Efficiency assessment of medical diagnostic laboratories using undesirable sustainability indicators: A network data envelopment analysis approach

Niloufar Ghafari Someh, Mir Saman Pishvaee, Seyed Jafar Sadjadi, Roya Soltani

Niloufar Ghafari Someh

Department of Industrial Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran
E- mail: niloufar.ghaffari@srbiau.ac.ir

Mir Saman Pishvaee (*Corresponding Author*)

School of Industrial Engineering, Iran University of Science and Technology, Tehran, Iran
Phone number: +989120909633
Fax: +9821 73225098
E- mail: pishvaee@iust.ac.ir

Seyed Jafar Sadjadi

School of Industrial Engineering, Iran University of Science and Technology, Tehran, Iran
Phone number: +982177240129- +9873225027
Mobil phone: +989121880060
E- mail: sjsadjadi@iust.ac.ir

Roya Soltani

Department of Industrial Engineering, KHATAM University, Tehran, Iran
E- mail: r.soltani@khatam.ac.ir

Efficiency assessment of medical diagnostic laboratories using undesirable sustainability indicators: A network data envelopment analysis approach

Niloufar Ghafari Someh[a], [*]Mir Saman Pishvaee[b], Seyed Jafar Sadjadi[b], Roya Soltani[c]

[a] *Department of Industrial Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran*

[b] *School of Industrial Engineering, Iran University of Science and Technology, Tehran, Iran*

[c] *Department of Industrial Engineering, KHATAM University, Tehran, Iran*

Abstract

Assessing the performance of health systems assists health decision-makers. Medical diagnostic laboratories are one of the most important sectors in the healthcare system of all countries. Thus, an assessment of the performance of medical diagnostic laboratories is of particular importance. This paper aims to propose a network data envelopment analysis (NDEA) model to assess the performance of medical diagnostic laboratories and decomposing the efficiency of the system based on sustainable development indicators. In addition, the proposed model is designed according to the internal structure of the medical diagnostic laboratory, which includes three main laboratory processes (the pre-test, the test and the post-test) with a combination of additional inputs and outputs (including both desirable and undesirable). The proposed model is a multiplicative DEA approach to estimate and decompose the efficiencies of system. Thus, a heuristic method is used as a suitable solution to convert a multiplicative NDEA approach into an equivalent linear program. In this study, the criteria for evaluation are obtained by using the Fuzzy TOPSIS- Delphi method. The performance proposed model is shown through a real study in Iran. The computational results demonstrate the applicability of the proposed model in determining the most efficient laboratory using undesirable sustainability indicators.

Keywords: *Network Data Envelopment Analysis; Sustainable development; Medical diagnostic laboratories; Efficiency evaluation; Additional data (desirable and undesirable).*

1. Introduction

In recent years, the health status of most countries, especially in the area of epidemic diseases, has faced a great challenge [1]. These apprehensions include inequalities in access to health services, changes in quality and care safety, lack of health facilities and rising costs of health care [2]. According to global standards, about 10% of total healthcare expenditure is spent on laboratory services [3].In addition to the economic dimension, environmental and social dimensions are important so that, leading diagnostic laboratory services have increasingly recognized the critical importance of managing and controlling social, environmental, and economic performance. Therefore, managers' attention to sustainability factors in the field of diagnostic laboratories can play an effective role in influencing the three sustainability factors (social, environmental and economic) in promoting community health. Thus, measuring the performance of diagnostic laboratories, as one of the most important and largest providers of health care services that play a crucial role in health, is mandatory.

The performance of medical diagnostic laboratories can be measured by measuring efficiency. In this regard, we can assess the strengths and weaknesses, or the efficiency and inefficiency of the units. Then the units can eliminate the defects and fortify their strong points. [4].The Laboratories can prevent errors by improving performance, and ensure that the laboratory results are accurate. The goal of this approach is to provide high return services. Even a negligible upgrade in lab improvement programs will assist in attentiveness towards serving the people. It is obvious that, in order to analyze the effectiveness of diagnostic laboratories, we need to use a suitable tool. One of the most suitable and effective tools in this field is Data Envelopment Analysis (DEA). DEA is a mathematical method for measuring the relative efficiency of decision-making units (DMUs) and it was first introduced by [5].

The traditional DEA models disregard the internal operations or structure of the DMUs, typically referring each DMU as a "black box" with single-process converting the multiple inputs to the multiple final outputs. These approaches lead to incorrect performance scores or misleading results for system with complex internal structure [6, 7]. To counter the constraints of traditional DEA models, a DEA network is proposed by [8]. It considers the structure of DMUs as a system consisting of a network of sub-DMUs, which has intermediate measures. These are sometimes applied as sources of production, and sometimes as consumable resources [9].

DEA models face limitations, one of the main limitations of the DEA model being the situation in which the process produces undesirable factors. The development of undesirable factors, especially in the health services sector, such as the production of infectious waste, is of particular importance. Färe et al. [10], for the first time, mentioned the aspect of undesirable factors, in evaluating efficiency performance.

In this paper, we explain summarize recent studies that have used the DEA method to evaluate performance in various areas of health care.

