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Performance Evaluation Accounting with Inputs Non-Discretionary Factors in an Integrated BSC-DEA Methodology

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Abstract

Measuring the performance of a production system has been an important task in management for control, planning, etc. The Balanced Scorecard (BSC) allows us to do just that. BSC is widely used in government and industry because of the clear representation of the relationship and logic between the Key Performance Indicators (KPIs) of 4 perspectives-financial, customer, internal process, and learning and growth. Conversely, traditional studies in Data Envelopment Analysis (DEA) view systems as a whole when measuring efficiency, ignoring the operation of individual processes within a system. We present and demonstrate a multi-criteria approach for evaluating every project in different stages. Our approach integrates the BSC and DEA and develops an extended DEA model. The input and output measures for the integrated DEA-BSC model are grouped in "cards," which are associated with "BSC". With efficiency decomposition, the process that causes the inefficient operation of the system can be identified for future improvement. Finally, we illustrate the proposed approach with a case study involving six banking branches.

Keywords: Measuring performance, Data envelopment analysis, Balanced scorecard, System improvement.

1 | Introduction

The key to achieving a state of continuous improvement depends on the ability to consistently and constantly measure the performance of key processes within an enterprise [1]. Many organizations have realized the importance of constant and consistent measurement and have adopted various Performance Measurement Systems (PMS) over the last few years [2].

According to Kaplan and Norton [3], the Balanced Scorecard (BSC) is based on the concept that managers must manage and evaluate their business from at least four major perspectives: 1) how do customers view the firm?, 2) what business process must we improve and excel at?, 3) can the firm continue to learn and innovate?, 4) how does the firm appear to its shareholders? The BSC translates an organization's mission and strategy into a comprehensive set of performance measures and provides the framework for strategic measurement and management [3], [4].

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The BSC is a model for analyzing strategic information for all types of organizations. Since then, it has been the subject of much research regarding its possibilities as a tool for strategic management. However, few references have been found for its development and implementation in companies for their strategy. Moreover, there are very few studies on management control and new product development in which relationships are established between the results from these activities, measured employing the BSC, and the efficiency with which they are performed. For this reason, the objective of this article is to propose a framework for the analysis of these relationships [3], [5].

In addition, to evaluate the firm's competitive position, managers must apply Data Envelopment Analysis (DEA) to identify the efficient frontier, benchmarking partners, and inefficient slack for the firms. The firm needs to understand its relative position in terms of productivity and efficiency. DEA is viewed as a methodology that provides a valid starting point for specifying balanced performance. Previous studies applying BSC and DEA to evaluate the competitive positions of every organization are not available. Thus, further empirical validations are required [3], [6].

The method we propose in this paper uses an extended DEA model, quantifying some of the qualitative concepts embedded in the BSC approach. The integrated DEA-BSC model addresses four common goals that firms are trying to accomplish: 1) achieving strategic objectives (effectiveness goal), 2) optimizing the usage of resources in generating desired outputs (efficiency goal), 3) obtaining balance (balance goal), and 4) obtaining cause and effect in perspectives. The model applies to every organization's for-profit. The contribution of the model presented in this paper is conceptual and executive for any given DMU devoted to specific output/input measures.

The rest of the paper is organized as follows: Section 2 provides dea models and a BSC. The integrated DEA-BSC simulation model is presented in Section 3. Section 4 discusses a case study that applies the DEA-BSC model. Finally, Section 5 presents concluding remarks.

2 | Literature Review

2.1 | Theory of the Balanced Scorecard

The BSC approach was first identified and implemented by Kaplan and Norton [7] as a performance management tool following a 1-year multi-company study in 1990. It aimed to present management with a concise summary of a business's Key Performance Indicators (KPIs) and to facilitate alignment of business operations with the overall strategy. Kaplan and Norton [7] were keen to provide a medium to translate the company's vision into clear objectives. These objectives could be translated into a system of performance measurements that effectively communicated a powerful, forward-looking, strategic focus to the entire organization. Kaplan and Norton [7] were motivated by companies' reliance on traditional financial accounting measures (like the ROI and payback period) to determine a 'narrow and incomplete picture of business performance.' As a result, they suggested that financial measures be supplemented with additional indicators that reflected customer satisfaction, internal business processes, and the ability to learn and grow. Their BSC was designed to complement 'financial measures of past performance with measures of the drivers of future performance' [4], [7]. It can be seen that they intended to keep the score of a set of KPIs that could maintain a balance between short and long-term objectives, financial and non-financial measures, lagging and leading indicators, and internal and external performance perspectives. By adopting such a 'holistic' view, Kaplan and Norton [7] hoped that managers, traditionally overwhelmed with data, would spend more time on decision-making rather than data analysis. The original BSC design identified the following four perspectives: the financial, customer, internal-business-process, and learning and growth perspectives. These perspectives represent three major business stakeholders (shareholders, customers, and employees), ensuring a holistic view of the organization is used for strategic reflection and implementation. The success of these perspectives depends on the fact that the perspectives themselves and the measures chosen have to be consistent with the corporate strategy [3], [7].

