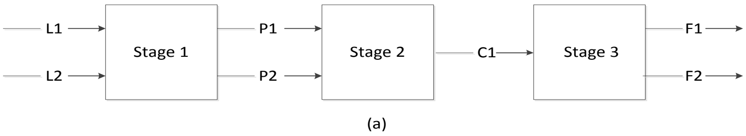
	Stage 2 (P1,P2)	Stage 2 (P2)
DMU1	0.972	0.972
DMU2	0.892	0.892
DMU3	1.000	1.000
DMU4	1.000	1.000
DMU5	0.980	0.980
DMU6	1.000	1.000

As shown in Table 6a, when only advanced services (P1) is chosen as the input, the efficiency variations are significant in all DMUs excepting DMU3. On the other hand, Table 6b shows that when only high-speed services (P2) is the input of stage two, the variations in efficiency equals zero.

Efficiency variations of stage three by individual inputs.

Two states are supposed in order to investigate the efficiency variations of stage three. At first, customer satisfaction (C1) factor is used as the input and the efficiency is calculated (Fig. 6a). Second, customer attraction rate (C2) factor is selected as the input and the efficiency is computed again (Fig. 6b).

Table 7a and 7b show the efficiency of stage three for each DMU based on the model shown in Figure 6a and 6b, respectively. Obtained efficiency scores for stage three are compared to the efficiency scores of stage three in the basic model.



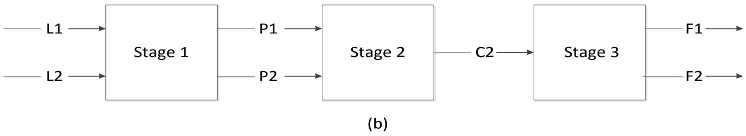


Fig. 6a. Three-stage DEA model based on the (C1) input
Fig. 6b. Three-stage DEA model based on the (C2) input

Table 7a. Efficiency of stage three, input: (C1) or (C1, C2)

	Stage 3 (C1,C2)	Stage3 (C1)
DMU1	0.798	0.684
DMU2	1.000	1.000
DMU3	1.000	1.000
DMU4	0.434	0.434
DMU5	0.563	0.421
DMU6	0.482	0.197

Table 7b. Efficiency of stage three, input: (C2) or (C1, C2)

	Stage 3 (C1,C2)	Stage 3 (C2)
DMU1	0.798	0.798
DMU2	1.000	1.000
DMU3	1.000	1.000
DMU4	0.434	0.354
DMU5	0.563	0.563
DMU6	0.482	0.482

When customer satisfaction (C1) is used as the input of stage three, inspection of Table 7a shows that the efficiency variations are meaningful. Table 7b shows that the efficiency variations are generally intangible when customer attraction rate (C2) is considered as the individual input of stage three.

Dicussion

The combination of balanced scorecard and data envelopment analysis in order to detrmine the right indices is the main objective of the current study. So far, none of previous researches have employed these techniques for this purpose. We applied measures of different BSC's perspective as inputs and outputs in three-stage DEA and calculated the efficiency of each stage as primary efficiency score (Table 4). Figure 7 shows the causal relations among indicators in various stages. In the next step, we considered each input factor individually and compute the efficiency of each stage again. Obtained scores were compared to the primary efficiency scores and the efficiency variations less than 0.1 were neglected. In stage one, the efficiency variations were meaningful when incentive fee was the input and these variations were intangible when increased staff expertise was the input of this stage. In other words, increased staff expertise can individually lead to improvement in internal processes, therefore, this measure is more appropriate than incentive fee. In stage two, when only advanced services were chosen as the input, the variations in efficiency were significant; when only high-speed services were the input of this stage, the efficiency variations were negligible. Therefore, high-speed services result in customer satisfaction and new customer attraction by itself and this component can be more appropriate than advanced services. In stage three, the variations are meaningful when customer satisfaction is used as the individual input, therefore, this factor is not adequate to increase profitability of organization. On the other hand, because of similarity in values of customer satisfaction component, we cannot judge about the effect of customer satisfaction indicator on efficiency. In other words, we cannot say that the customer satisfaction measure does not affect efficiency score. Consequently, this issue remains as the research's question: in order to increase organization's profitability, is customer attraction rate an adequate measure or is it necessary to consider another more appropriate measure? Figure 8 shows relationships among measures according to our proposed approach. In stage three, although it was not clear that customer attraction rate individually can lead to increase in profitability of organization or not, because of its importance based on litrature review, we showed this factor as the input factor of stage three.