A review of related literature shows that a significant number of studies have attempted to evaluate performance in areas related to health care, although many studies on hospital performance evaluation are available [11]. Among the review papers published in the field of hospital performance evaluation, we can mention the one by Nayar and Ozcan [12], which examined qualitative performance criteria using a sample of Virginia hospitals. The performance scores of hospitals were calculated using DEA. The studies by Audibert et al. [13] and Varabyova and Schreyögg [14] evaluated health care. Audibert et al. [13] first considered the increased access to health care for the rural populations and then, they examined the performance of the health system. In this study, 24 urban hospitals in Weifang (Shandong) were surveyed from 2000 to 2008. They measured the efficiency of urban hospitals through a two-step approach. Varabyova and Schreyögg [14] compared the technical efficiency of the hospital departments. They used the unbalanced panel data of the OECD countries from 2000 to 2009. In this study, the estimation of the technical efficiency of the hospital departments was performed using non-parametric DEA and parametric stochastic frontier analysis (SFA). The internal and external validity of the findings were measured by Spearman's rank correlation estimation. This study only analyzed one aspect of efficiency, namely technical efficiency. Review papers show that many health studies have been published in 2014, and we discuss a number of these studies here. The analysis of the effectiveness of health care systems plays an important role in relation to public health costs and health assessment; the work by Leleu et al. [15] is significant in this regard. In this study, two issues were considered to describe the factors affecting financial sustainability. The first is the cost of patients who cannot afford paying for hospital services while the second issue is associated with internal management. The purpose of this study was to investigate the effect of these two issues on the profitability of hospitals. Therefore, using the DEA method, input inefficiencies were measured in the manufacturing process for 138 hospitals Florida in 2005. In the same year, two studies were conducted to evaluate the European health system. In the first accomplished by Popescu et al. [16], they evaluated the efficiency of European health systems. In this study, DEA approach was used to evaluate the efficiency of health systems. The study emphasizes that Romania has an inappropriate health system. Even though the Romanian health system has made significant progress during the past two decades, some of its areas still have a lower quality than the average of other European countries do. Therefore, the system is not yet able to provide appropriate services for its citizens. In another study Asandului et al. [17] studied the performance evaluation of public health systems in Europe based on a nonparametric DEA method and the statistical data applied was for the 30 European countries in 2010. The latest study in 2014 is that of Al-Refaie et al. [18]. They measured the average waiting time for patients of emergency department (ED) and then focused on the number of physicians and nurses in the ED by considering a cellular service system. Performance evaluation was simulated over the period of a month (672 hours) with 10 replications. Then, the best scenario was presented using aggressive formulation in DEA. Chowdhury and Zelenyuk [19] examined the performance of hospital services in Ontario (Canada). In this paper, DEA was applied to evaluate efficiency and then truncated regression estimation with double-bootstrap was used to test the importance of explanatory variables. Campos et al. [20] applied the input-oriented DEA approach to examine the efficiency of health systems in Spain (Autonomous Communities). The aim of this work was to analyze the efficiency of public resources. Since the need to improve efficiency in the field of health care is essential, Johannessen et al. [21] examined the effectiveness of full-time physicians (FTE) in hospitals using some Panel Analysis and DEA. The efficiency of the physicians' workforce and the impact of personnel workforce was studied from 2001 to 2013 in 19 Norwegian hospitals. However, in their study, they ignored the evaluation of the network structure. Khushalani and Ozcan [22] investigated the returns of United States hospital over five years from 2009 to 2013. In this study, the Dynamic Network DEA Structure was applied to calculate performance evaluation for different hospital departments, such as medical/surgical care (patient visits, surgeries and discharges) and quality. Patra and Ray [23] examined the efficiency of hospital systems. In this study, the Malmquist productivity index was applied based on the DEA to measure productivity and efficiency of an Indian hospital system. The efficiency of several hospital departments was analyzed and improvement alternatives were identified. From other studies in the field of health services, an assessment of the efficiency of dental services in the provincial level in Turkey was performed by Şahin and İlgün [24]. The study population consists of hospitals and dental care centers under the Ministry of Health located in 81 provinces of Turkey. The efficiency of oral and dental centers is evaluated using DEA method. With a mixed sustainability-resilience view, a mixed sustainability-resilience framework for evaluating HIS (hospital information system) is proposed by Motevali Haghighi and Torabi [25]. Thus they can utilize this model to enhance their performance. In a real case study, a DEA model is applied to evaluate HIS performance. In order to determine the attitude of DMUs using the optimistic-pessimistic parameters, a novel fuzzy DEA model based on general fuzzy measure is proposed by Peykani et al. [26]. By measuring the efficiency of 38 hospitals in United States, the practical use of this approach on a real data set is illustrated. In order to understand the variation in access to early prenatal care in a more complete manner, Thorsen et al. [27] identify the unique compositions of CHCs (Community health centres). In this study, A DEA approach is performed to evaluate the operational efficiency of CHCs. Abolghasem et al. [28], report the data of the healthcare systems indicators of 120 countries in the period from 2010 to 2017 and then evaluate the efficiency using the DEA method to. On the other hand, laboratory services are one of the important components of the quality of health care. Therefore, evaluating performance of the laboratory field is important. However, few studies have been performed in this area. One of the papers published in the field of laboratory performance evaluation is the work of Chawla et al. [29]. Quality indicators in the clinical laboratory are a useful tool for continuously improving laboratory services. The aim of this study is to design and evaluate quality indicators over time in order to improve the performance of the laboratory. This study evaluates various qualitative indicators. Indicators are related to a biochemistry laboratory of the hospital in New Delhi. They helped to improve the quality of laboratory services and patient health care by taking corrective measures over a period of time. Another study pertinent to the field of laboratories is Hamid Abu Bakar and Lukman Hakim [30]. The purpose of this paper was to review the efficiency of public hospital laboratories in order to examine the satisfaction of doctors. Data were collected from interviews with two senior laboratory administrators and 30 doctors of two laboratories in Malaysia. The interview used two sets of structured questionnaires, which included of two dimensions, Doctor Satisfaction dimension (DSD) and Supply inputs (SCI).

In recent studies, only single-stage DEA models have been used in a traditional way. As a result of this single-stage approach, the health systems are analysed as having a black-box nature. To eliminate this limitation, we develop this concept in three-stage health systems. Another improvement in our approach is the use of desirable and undesirable sustainability indicators in order to measuring the performance of the healthcare facilities, thus filling a conspicuous gap in the literature. Here, a three-stage laboratory is designed and then sustainability indicators (economic, environmental, and social) are used to evaluate the efficiency of diagnostic laboratories. The undesirable factors in the data are important in the analysis. Next, a heuristic method is proposed and the multiplicative NDEA approach is converted into an equivalent linear program. A real case study has been conducted in Iran, thus demonstrating the use of the proposed approach in practice.

The most salient contributions of this paper are highlighted as follows:

- Undesirable sustainability indicators (social, economic and environmental) are considered in proposed approach.

- Assessments performance three major laboratory processes (pre- testing, testing, post-testing) in a network DEA model.
- Investigates a real case study of diagnostic laboratories that has not been considered despite the importance of diagnostic laboratories in the field of health services.
- Proposing a heuristic model to convert a multiplicative NDEA approach into an equivalent linear program.

This paper is organized as follows: Section 2 discusses the research methodology. In this Section, first, identify indicators by using Fuzzy TOPSIS- Delphi method then the mathematical modelling of the problem is described and then a heuristic approach is introduced to solve the nonlinear program. Section 3, illustrates the proposed model using a real case study of measuring efficiency of 25 private medical diagnostic laboratories in Iran to show the applicability and usefulness of model. Section 4 we shall analyze the results. Finally, Section 5 concludes the paper and some directions for future research.

2. Methodology

Considering that our case study is a medical diagnostic laboratory, effective factors consist of quantitative data. Studies show that although many variables can be considered, in most cases there is no relative data. So this is one of the real world problems that make variables difficult to determine. In this way, an appropriate selection of variables is very important. In this study, the methodology is designed in two steps; in the first step, since variables are not identified and there is no structural and theoretical guidance, the factors affecting each dimension of the model by analyzing organizational documents, library studies, observation and the interview will be obtained. Then we used the Fuzzy TOPSIS approach to select the optimal indicators among the available indicators. Finally, for evaluating and screening the findings of this stage, experts' opinions and the Delphi method are applied to achieve consensus about the influential factors. In the second step, a network data envelopment analysis (NDEA) approach is designed to measure the performance of laboratories. In Fig.1, the methodology is showed in two steps.