BSC requires that KPIs be classified into four perspectives, as shown in *Fig. 1*. Companies must categorize their KPI in these four boxes and develop performance measures within each perspective or category. The technique is based on interviews with managers by internal or external consultants to identify the 'strategic objectives' for each perspective. Then, through meetings with executives, specific measures are developed for these objectives. This list is edited, leaving the performance measures in the final scorecard [5], [8].

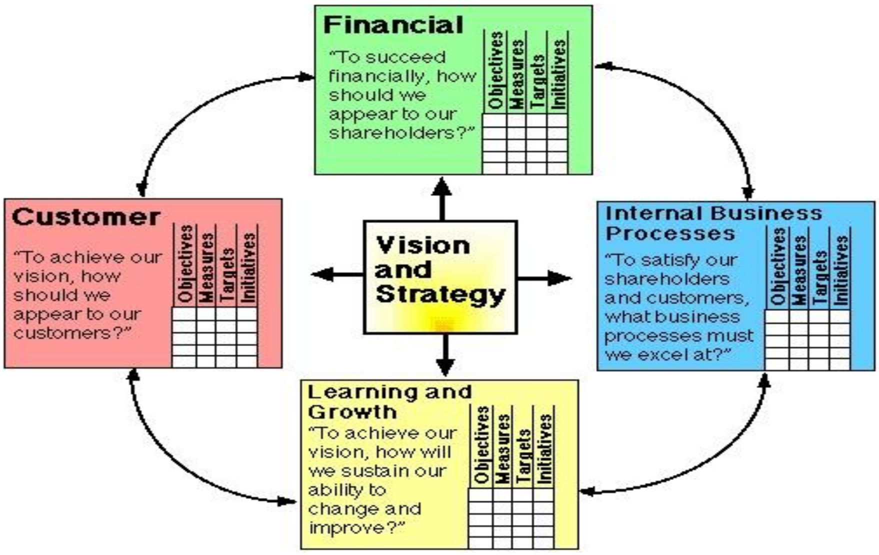

Fig. 1. Four perspectives of the BSC [4].

However, there are several major limitations of the BSC approach. First, it is a top-down approach only [9], [10]. Therefore, the interaction between the top management team and working-level employees is limited.

As seen from *Fig. 1*, the BSC approach intended to translate the vision and strategy of a business unit into objectives and measures in four different areas: the financial, customer, internal business process, and learning and growth perspectives [3].

2.2 | Perspectives

In this section, we will examine each of the four perspectives of the BSC:

I. Customer perspective: when choosing measures for the customer perspective of the scorecard, organizations must answer two critical questions: 1) who are our target customers? and 2) what is our value proposition in serving them?

II. Internal process perspective: in the internal process perspective of the scorecard, we identify the key processes the firm must excel at to continue adding value for customers and, ultimately, shareholders.

III. Learning and growth perspective: where are these gains found if you want to achieve ambitious results for internal processes, customers, and, ultimately, shareholders? The measures in the learning and growth perspective of the BSC are the enablers of the other three perspectives. Essentially, they are the foundation for this entire house of a BSC.

IV. Financial measures: financial measures are important to the BSC, especially in the for-profit world. The measures in this perspective tell us whether our strategy execution, which is detailed through measures chosen in the other perspectives, is leading to improved bottom-line results.

These four strategic areas should have lead and lag indicators, yielding two directional cause-and-effect chains: lead and lag indicators applied horizontally within and vertically between areas. The causal paths from the measure indicators on the scorecard should be linked to financial objectives. This procedure implies that strategy is translated into a set of hypotheses about cause and effect relationships, which are essential because it allows the measurements in non-financial areas to be used to predict future financial performance. Thus, the claim is that financial measures say something about past performance while non-financial measures drive future performance. However, the model's validity relies on the assumption that the cause-and-effect relationship exists between the measurement areas suggested [3], [4], [7], [11].