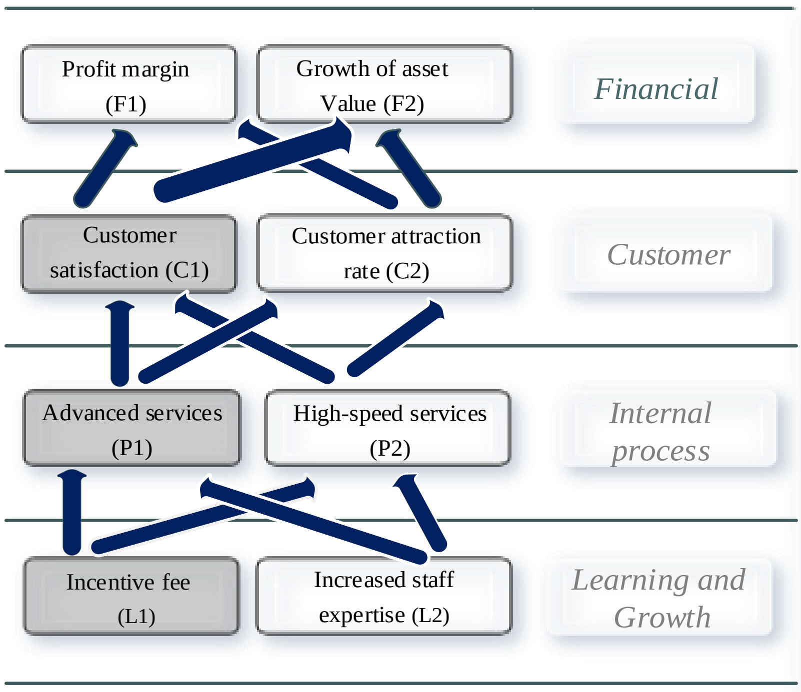


Fig. 7. The cause and effect relationships among measures

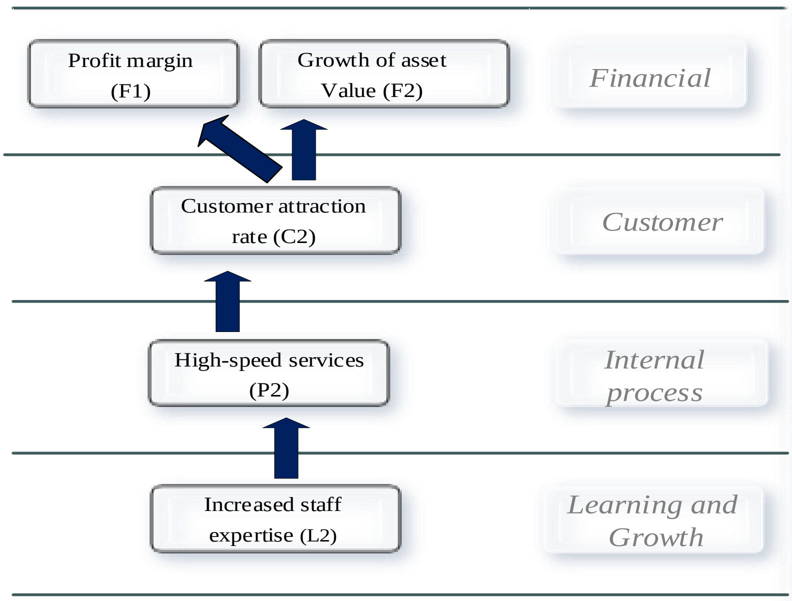


Fig. 8. The relationships among appropriate measures according to our proposed approach

Conclusion

The momentous issue, in implementation of BSC, is the proper selection of its measures. This paper presented a new approach in order to choose appropriate measures based on efficiency variations. At first, we considered two measures for each BSC's perspective; with regard to the BSC's causal relationships, these measures were utilized as input and output variables of three-stage DEA model. This structure was assumed as the basic model and the efficiency of all stages was computed. At the next step, individual inputs were considered in each stage and the efficiency of that stage was calculated; the computed efficiency was compared to the efficiency score of the same stage in the basic model. The efficiency variations equal to 0.1 or more were assumed meaningful and variations less than 0.1 were neglected. Ultimately, with the analysis of results, we could detect the most appropriate measure in each BSC's perspective. In this study, increased staff expertise in stage one, and high-speed services in stage two were chosen as the right indicators. In stage three, customer satisfaction could not be an appropriate indicator to increase profitibility of organization. Also, because of the similarity in values of this factor in all DMUs, we could not judge that customer attraction rate is an adequate measure or it is necessary to consider another appropriate measure. The presented approach in this study can be utilized as a valuable guideline by decision makers and managers in various firms to recognize appropriate measures for employee empowerment, internal processes improvement, customer satisfaction increase, and organization's financial outcomes improvement. After recognition of these appropriate measures, it is the firm's duty to gather, share, and follow innovative procedures to employ these measures. Additionally, these factors can act as ways for staff to comprehend organizational strategy and to increase collaboration. In various industries, these factors are different, thus, to enhance operational performance through these factors, the propriety of measures should be adapted to the organization's operational programs, customers' requirement, and environmental alterations.

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