[Insert Figure 1 about here]

2.1. Identify indicators using qualitative studies

Initially, we used two methods of documentation and observation to obtain the most important indicators in the laboratory field and to compile indicators. Some of the indicators we required were in the form of documents and articles. Then, by attending laboratories, we got the overall effective factors in laboratory processes through the observation of the organization. The appropriate indicators are showed in Table (1) following as presence.

[Insert Table 1 about here]

2.2. FUZZY TOPSIS Technique

In this step, the Fuzzy TOPSIS method is used to evaluate the improvement. Fuzzy TOPSIS is an approach that deals with complex systems of choice between different indicators. In other words, Fuzzy TOPSIS offers a way to compare indicators [31]. Fuzzy TOPSIS approach creates consistent and systematic criteria, based on selecting the best indicators with the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution. The positive ideal solution is one of the most advantageous of all indicators and the negative ideal solution is one of the lowest advantageous. Therefore, indicators are ranked according to their relative proximity to ideal solutions. The goal is to prioritize the optimal indicators so that they are closest to the positive ideal solution and the farthest from the negative ideal solution [32].

Fuzzy TOPSIS includes the following steps:

Step 1: Definition of linguistic variables

The questionnaire was designed with the aim of obtaining expert opinions about the extent to which they agreed with the model's criteria. Thus, the experts have expressed their consent through verbal variables such as Very Low, Low, Medium, High and Very High. Since the different characteristics of individuals affect their mental interpretation of the qualitative variables, by defining the range of qualitative variables, the experts with the same mindset respond to the questions. These variables are defined in the form of triangular fuzzy numbers according to Table (2).

[Insert Table 2 about here]

It should be noted that in Table (2), the defuzzification value were calculated by $x = m + \frac{\beta - \alpha}{4}$.

Step 2: Establishment of Decision Matrix for evaluating of indicators:

At this stage, 20 experts (experts of medical diagnostic laboratories) evaluated of the identified indicators on based of linguistic variables.

Step3: Calculation of the normalized decision matrix $\tilde{R} = \left[\tilde{r}_{ij} \right]_{m \times n}$ i=1,2,...,n j=1,2,...,n. Where, m is number of indicators and n is number of experts.

Step 4: Calculation of the weighted normalized decision matrix. The weighted normalized value $\tilde{V} = [\tilde{v}]_{ij}$ i=1,2,...,n j=1,2,...,m is calculated as: $\tilde{v} = w_{ij} \times v_{ij}$. Here, the meaning of W_{ij} is the weighted based on the opinion of experts.

Step 5: Defining the positive ideal solution $\left(A^+\right)$ and negative ideal solution $\left(A^-\right)$ respectively. Here the positive ideal value and the negative ideal value by Chen [33] are used.

Step 6: Calculating the total distances of each of the indicators from the fuzzy positive ideal and the fuzzy negative ideal: If $\tilde{A} = (a_1, a_2, a_3)$ and $\tilde{B} = (b_1, b_2, b_3)$ are two fuzzy numbers, then the distance between these two fuzzy numbers is obtained as $\left(\tilde{A}, \tilde{B}\right) = \sqrt{\frac{1}{3}\left[(b_1 - a_1)^2 + (b_2 - a_2)^2 + (b_3 - a_3)^2\right]}$.

Depending on how the distance between the two fuzzy numbers is calculated, the distance between each of the positive ideal and negative ideal components is obtained as $d_i^+ = \sum_{j=1}^{n} d\left(\tilde{v}_{ij} - \tilde{v}_{ij}^+\right)$ i=1,2,...,m j=1,2,...,n and $d_i^- = \sum_{j=1}^{n} d\left(\tilde{v}_{ij} - \tilde{v}_{ij}^+\right)$ i=1,2,..,n j=1,2,...,m.

Step 7: Calculating the relative closeness of the each indicator to the ideal solution: This relative closeness can be expressed as $c_i = \frac{D_i^-}{D_i^- + D_i^+}$ i=1,2,...,m.

Step 8: Ranking of the indicators: Based on the order of decreasing C value, the existing indicators were ranked. This means that each indicators be C value larger, will be more important. The results of ranking of indicators are shown in Table (3).

[Insert Table 3 about here]

2.3. Delphi method

The Delphi Method is the most effective method for identifying the indices. It is an iterative process to collect and modify judgments of experts using a series of data collection. This method is especially useful for healthcare providers where standards and benchmarks for evaluation are not available. In this step, experts identify the required indicators according to the rankings of the indicators obtained in the Fuzzy TOPSIS method.

To extract the factors, using the ranking of the indicators obtained in Table (3), the effective criteria of the three laboratory processes (pre-test, test and post-test) were gained from the Delphi method in the following steps.

Step 1: All members of the group received the first questionnaire which was designed in a semi-structured manner based on the information in Table (3). Next, a second questionnaire was designed based on the data extracted from the first one.

Step 2: Members of the Delphi team were given a questionnaire and were asked to indicate the importance of the criteria using the Likert Scale in Table (4).

[Insert Table 4 about here]

Starting with this step onwards, we aim to reach a consensus among the respondents.

Step 3: Using the data from the first Delphi stage, the average value of each criterion was calculated. The experts were given a third questionnaire, and the processing of the data was conducted in the usual way similar to the previous step. Here, respondents have the option of changing their past opinion, as well as checking and evaluating other experts' opinion, thus channeling the process towards reaching a consensus that everybody agrees on. Table (5) shows the final performance indicators in the field of diagnostic labs using the Delphi Method.

[Insert Table 5 about here]

2.4. Model description

2.4.1. Three-stage process

We considered three stages according to Fig. 2. Then we defined each time period as a decision-making unit and denoted it as $DMU_j\left(j=1,2,....n\right)$. It actually simulates a medical diagnostic lab in the real world. The laboratory consists of three main processes pre-testing, testing and post-testing. The first stage is the reception unit, the second stage of the sampling & testing unit and the third stage of the test results unit. In the reception unit, we consider the desired inputs and the undesirable inputs, which we denoted as $x_{i_1 j}\left(i_1=1,2,...,I_1\right)$ and $x_{i_2 j}\left(i_2=1,2,...,I_2\right)$, respectively. The desired output and the undesirable output are considered as additional outputs, denoted by $y_{r_1 j}\left(r_1=1,2,...,R_1\right)$, $y_{r_2 j}\left(r_2=1,2,...,R_2\right)$, respectively. The intermediate measures between the reception unit and the sampling & testing unit, which is introduced by $z_{d_1 j}\left(d_1=1,2,...,D_1\right)$. The additional inputs to the sampling & testing unit are represented by $x_{i_3 j}\left(i_3=1,2,...,I_3\right)$.The intermediate measures of the sampling and testing unit and the test results unit represented by $z_{d_2 j}\left(d_2=1,2,...,D_2\right)$. The additional outputs to the sampling and testing unit as presented by $y_{r_3 j}\left(r_3=1,2,...,R_3\right)$.In the test results unit, an additional input represented by $x_{i_4 j}\left(i_4=1,2,...,I_4\right)$. Finally, we define the outputs of the test results unit, which we introduce by $y_{r_4 j}(r_4=1,2,...,R_4)$.