2.3 | Interrelationships among Four Perspectives of BSC

The BSC approach emphasizes that to achieve objectives from the financial perspective, all objectives and measures from other perspectives should be linked [12]. For most organizations, the financial themes of increasing revenues, improving productivity, and enhancing asset utilization could provide the necessary linkages. Firms should emphasize the cause-and-effect relationship among the BSC measures to achieve a synergetic effect. Roy and Wetter [13] argued that improved value in human resource and development capital should be the leading indicators of improvement in customer capital and profitability. These authors develop a cause-and-effect relationship among the BSC measures. Their cause-and-effect model indicates that human resource development measures would influence the firm's internal business process. These interrelationships are shown in *Fig. 2*.

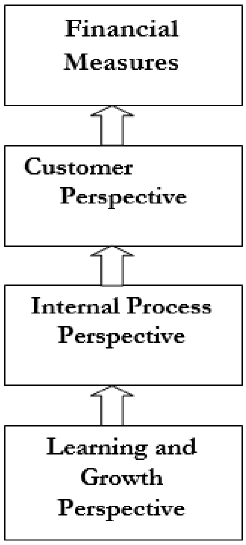

Fig. 2. Cause-and-effect relationship.

On the other hand, Paul Niven's analogy of the BSC is that of a tree (*Fig. 3*). The learning and growth perspective is the root, the trunk is the internal process perspective, customers are the branches, and the leaves are the financial perspective. Each perspective is interdependent on those below as well as those above. It is a continuous cycle of renewal and growth. Leaves (finances) fall to fertilize the ground and root system, stimulating growth throughout the organization. In this analogy, learning and growth are the foundation on which all other perspectives are built [14].

A well-designed, BSC should describe your strategy through the objectives and measures you have chosen. These measures should link together in a chain of cause-and-effect relationships from the performance drivers in the learning and growth perspective to improved financial performance as reflected in the Financial perspective. Based on the above literature review, the interrelationships among the four perspectives of BSC have drawn significant attention. However, scholars seem not to agree on the interrelationships among the four perspectives of the BSC. These interrelationships are as follows: 1) the learning and growth perspective of the BSC impacts the internal business process perspective of the BSC, 2) the internal process perspective of the BSC influences the customer perspective of the BSC, and 3) the learning and growth, internal business process, and customer perspective of the BSC will significantly impact on the financial perspective of the BSC.

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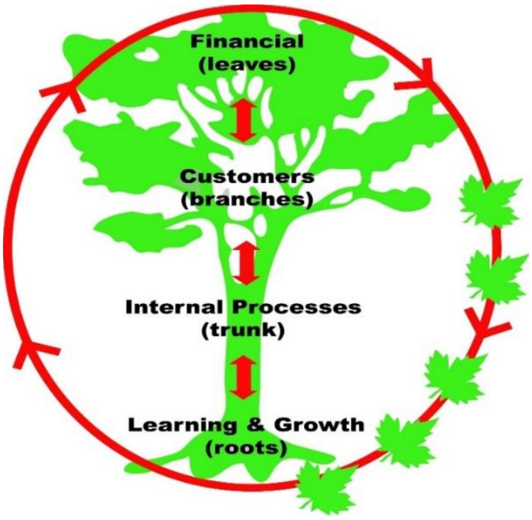

Fig. 3. Cause and effect.

2.4 | Balance in the BSC

One of the reasons the BSC has been so successful is that it is a balanced approach. This balance includes:

I. Balance between financial and non-financial indicators of success.

II. Balance between internal and external constituents of the organization.

III. Balance between lag and lead indicators of performance internal constituents might include employees, whereas external constituents might include physician groups or insurers. Lag indicators generally represent past performance and might include customer satisfaction or revenue. Although these measures are objective and accessible, they lack any predictive power. Lead indicators are the performance drivers that lead to the achievement of lag indicators and often include the measurement of processes and activities. For example, ER wait time might represent a leading indicator of patient satisfaction. A BSC should contain a variety of different measures.