[Insert Figure 2 about here]

We assign v_{i_1} and v_{i_2} as the weights of the inputs to the reception unit. We denote $z_{d_1 j}$ as the weights of the intermediate measures between the reception unit and the sampling & testing unit that play dual role in the reception unit and in the sampling & testing unit. Assign $z_{d_1 j}$ in the reception unit, η_{d_1} plays a role as the weight of the output. Finally, we introduce u_{r_1} and u_{r_2} as the weights on the outputs flowing from the reception unit. According to the three-stage network shown in Fig. 3, the efficiency of the reception unit is determined by $\theta_0^{\text{Reception unit}}$.

In the sampling & testing unit, we consider v_{i_3} and u_{r_3} are the weights on inputs and outputs, respectively. Let η_{d_2} denote the weights on the intermediate measures to the sampling & testing unit. Given the dual role of $z_{d_2 j}$ in the sampling & testing unit and the test results unit, we signify η_{d_2} and η_{d_1} as the weights associated with the outputs and inputs flowing from the sampling & testing unit, respectively. We show the efficiency of the sampling & testing unit by $\theta_0^{\text{Sampling \& Testing unit}}$.

In the test results unit, we define η_{d_2} and u_{r_4} are the weights on inputs and outputs, respectively. Also, we adopt η_{d_2} as the weights on the intermediate measures to the test results unit. As the intermediate measures play dual role of $z_{d_2 j}$, we explain η_{d_2} as the weights associated with the inputs flowing from the test results unit. The efficiency of the test results unit is shown by $\theta_0^{\text{Test Results unit}}$.

In this study, the intermediate measures are evaluated and re-modelled, regardless of the dual role (as inputs of one stage or as output of the next stage). Therefore we used the same weights for the intermediate measures. This is a common assumption in DEA studies [34].

For the network system shown in Fig. 2, the reception unit, the sampling & testing unit and the test results unit are connected by intermediate measures $z_{d_1 j}\left(d_1 = 1,2,...,D_1\right)$ and $z_{d_2 j}\left(d_2 = 1,2,...,D_2\right)$ in series. The overall efficiency of the system can be calculated by means of formula (1) conforming to the tandem system of Kao and Hwang [35]:

$$\theta_0^{overall} = \max\ \theta_0^{\text{Reception unit}} . \theta_0^{\text{Sampling \& Testing unt}} . \theta_0^{\text{Test Results unit}} \quad (1)$$

Where $\theta_0^{overall}$ is the efficiency of whole system. The overall efficiency DMU_0 can be achieved by solving fractional program (2).

$$\theta_0^{overall}=\max\frac{\sum_{d_1=1}^{D_1}\eta_{d_1}z_{d_10}+\sum_{r_2=1}^{R_2}u_{r_2}y_{r_20}-\sum_{r_1=1}^{R_1}u_{r_1}y_{r_10}}{\sum_{i_1=1}^{I_1}v_{i_1}x_{i_1o}-\sum_{i_2=1}^{I_2}v_{i_2}x_{i_20}}\cdot\frac{\sum_{d_2=1}^{D_2}\eta_{d_2}z_{_20}-\sum_{r_3=1}^{R_3}u_{r_3}y_{r_30}}{\sum_{i_3=1}^{I_3}v_{i_3}x_{i_30}+\sum_{d_1=1}^{D_1}\eta_{d_1}z_{d_10}}\cdot\frac{\sum_{r_4=1}^{R_4}u_{r_4}y_{r_40}}{\sum_{i_4=1}^{I_4}v_{i_4}x_{i_40}+\sum_{d_2=1}^{D_2}\eta_{d_2}z_{d_20}}$$

$$s.t.\frac{\sum_{d_1=1}^{D_1}\eta_{d_1}z_{d_1j}+\sum_{r_2=1}^{R_2}u_{r_2}y_{r_2j}-\sum_{r_1=1}^{R_1}u_{r_1}y_{r_1j}}{\sum_{i_1=1}^{I_1}v_{i_1}x_{i_1j}-\sum_{i_2=1}^{I_2}v_{i_2}x_{i_2j}}\le 1,\quad \text{j=1,2,....,n} \qquad (2)$$

$$\frac{\sum_{d_2=1}^{D_2}\eta_{d_2}z_{d_2j}-\sum_{r_3=1}^{R_3}u_{r_3}y_{r_3j}}{\sum_{i_3=1}^{I_3}v_{i_3}x_{i_3j}+\sum_{d_1=1}^{D_1}\eta_{d_1}z_{d_1j}}\le 1,\quad \text{j=1,2,...,n}$$

$$\frac{\sum_{r_4=1}^{R_4}u_{r_4}y_{r_4j}}{\sum_{i_4=1}^{I_4}v_{i_4}x_{i_4j}+\sum_{d_2=1}^{D_2}\eta_{d_2}z_{d_2j}}\le 1,\quad \text{j=1,2,...,n}$$

$$\eta_{d_1},\eta_{d_2},u_{r_1},u_{r_2},u_{r_3},u_{r_4},v_{i_1},v_{i_2},v_{i_3},v_{i_4}\ge\varepsilon; d_1=1,2,...,D_1; d_2=1,2,...,D_2; r_1=1,2,...,R_1;$$
$$r_2=1,2,...,R_2; r_3=1,2,...,R_3; r_4=1,2,...,R_4; i_1=1,2,...,I_1; i_2=1,2,...,I_2; i_3=1,2,...,I_3; i_4=1,2,...,I_4.$$

Given the fact that the performance of all stages is less than one, the Model (2) is a linear program, so, in the next section of this paper, we present a heuristic method to solve.

2.4.2. Model solution and efficiency decomposition

Due to additional inputs and outputs, the Model (2) cannot be converted to a linear program. To solve this model, we propose a hybrid approach for evaluating and analyzing performance in the network of three-stage model. Since the objective function of Model (2) is obtained through the multiplicative efficiency of the three-stage by $\theta_0^{overall}=\max\theta_0^{\text{Reception}uni\ \text{unit}}.\theta_0^{Sampling\ \text{\& Testing unit}}.\theta_0^{Test\ \text{Results unit}}$ We can examine the efficiency of the reception unit $\theta_0^{\text{Reception unit}}$ and the efficiency of the sampling and testing unit $\theta_0^{Sampling\ \text{\& Testing unit}}$ as two variables in the objective function, which will change between the intervals $\left[0,\theta_0^{\text{Reception unit-max}}\right]$ and

$\left[0,\theta_0^{\textit{Sampling} \text{ \& Testining unit-max}}\right]$, respectively. We define the optimal efficiency of the reception unit and the sampling & testing test as follows Model (3):

$$\begin{aligned}
&\theta_0^{\text{R}\textit{eception}\text{ unit}} = \theta_0^{\text{R}\textit{eception}\text{ unit-max}} - k_1\Delta\varepsilon, \quad \text{k}_1 = 0,1,2,...,\left[\frac{\theta_0^{\text{R}\textit{eceptionun}\text{ unit- max}}}{\Delta\varepsilon}\right]+1 \\
&\theta_0^{\text{Sampling \& Testing unit}} = \theta_0^{\textit{Sampling}\text{ \& Testing unit-max}} - k_2\Delta\varepsilon, \quad \text{k}_2 = 0,1,2,...,\left[\frac{\theta_0^{\text{Sampling \& Testing unit-max}}}{\Delta\varepsilon}\right]+1
\end{aligned} \tag{3}$$

We take $\Delta\varepsilon$ as a step size and of a very small value. Note that the smaller Δε value is chosen, the more precise results will be gained. We define $\theta_0^{\text{Reception unit-max}}$ and $\theta_0^{\textit{Sampling}\text{ \& Testing unit-max}}$ as the maximum efficiency of the first stage and the second stage, respectively, which, by following Formulas (4) can be calculated.

$$\begin{aligned}
&\theta_0^{\text{R}\textit{eception}\text{ unit- max}} = \max\left\{\theta_0^{\text{R}\textit{eception}\text{ unit}} \middle| \theta_j^{\text{R}\textit{eception}\text{ unit}} \le 1, \theta_j^{\text{Sampling \& Testing unit}} \le 1, \theta_j^{\textit{Test}\text{ Results unit}} \le 1, j=1,2,...,n\right\} \\
&\theta_0^{\text{Sampling \& Testing unit-max}} = \max\left\{\theta_0^{\textit{Sampling}\text{ \& Testing unit}} \middle| \theta_j^{\text{R}\textit{eception}\text{ unit}} \le 1, \theta_j^{\text{Sampling \& Testing unit}} \le 1, \theta_j^{\textit{Test}\text{ Results unit}} \le 1, j=1,2,...,n\right\}
\end{aligned} \tag{4}$$

Note that in formulas (4), the maximum optimistic efficiency of the first and second stages are achieved under conditions where the efficiency of all stages is less than one. It should be noted that all variables in the formula (3) are non-negative. Applying by Charnes and Cooper [36] transformation the fractional programs are converted to linear program models by the following Models (5) and (6).

$$\begin{aligned}
&\theta_0^{\text{Reception unit-max}} = \max \sum_{d_1=1}^{D_1}\eta_{d_1} z_{d_1 0} + \sum_{r_2=1}^{R_2} u_{r_2} y_{r_2 0} - \sum_{r_1=1}^{R_1} u_{r_1} y_{r_1 0} \\
&s.t. \quad \sum_{i_1=1}^{I_1} v_{i_1} x_{i_1 0} - \sum_{i_2=1}^{I_2} v_{i_2} x_{i_2 0} \\
&\sum_{d_1=1}^{D_1}\eta_{d_1} z_{d_1 j} + \sum_{r_2=1}^{R_2} u_{r_2} y_{r_2 j} - \sum_{r_1=1}^{R_1} u_{r_1} y_{r_1 j} - (\sum_{i_1=1}^{I_1} v_{i_1} x_{i_1 j} - \sum_{i_2=1}^{I_2} v_{i_2} x_{i_2 j}) \le 0, \quad \text{j=1,2,...,n} \\
&\sum_{d_2=1}^{D_2}\eta_{d_2} z_{d_2 j} - \sum_{r_3=1}^{R_3} u_{r_3} y_{r_3 j} - (\sum_{i_3=1}^{I_3} v_{i_3} x_{i_3 j} + \sum_{d_1=1}^{D_1}\eta_{d_1} z_{d_1 j}) \le 0, \quad \text{j=1,2,...,n} \\
&\sum_{r_4=1}^{R_4} u_{r_4} y_{r_4 j} - (\sum_{i_4=1}^{I_4} v_{i_4} x_{i_4 j} + \sum_{d_2=1}^{D_2}\eta_{d_2} z_{d_2 j}) \le 0, \quad \text{j=1,2,...,n} \\
&\eta_{d_1},\eta_{d_2},u_{r_1},u_{r_2},u_{r_3},u_{r_4},v_{i_1},v_{i_2},v_{i_3},v_{i_4} \ge \varepsilon; d_1 = 1,2,...,D_1; d_2 = 1,2,...,D_2; r_1 = 1,2,...,R_1; \\
&r_2 = 1,2,...,R_2; r_3 = 1,2,...,R_3; r_4 = 1,2,...,R_4; i_1 = 1,2,...,I_1; i_2 = 1;2,...,I_2; i_3 = 1,2,...,I_3; i_4 = 1,2,...,I_4.
\end{aligned} \tag{5}$$

$$\theta_0^{\text{Sampling \& Testing unit-max}} = \max \sum_{d_2=1}^{D_2} \eta_{d_2} z_{d_2 0} - \sum_{r_3=1}^{R_3} u_{r_3} y_{r_3 0}$$

$$\sum_{i_3=1}^{I_3} v_{i_3} x_{i_3 0} + \sum_{d_1=1}^{D1} \eta_{d_1} z_{d_1 0} = 1$$

$$\sum_{d_1=1}^{D_1} \eta_{d_1} z_{d_1 j} + \sum_{r_2=1}^{R_2} u_{r_2} y_{r_2 j} - \sum_{r_1=1}^{R_1} u_{r_1} y_{r_1 j} - (\sum_{i_1=1}^{I_1} v_{i_1} x_{i_1 j} - \sum_{i_2=1}^{I_2} v_{i_2} x_{i_2 j}) \le o, \ \text{j=1,2,...,n}$$