2.5 | Data Envelopment Analysis

One of managers' major concerns in evaluating an operation's performance is efficiency. Efficiency measures whether resources, equipment, and/or people are being put to good use. One dimension of any organization's efficiency is how it selects and uses resources to produce its products. The more products are produced for a given amount of resources, the more efficient (i.e., less wasteful) the operation. Charnes et al. [15] proposed an innovative quantitative technique named DEA to evaluate the relative efficiency of an organization's comparable components.

DEA utilizes linear programming to measure the relative efficiency of comparable Decision Making Units (DMUs) that employ multiple inputs and outputs. DEA uniquely evaluates all the DMUs and all their inputs and outputs simultaneously and conservatively identifies the sets of relatively efficient and relatively inefficient DMUs. Thus, the solution of a DEA model provides a manager with a summary of comparable DMUs grouped and ranked by relative efficiency [15]–[17],

Mathematically, efficiency can be defined as the ratio of weighted outputs to weighted inputs,

$$\text{Efficiency} = \frac{\text{weighted sum of outputs}}{\text{weighted sum of inputs}}.$$

The DEA approach identifies the set of weights (all weights must be positive) that individually maximizes each DMU's efficiency while requiring the corresponding weighted ratios (i.e., using the same weights for all DMUs) of the other DMUs to be less than or equal to one.

Let Xij, i = 1,...,m, and Yrj, r = 1,..., s, be the ith input and rth output, respectively, of the jth DMU, j = 1,...,n. The DEA model for measuring the relative efficiency of DMU k under an assumption of constant returns to scale is the CCR model [15]:

$$\begin{aligned} &\max \quad E_k^{CCR} = \frac{\sum_{r=1}^{S} u_r y_{rp}}{\sum_{i=1}^{m} v_i x_{ip}}, \\ &\text{s.t.} \quad \frac{\sum_{r=1}^{S} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1 \qquad j=1,\dots,n, \\ &u \ge 0 \qquad , v \ge 0, \end{aligned} \tag{1}$$

where E_k^{CCR} is the efficiency of DMU k, u_r and v_i are the multipliers associated with the r[th] output and i[th] input, respectively, to be determined by this mathematical program, and e is a small non-Archimedean number [18], [19] which is imposed to prohibit each DMU to assign zero weights to unfavorable input/output factors. This model is a fractional linear program which can be transformed into the following linear program:

$$\begin{aligned} &\max \quad E_k^{CCR} = \sum_{r=1}^{S} U_r Y_{rp}, \\ &\text{s.t.} \quad \sum_{r=1}^{S} U_r Y_{rp} \;\; \sum_{i=1}^{m} V_i X_{ip} \le 0, \qquad j=1,\dots,n, \\ &\sum_{i=1}^{m} V_i X_{ip} = 1, \\ &V_i \ge 0, \qquad i=1,\dots,n, \\ &U_r \ge 0, \qquad r=1,\dots,s. \end{aligned} \tag{2}$$

For systems composed of several interrelated processes, this model ignores the performance of individual processes. Consequently, the efficiency ECCR k does not properly represent the aggregate performance of the component processes. Certainly, *Model (2)* can be applied to measure the efficiency of each process independently; however, the relationship between the system efficiency and process efficiencies is not revealed [20].

Systems with more than one process connected are networks. A network DEA model is needed to measure the efficiency of a network system. The network DEA model has no standard form, unlike the conventional DEA model. It depends on the structure of the network in question. Färe and Grosskopf [21], [22] and Färe et al. [23] developed several network models that can be used to discuss variations of the standard DEA model.

2.6 | Series Structure

For a system consisting of two processes connected in series, Seiford and Zhu [24] applied the conventional DEA model to calculate the efficiency of each process independently. Kao and Hwang [25] developed a relational model to calculate the system's efficiency, considering the series relationship of the two processes. The major difference between the independent and relational models is that the latter requires the same factor to have the same multiplier, no matter how it is used. At the same time, the former allows a factor to have different multipliers when used in different places. An interesting result of the relational model is that the system efficiency is the product of the two process efficiencies. Their conclusion can be extended to general series systems of more than two processes. Note that a series model may be solved using backward induction [20], [25].

Consider a series system of h processes. As in the preceding section, let Xij and Yrj be defined as the inputs and outputs of the system, respectively. Denote Z_{pj}^{t} as the pth intermediate product, p = 1,...,q of process t, (t = 1,...,h -1) for DMU j. The intermediate products of process t are the outputs of process t and the inputs of process t + 1. Note that the intermediate products of the last process, h, are the system's outputs. The number of intermediate products, q, can differ for each process. It is assumed that they are the same for all processes to simplify notation.