$$\sum_{d_2=1}^{D_2} \eta_{d_2} z_{d_1 j} - \sum_{r_3=1}^{R_3} u_{r_3} y_{r_3 j} - (\sum_{i_3=1}^{I_3} v_{i_3} x_{i_3 j} + \sum_{d_1=1}^{D_1} \eta_{d_1} z_{d_1 j}) \le 0, \ \text{j=1,2,...,n} \tag{6}$$

$$\sum_{r_4=1}^{R_4} u_{r_4} y_{r_4 j} - (\sum_{i_4=1}^{I_4} v_{i_4} x_{i_4 j} + \sum_{d_2=1}^{D_2} \eta_{d_2} z_{d_2 j}) \le 0, \ \text{j=1,2,...,n}$$

$$\eta_{d_1}, \eta_{d_2}, u_{r_1}, u_{r_2}, u_{r_3}, u_{r_4}, v_{i_1}, v_{i_2}, v_{i_3}, v_{i_4} \ge \varepsilon; d_1 = 1,2,...,D_1; d_2 = 1,2,...,D_2; r_1 = 1,2,...,R_1; r_2 = 1,2,...,R_2;$$
$$r_3 = 1,2,...,R_3; r_4 = 1,2,...,R_4; i_1 = 1,2,...,I_1; i_2 = 1,2,...,I_2; i_3 = 1,2,...,I_3; i_4 = 1,2,...,I_4.$$

By specifying the values of $\theta_0^{\text{Reception unit-max}}$ and $\theta_0^{Sampling \text{ \& Testing unit-max}}$ through Models (5) and (6), we transform the Model (2) into the following Model (7).

$$\theta_0^{overall} = \max \left\{ \theta_0^{Reception \text{ unit}} . \theta_0^{Sampling \text{ \& Testing unit}} . \theta_0^{Test \text{ Results unit}} \middle| \begin{array}{l} \theta_j^{Reception \text{ unit}} \le 1, \theta_j^{Sampling \text{ \& Testing unit}} \le 1, \\ \theta_j^{Test \text{ Results unit}} \le 1, \theta_0^{Reception \text{ unit}} = \dfrac{o_0^{Reception \text{ unit}}}{I_0^{Reception \text{ unit}}}, \\ \theta_0^{Sampling \text{ \& Testing unit}} = \dfrac{o_0^{Sampling \text{ \& Testing unit}}}{I_0^{\text{Sampling \& Testing unit}}} \\ , \theta_0^{Reception \text{ unit}} \in \left[0, \theta_0^{\text{Reception unit-max}}\right], \\ \theta_0^{\text{Sampling \& Testing unit-max}} \in \left[0, \theta_0^{Sampling \text{ \& Testing unit-max}}\right], \ \text{j=1,2,...,n} \end{array} \right\} \tag{7}$$

In the Model (7), $\theta_0^{\text{Re}ception \text{ unit}}$ and $\theta_0^{\text{Sampling \& Testing unit}}$ in the objective function are considered as two variables, and two constraints which specify these two variables and together with its interval modifications, it was supplemented to the model. In the Model (6), the efficiency of the two stages is shown as the output ratio to the input of each stage by $\theta_0^{\text{Re}ception \text{ unit}} = \dfrac{o_0^{\text{Re}ception \text{ unit}}}{I_0^{\text{Re}ception \text{ unit}}}$ and $\theta_0^{Sampling \text{ \& Testing unit}} = \dfrac{o_0^{Sampling \text{ \& Testing unit}}}{I_0^{Sampling \text{ \& Testing unit}}}$. The Model (7) is a fractional model and by utilizing the Charnes and Cooper [36] conversion, such as given below, is modified by the following linear program (8).

$$\theta_0^{overall} = \max \theta_0^{\text{Reception unit}} . \theta_0^{Sampling \text{ \& Testing unit}} . (\sum_{r_4=1}^{R_4} u_{r_4} y_{r_4 0}) \qquad (8)$$

$$s.t. \sum_{i_4=1}^{I_4} v_{i_4} x_{i_4 0} + \sum_{d_2=1}^{D_2} \eta_{d_2} z_{d_2 0} = 1$$

$$\sum_{d_1=1}^{D_1} \eta_{d_1} z_{d_1 j} + \sum_{r_2=1}^{R_2} u_{r_2} y_{r_2 j} - \sum_{r_1}^{R_1} u_{r_1} y_{r_1 j} - (\sum_{i_1=1}^{I_1} v_{i_1} x_{i_1 j} - \sum_{i_2=1}^{I_2} v_{i_2} x_{i_2 j}) \le 0, \quad \text{j=1,2,...,n}$$

$$\sum_{d_2=1}^{D_2} \eta_{d_2} z_{d_2 j} + \sum_{r_3=1}^{R_3} u_{r_3} y_{r_3 j} - (\sum_{i_3=1}^{I_3} v_{i_3} x_{i_3 j} - \sum_{d_1=1}^{D_1} \eta_{d_1} z_{d_1 j}) \le 0, \quad \text{j=1,2,...,n}$$

$$\sum_{r_4=1}^{R_4} u_{r_4} y_{r_4 j} - (\sum_{i_4=1}^{I_4} v_{i_4} x_{i_4 j} - \sum_{d_2=1}^{D_2} \eta_{d_2} z_{d_2 j}) \le 0, \quad \text{j=1,2,...,n}$$

$$\sum_{d_1=1}^{D_1} \eta_{d_1} z_{d_1 0} + \sum_{r_2=1}^{R_2} u_{r_2} y_{r_2 0} - \sum_{r_1=1}^{R_1} u_{r_1} y_{r_1 0} - \theta_0^{\text{Reception unit}} (\sum_{i_1}^{I_1} v_{i_1} x_{i_1 0} - \sum_{i_2=1}^{I_2} v_{i_2} x_{i_2 0}) = 0$$

$$\sum_{d_2=1}^{D_2} \eta_{d_2} z_{d_2 0} + \sum_{r_3=1}^{R_3} u_{r_3} y_{r_3 0} - \theta_0^{\text{Sampling \& Testing unit}} (\sum_{i_3}^{I_3} v_{i_3} x_{i_3 0} - \sum_{d_1=1}^{D_1} \eta_{d_1} z_{d_1 0}) = 0$$

$$\theta_0^{\text{Sampling \& Testing unit}} \in \left[0, \theta_0^{\text{Sampling \& Testing unit-max}} \right]$$

$$\eta_{d_1}, \eta_{d_2}, u_{r_1}, u_{r_2}, u_{r_3}, u_{r_4}, v_{i_1}, v_{i_2}, v_{i_3}, v_{i_4} \ge \varepsilon; d_1 = 1,2,...,D_1; d_2 = 1,2,...,D_2; r_1 = 1,2,...,R_1; r_2 = 1,2,...,R_2;$$
$$r_3 = 1,2,...,R_3; r_4 = 1,2,...,R_4; i_1 = 1,2,...,I_1; i_2 = 1,2,...,I_2; i_3 = 1,2,...,I_3; i_4 = 1,2,...,I_4.$$

We increase the values of k_1 and k_2 independently, from (0) to a high level for each one, so that each time the model can be solved with the new $\theta_0^{\text{Reception unit}}$ and $\theta_0^{\text{Sampling \& Testing unit-max}}$. We solve the model for all modes of the k_1 and k_2. Then the model responses are displayed by $\theta_0^{overall}(k_1, k_2)$. By comparing the overall values of $\theta_0^{overall}(k_1, k_2)$, the maximal efficiency of $\theta_0^{overall}(k_1, k_2)$ as the performance of the network shown in Fig. 2.