Fig. 1 is a pictorial expression of the series system. Denote $w_p^{(t)}$ as the multiplier, or the importance, associated with the pth intermediate product of process t. The system efficiency of DMU k is calculated by the following model generalized from the tandem system of Kao and Hwang [25]:

$$\max \quad E_k = \sum_{r=1}^{S} U_r Y_{rp}, \tag{3-0}$$

$$\text{s.t.} \quad \sum_{i=1}^{m} V_i x_{IP} = 1, \tag{3-1}$$

$$\sum_{r=1}^{S} U_r y_{rj} - \sum_{i=1}^{m} V_i x_{ij} \leq 0, \qquad j = 1,\ldots,n, \tag{3-2}$$

$$\sum_{p=1}^{q} W_p^1 Z_{pj}^1 - \sum_{i=1}^{m} V_i x_{ij} \leq 0, \qquad j = 1,\ldots,n, \tag{3-3}$$

$$\sum_{p=1}^{q} W_p^{(t)} Z_{pj}^{(t)} - \sum_{p=1}^{q} W_p^{(t-1)} Z_{pj}^{(t-1)} \leq 0, \qquad j = 1,\ldots,n, \ \ t = 2,\ldots,h \ast 1, \tag{3-4}$$

$$\sum_{r=1}^{S} U_r y_{rj} - \sum_{p=1}^{q} W_p^{(h-1)} Z_{pj}^{(h-1)} \leq 0, \qquad j = 1,\ldots,n, \tag{3-5}$$

$$\begin{aligned} & V_i \geq \varepsilon, && i = 1,\ldots,n, \\ & U_r \geq \varepsilon, && r = 1,\ldots,s, \\ & w_p^{(t)} \geq \varepsilon, && p = 1,\ldots,q, \quad t = 1,\ldots,h-1, \end{aligned} \tag{3-6}$$

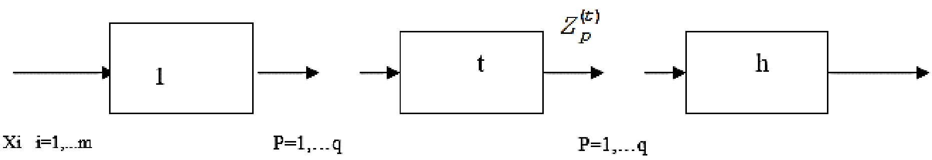

Fig. 4. Serice system.

Where *Constraint Set (3.2)* corresponds to the system and *Constraints Sets (3.3)* to *(3.5)* correspond to h processes. Note that the sum of the process constraints of a DMU, i.e., *Constraint Sets (3.3)* to *(3.5)*, is equal to its system *Constraint (3.2)*. Hence, the system constraint is redundant and can be omitted. Basically, the number of constraints required in this model equals the number of DMUs multiplied by the number of processes in the system. Let $U_r^{\times}$ $V_i^{\times}$ and $w_p^{(t)\times}$ denote the optimal multipliers solved from *Model (3)*. The efficiency of each process for DMU k is calculated as:

$$E_k^{(1)} = \frac{\sum_{p=1}^{q} w_p^{(1)} z_{pk}^{(1)}}{\sum_{i=1}^{m} v_i^* x_{ik}}.$$

$$E_k^{(t)} = \frac{\sum_{p=1}^{q} w_p^{(t)} z_{pk}^{(t)}}{\sum_{i=1}^{m} w_p^{(t-1)} \ z_{pk}^{(t-1)}}.$$

$$E_k^{(h)} = \frac{\sum_{r=1}^{s} u_r^* y_{rk}}{\sum_{p=1}^{q} w_p^{(h-1)} z_{pk}^{(h-1)}}.$$

A DMU is efficient only if all its processes are efficient. Mathematically, the system efficiency will be low if there is a very inefficient process, which will be high only when all processes have high efficiencies. In *Model (3)*, when process *Constraints (3.3)* to *(3.5)* are removed, the conventional CCR model is obtained.

2.7 | DEA with Non-Discretionary Factors (Banker and Morey's Model)

Banker and Morey [26] provided the first DEA model for evaluating efficiency in the presence of "exogenously fixed" inputs. The following modification of the CCR model gives Banker and Morey's [26] model to evaluate the efficiency of any DMU:

$$\min \quad \theta\_\varepsilon(\sum_{r=1}^{s} s_r^+ - \sum_{i\in D} s_i^-), \tag{4-0}$$

$$\text{s.t.} \quad \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{io}, \qquad i \in D, \tag{4-1}$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{io}, \qquad i \in ND, \tag{4-2}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_i^+ = y_{ro}, \qquad r = 1,\dots,s. \tag{4-3}$$

where all variables (except θ) are constrained to be nonnegative and $\varepsilon \succ 0$ is a non-Archimedean infinitesimal constant to assure strongly efficient solutions; here, the symbols $i \in D$ refer to the sets of discretionary and non-discretionary inputs. The dual of the *Model (4)* in the form of a (modified) multiplier:

$$
\begin{aligned}
\max \quad & \sum_{r=1}^{s} u_r y_{ro} - \sum_{i \in ND} v_i x_{io}, \\
\text{s.t.} \quad & \sum u_r y_{rj} - \sum_{i \in ND} v_i x_{ij} - \sum_{i \in D} v_i x_{ij} \le 0, \quad j = 1, \dots, n, \\
& \sum_{i \in D} v_i x_{io} = 1, \\
& v_i \ge \varepsilon, \quad i \in D, \\
& v_i \ge 0, \quad i \in ND, \\
& u_r \ge \varepsilon, \quad r = 1, \dots s.
\end{aligned} \tag{5}
$$

Note: The variable θ is not applied to the input *Constraints (4-2)* because these values are exogenously fixed, and it is therefore impossible to vary them at the discretion of management. Therefore, this is recognized by entering all $x_{io}, i \in ND$ at their fixed (observed) values.

Note: Only the non-discretionary inputs enter the *Objective (5)*. The multiplier values associated with these non-discretionary inputs may be zero. If at any optimal solution of *Eq. (4)*, $s_k^{-*} \succ 0$ for some $k \in ND$, then $v_k^* = 0$ and this x_{ko} does not affect the evaluation recorded in *Eq. (4)*. Also, if $v_k^* \succ 0$ for some $k \in ND$, then the efficiency score recorded in *Eq. (4)* is reduced by the multiplier, x_{ko}, for DMUo under evaluation.

3 | The Integrated DEA and BSC Simulation Model

The purpose of this study is to find out the relationships among four output perspectives. For such an objective, a structure equation model is employed to test the interrelationships of all the variables in the model. The proposed structural equation model is shown in *Fig. 4*.

Techniques such as BSC and DEA are instruments that can't be stipulated as an alternative technique, but their combined use in the performance evaluation system appears essential. On the other hand, a systematic link between the two models can be created. It is done so that one of them can be used as a complementary and improve the weak points of the model, so using the correct and accurate structure of them can be an important issue of the performance rating in the organization.

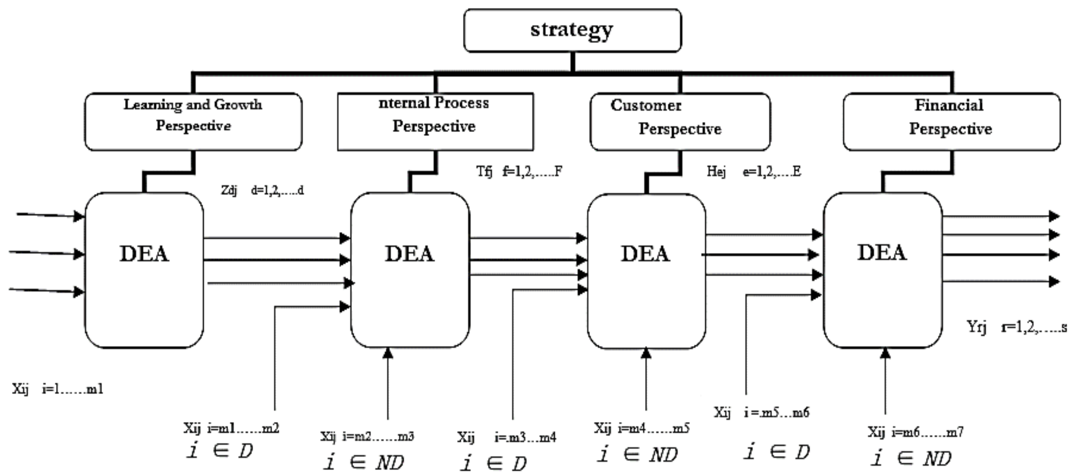

Fig. 5. Combined BSC and DEA model.