We have tested our proposed approach in three modes and take two stages each time. Given the fact that the productivity of Fig. 2 is unique, the results of these three methods are remarkably approximated to each other. For this purpose, we have presented one of these three conditions to describe above approach.

3. Case Study

According to statistics health reference laboratories, there are 5611 laboratories operating in Iran. Of these, the share of the public sector and share of the private sector is 57% and 43%, respectively.

There are 933 active laboratories in Tehran, which include 16.7% of the total share of the country. Of these, 71% and 29% are managed by the private sector and the public sector, respectively. The statistics show that, unlike the number of laboratories in the country, most of which are available to the public sector, most of the labs are under private sector management in Tehran. Considering the importance of the private sector in Tehran, our case study is related to the private laboratories of Tehran. In this regard, the sample size in this study includes 25 medical diagnostic laboratories selected by cluster sampling from private laboratories in Tehran.

3.1. Inputs and outputs

In this section we will examine the performance of private medical diagnostic laboratories in Tehran. Medical diagnostic laboratories of three main processes: the pre-test process, the testing process, and the post-test process as shown in Fig. 3.

[Insert Figure 3 about here]

The reception unit is the only component of the pre-test process. It has two inputs, i.e. the number of active experiments (x_1) and the available space for service (x_2). Its outputs are the average waiting time for sampling (y_1), the income from admission (economic criterion) (y_2) and income from admission (economic criterion) (y_3). The number of samples (z_1) is relevant to the reception, the sampling, and the testing units. The sampling and testing units comprise the testing process. Together, they have four inputs, i.e. the cost of consumables (economic criterion) (x_3), safety cost of sampling unit (social criterion) (x_4), safety cost of test unit (social criterion) (x_5) and the number of kits (x_6). Their outputs are the average sample transfer time (y_4), the number of false tests (y_5), test response time (y_6) and the garbage weight (environmental criterion) (y_7). The reception and the sampling and testing units are linked in series. As intermediate measures of the sampling & testing unit and the test unit is defined as the correct number of tests (z_2). The post-test process involves just one stage, i.e. the test results stage. The results unit and the sampling and testing unit are linked in series. The test results unit has three outputs, i.e. the number of responses of the prepared tests (y_8), the sum of the scores of the laboratory standards (y_9), and Lab Profit (economic criterion) (y_{10}). The staff wage (x_7) (economic criterion) is expressed as an additional input for the results test unit.

4. Results

According the opinions of the experts, we consider the step size in the models $\Delta\varepsilon = 0.01$. In the following, we obtain the overall efficiency and the efficiency of the stages shown in Fig. 2, using the model (7). For this purpose, we first obtained the performance of first and second stage by using Model (3). Then, applying formula (4), we calculate the efficiency of the model (8) by changing the variables k_1 and k_2. Table (6) shows the score of overall efficiency and the score of efficiency of the three stages (the reception unit, the sampling & testing unit and the test results unit) of medical diagnostic laboratories in Tehran.

[Insert Table 6 about here]

By studying the values of k_1 and k_2, we found the optimal values of network shown in Fig. 2 to occur when the first and second stages are at their maximum values. For this reason, all values of k_1 and k_2 vanish. The second column of Table (6) demonstrates the overall efficiency of the medical diagnostic laboratory units. We identified the efficiency labs in gray. The results illustrate that one lab is efficient and twenty four labs are inefficient. Also, the average efficiency of the reception unit, the sampling and testing unit and the test results unit are 0.74, 0.99, and 0.83, respectively.

It can be clearly observed that the discriminatory power of proposed Network DEA model in field of health systems is more than traditional DEA models. This paper proposes a heuristic model to convert a multiplicative NDEA approach into an equivalent linear program that, in addition to simplifying complex calculations, also increases the accuracy of performance scores. Also, our proposed Network DEA model may be used for ranking of all stages, while the traditional DEA model only has the ability to rank DMUs that cannot show real rankings Given the importance of medical laboratory services. In previous studies conducted in various areas of health services, the evaluation of the performance of the internal structure using undesirable sustainability indicators has been neglected, which leads to a reduction in the accuracy of the results. In the present age due to the prevalence of chronic epidemic diseases, real ranking is of particular importance so that the flexible and adjustable results can be used, for the managers of medical diagnostic laboratory units. So, the proposed model in this paper provides a functional platform for managers to make the correct decisions.

Based on the results, the final ranking of laboratories is as follows:

Where the ">" symbol means that the performance is better.

$$Lab_{22} > Lab_{18} > Lab_{13} > Lab_{3} > Lab_{20} > Lab_{21} > Lab_{10} > Lab_{15} > Lab_{19} > Lab_{11} > Lab_{7} >$$
$$Lab_{6} > Lab_{4} > Lab_{16} > Lab_{1} > Lab_{17} > Lab_{14} > Lab_{2} > Lab_{5} > Lab_{24} > Lab_{25} > Lab_{9} > Lab_{23} >$$
$$Lab_{12} > Lab_{8},$$