In this section, we introduce the mathematical formulations of the proposed network-DEA model and efficiency measures with non-discretionary inputs. Following the formulation of *LP (3)* shown earlier, we limit our discussion to the output-oriented measure only, and the technology is assumed to exhibit Constant Returns-to-Scale (CRS). A DEA model is output-oriented if it seeks to increase outputs without increasing inputs. Our approach to the network DEA model extends the four-stage DEA Model.

$$
\begin{aligned}
&\max_{z} \quad ep = \sum_{i=1}^{S} U_r y_{rp}, \\
&\text{s.t.} \quad \sum_{i=1 \;\; i\&D}^{m_4} V_i x_p = 1, \\
&\sum_{i=1}^{S} U_r y_{rj} - \sum_{i=1 \;\; i\&D}^{m_8} V_i x_{ij} - \sum_{i=1 \;\; i\&ND}^{m_8} v_i (x_{ij} - x_{io}) \le 0, \qquad j = 1,....,n, \\
&\sum_{d=1}^{D} \eta_d Z_{dj} - \sum_{i=1 \;\; i\in D}^{m_1} V_i x_{ij} - \sum_{i=1 \;\; mi\in ND}^{m_2} v_i (x_{ij} - x_{io}) \le 0, \qquad j = 1,...,n, \\
&\sum_{f=1}^{F} \gamma_f T_{fj} - \sum_{d=1}^{D} \lambda_j z_{dj} - \sum_{i=m_2 \;\; i\in D}^{m_3} v_i x_{ij} - \sum_{i=m_3 \;\; i\in ND}^{m_4} v_i (x_{ij} - x_{io}) \le 0, \qquad j = 1,...,n, \qquad (6) \\
&\sum_{e=1}^{E} \pi_e H_{ej} \quad \sum_{f=1}^{F} \gamma_f T_{fj} - \sum_{i=m4}^{m5} V_i x_{ij} - \sum_{i=m7 \;\; i\in ND}^{m8} v_i (x_{ij} - x_{io}) \le 0, \qquad j = 1,...,n, \\
&\sum_{r=1}^{S} U_r y_{rj} \quad \sum_{e=1}^{E} \pi_e H_{ej} - \sum_{i=m6}^{m7} v_i X_{ij} - \sum_{i=m7 \;\; i\in ND}^{m8} v_i (x_{ij} - x_{io}) \le 0, \qquad j = 1,...,n, \\
&U_r \ge \varepsilon \qquad , V_i \ge \varepsilon \qquad \eta_d \ge \varepsilon, \\
&\gamma_f \ge \varepsilon \qquad , \pi_e \ge \varepsilon.
\end{aligned}
$$

The processes of measurement and performance rating using two techniques, BSC and DEA, can be outlined in the following issues:

I. The identification of organization: In the processes, the purposes, and strategies of relevant organizations identified and using BSC techniques, the measurement is designed in every view. The measurements are created in balance with different views.
II. Performance rating: The measurements created by BSC are in two groups, input, and output, classified using DEA horizontal evaluation (during the period) and/or vertical evaluation (in comparison with similar units in the chronological period).
III. The design of the path of modification and recovery: The path of modification and recovery is identified by DEA. The modification and recovery path increased for the output measurements and decreased for the input measurements.
IV. The determination of measurement goals for the next period: The measurement goals are determined by DEA and placed as measurement goals for the next performance of BSC.

In this method, each time BSC performance, that is, every time the organization's data is entered into the BSC system, and the results are presented, DEA evaluates the organization, and the goals of measurements are recognized in the following period. If you achieve the determined goals, the organization will be efficient and expected conditions.

In the next two performance evaluation periods, the organization's condition is compared with the expected conditions of the previous period, and the efficiency of new goals is determined.

4 | Case Study

We have applied our new approach to six bank branches in Iran. The data for the case study are presented in *Table 1* and *Table 2*. We have four stages for the production process. Evaluating these units involves many performance aspects; therefore, using 3 final output measures, two first input measures, and 9 intermediate measures for this evaluation is quite reasonable.

Table 1. The case study data.

X8** Facilities Back-Log Rate	X7* Cost to Income	X6** Competitional Value	X5* On Line Service	X4* High Services Rate	X3* Electronical Service	X2* Incrasing Personnel Major	X1* Motivation Cost	
%2.68	%52.84	%15.7	1376	%3.13	1305	12.11	%23.03	DMU1
%9.5	%42.77	%18.9	1896	%3.41	1906	11.96	%18.72	DMU2
%15	%60	%34	1842	%3.25	1758	12.08	%18.5	DMU3
%8.5	%60.20	%33.5	1315	%3.32	1500	12.07	%5.30	DMU4
%7.3	%57.90	%30.4	787	%3.25	745	11.96	%17	DMU5
%14	%96	%14	510	%3.35	517	13.66	%3	DMU6

(discretionary input =* and non discretionary input =**)

Table 2. The case study data.

Y3 Return of Investment	Y2 Growth Rate of Resource	Y1 Profit Margin	H2 Customer Fit of Rate	H1 Customer Satisfaction	T2 Forward Service	T1 High Quality Services Rate	Z2 Increasing Services Rate	Z1 Incrasing Personnel Skill	
%4.81	%17.42	%1.48	%22.91	%3.25	91	%3.19	800	58.54	DMU1
%7.16	%12.98	%2.62	%25.8	%3.21	57	%3.61	692	30.80	DMU2
%7	%47.59	%8	%29	%3.41	8	%3.34	718	46.25	DMU3
%1.4	%18.9	%2.7	%34.50	%3.12	37	%3.41	682	18.55	DMU4
%1.23	%20.13	%3	%21.8	%3.43	34	%3.93	643	39.10	DMU5
%1.02	%10.28	%4	%13	%3.74	10	%3.74	555	69	DMU6

The information data for the case study are presented in *Table 3*. We define two kinds of inputs (discretionary and non-discretionary).

Table 3. Inputs and outputs of the DEA-BSC model in the case study.

Perspective	Discretionary Inputs	Non-Discretionary Inputs	Outputs
Financial Perspective	1- Cost to income 2- Customer satisfaction 3- Customer fit of rate	1- Facilities back-log rate	1- Profit margin 2- Growth rate of resource 3- Return on investment
Customer Perspective	1- High services rate 2- Online service 3- High quality service rate 4- Forward service	1- Competitional value	1- Customer satisfaction 2- Customer fit of rate
Internal Process Perspective	1- Electronical service 2- Incrasing personnel skill 3- Increasing services rate	-	1- High quality service rate 2- Forward service
Learning and Growth Perspective	1- Motivation cost 2- Incrasing personnel major	-	1- Incrasing personnel skill 2- Increasing services rate

Table 4 presents the results of the implementation. The first column shows the overall efficiency results, and the others show each stage's efficiency.

Table 4. DEA-BSC results.

DMU	Overall Efficiency	First Stage Efficiency	Second Stage Efficiency	Third Stage Efficiency	Fourth Stage Efficiency
DMU1	0.947	1	0.917	0.762	1
DMU2	0.976	0.865	1	1	1
DMU3	0.819	0.897	0.953	0.861	1
DMU4	0.466	0.852	0.976	1	1
DMU5	0.925	0.803	0.958	0.678	1
DMU6	0.601	0.723	1	0.438	1

To achieve successful results, it is essential to invest time and effort in four key areas: learning and growth, internal processes, customer satisfaction, and financial performance. Achieving satisfactory outcomes won't be easy if these four areas are not functioning properly.

5 | Conclusion

This study has demonstrated an analytical technique that can be used to benchmark efficiencies to identify the most efficient "best practice" organization. The BSC-DEA methodology was designed to accommodate uncertain and qualitative data. Since non-financial performance measures, which are qualitative, become important, decision-makers must use techniques to include measures in the evaluation process.

DEA can be a useful tool in setting benchmarks and evaluating BSC results. The DEA-BSC model advances the individual capabilities of the DEA and BSC. From the viewpoint of DEA, the model generalizes the standard treatment of the data by splitting the inputs and outputs into subsets (cards) and adding constraints (balancing requirements) that reflect relationships among the cards. From the viewpoint of BSC, the model proposes a new approach to evaluate performance by applying quantitative analysis that combines the measures within each card into a single value. It also addresses some of the difficulties in existing BSC applications, namely, reliance on a known (sometimes arbitrarily chosen) baseline against which performance is evaluated and the fact that BSC does not produce a comprehensive measure of performance.

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