The results of this case study indicate that most private labs in Tehran are not efficient. The reasons of inefficiency of laboratories can be identified as follow: 1) one of the most important sources of municipal wastes production is hospitals, health centers, physicians, clinics and medical diagnostic laboratories. Among them, the laboratories produce the large amount of infectious waste that are of great importance to health and the environment. Releasing this waste into the environment can cause and transmit a variety of diseases, including hepatitis B, C, and AIDS. Proper management of waste plays an important role in the performance of laboratories. 2) Analyzing the standards and criteria that any laboratory system needs to be upgraded. Therefore, the quality management achievements in the lab are advantages, such as: enhancing the assurance of the accuracy of the results provided by the labs, ensuring the continuous calibration of lab equipment, standardizing the procedures for the management of laboratories, and improves the level of customer-oriented of laboratories. 3) The ability to differentiate and excel a laboratory is the extensive coverage of services. Therefore, increasing the geographic coverage of services each laboratory is important. 4) Factors such as currency fluctuations, price increases of kits, and the cost of implementing quality standards indicate the laboratories need to control and manage costs. On average, 45% of the total cost required is related to the consumables in each laboratory. Therefore the costs management has a significant role in increasing efficiency. Considering the reasons mentioned for increasing the efficiency of laboratories, the following solutions are suggested: 1) Separation of laboratory wastes at the place of production, collection and labelling, transportation to the location of safe place, packing, temporary storage, transportation from the place of production and loading, and also the final disposal stage. All steps are designed according to the performance and breadth of each laboratory. All staff members should be educated and notified of the procedures in writing. 2) Investigating the factors and determining the status of the laboratory and recording the results in the form of weaknesses and strengths, and determining the gap between the existing and the desired situation may provide appropriate and effective strategies for standardizing the laboratories. 3) Provision of services to smaller laboratories in view of the increasing diversity and capacity of the experiments is one of the ways in which successful labs operate. The use of sampling units and the use of information and communication technology is also one of the requirements for the coverage of services. 4) The operation management approach by identifying and eliminating unnecessary points lead to reduces additional laboratory costs and increases productivity.

5. Conclusion

Laboratory centers perform an important part of the activities of many health systems and research organizations. Since the performance of clinical and the researches laboratories plays a vital role in the quality and efficiency of health care and research activities, the need for solutions for evaluating and improving their performance has attracted the attention of the world's scientific and professional communities for many years. The performance measurement in laboratory centers is also important for managers and authorities in health centers and research organizations. By doing so, they can provide areas for improvement and increase productivity in the organization through identifying their strengths and weaknesses.

The purpose of any performance evaluation program is to increase efficiency and improve effectiveness. This goal is achieved through helping the laboratories to do their best, by developing their skills and knowledge to meet the future needs of the work units. It is important that the tasks are done properly in laboratories, which will improve the quality of the test results, increase the effectiveness of the services and research achievements. Effectiveness of services in clinical laboratories leads to a quick diagnosis of illness and to save the lives of patients. Also, the effectiveness of their research achievements and their commercialization will lead to the growth and self-sufficiency of research organizations. In this study, a multiplicative Network DEA model based on a heuristic model is proposed to convert a NDEA approach into an equivalent linear program. The proposed method has a number of advantages. It makes the ranking method more accurate, which is especially necessary in relation to the health services department. Another advantage is that in this method, the efficiency of each stage can be independently examined, based on which, managers can consider their different views in evaluating the performance of the units. Also, decision makers are able to obtain information about all the performance points attitudes, so they can make the right decisions. Therefore, the proposed model, in addition to assessing the performance of DMUs, also has the ability to rank more accurate them. In addition, in this paper, sustainability factors at three levels of economic, social and environmental indicators have been identified, which in previous studies in the field of health services, the factors of sustainable development have been neglected. Since undesirable data can play a significant role in the actual performance of medical diagnostic laboratories, so undesirable factors along with sustainable development have been identified and investigated in the indicators.

Note that to validate the presented proposed multiplicative Network DEA model, a real case study in Iran used for measuring of the effectiveness of medical diagnostic laboratories .For this purpose, we simulated a three-stage network with series structure of a medical diagnostic lab in a real-world. This network model consists of three main laboratory processes (The pre-test process, the test process and the post-test process). The pre-testing process contain of the reception unit. The testing process consists of the sampling & testing unit. Finally, the post-test process includes of the test results unit. The model presented in this article is an innovative model, and similar research was not found in the field of medical diagnostic laboratories as a network analysis.

For the future studies, we provided the results of this research to the managers which might lead to improved laboratory services by adopting appropriate approaches. Due to the numerous indexes and problems in collecting data, it is suggested that future research of modeling should be done with imprecise data. Also, since the activities of an enterprise such as medical diagnostic laboratories is not sectional over a period of time, but is continuous activity, therefore, the cross-sectional efficiency assessment cannot provide a realistic answer to the performance of laboratories. Therefore, network analysis in dynamic mode such as window NDEA model is also recommended.

Acknowledgments

Niloufar Ghafari Someh: Designing studying or analyzing and interpreting data

Mir Saman Pishvaee: Reviewing and modifying the article carefully and submit it.

Seyed Jafar Sadjadi: Reviewing and editing the article

Roya Soltani: Editing the article

References

[1] Nolte, E. and McKee, M. “Measuring the health of nations: analysis of mortality amenable to health care”. *Journal of Epidemiology & Community Health*, *58*(4), pp.326-326 (2004).

[2] The European health report 2009: health and health systems. Copenhagen, WHO Regional Office for Europe.

[3] Solnica, B., Dabrowska, M., and Sypniewska, G. “Laboratory Medicine as a Profession and Clinical Science–How to Perform Both of them well? ”. *EJIFCC*, *21*(3), 53 (2010).

[4] Engau, A. “Proper efficiency and tradeoffs in multiple criteria and stochastic optimization”. *Mathematics of operations research*, *42*(1), 119-134 (2016).

[5] Charnes, A., Cooper, W. W., and Rhodes, E. “Measuring the efficiency of decision making units”. *European journal of operational research*, *2(6)*, 429-444 (1978).

[6] Kao, C. “Network data envelopment analysis: A review”. *European journal of operational research*, *239(1)*, 1-16 (2014).

[7] Wei, Q., and Yan, H. “A data envelopment analysis (DEA) evaluation method based on sample decision making units”. *International Journal of Information Technology & Decision Making*, *9(04)* 601-624 (2010).

[8] Färe, R., and Whittaker, G. “An intermediate input model of dairy production using complex survey data”. *Journal of Agricultural Economics*, *46(2)*, 201-213 (1995).

[9] Lewis, H. F., and Sexton, T. R. “Network DEA: efficiency analysis of organizations with complex internal structure”. *Computers & Operations Research*, *31(9)*, 1365-1410 (2004).

[10] Färe, R., Grosskopf, S., Lovell, C. K. et al. “Multilateral productivity comparisons when some outputs are undesirable: a nonparametric approach”. *The review of economics and statistics*, 90-98 (1989).

[11] Rosko, M.D. and Mutter, R.L. “What have we learned from the application of stochastic frontier analysis to US hospitals?”. *Medical Care Research and Review*, *68*(1_suppl), pp.75S-100S (2011).

[12] Nayar, P. and Ozcan, Y.A. “Data envelopment analysis comparison of hospital efficiency and quality”. *Journal of medical systems*, *32*(3), pp.193-199 (2008).

[13] Audibert, M., Mathonnat, J., Pelissier, A. et al. “Health insurance reform and efficiency of township hospitals in rural China: An analysis from survey data”. *China Economic Review*, *27*, pp.326-338 (2013).

[14] Varabyova, Y. and Schreyögg, J. “International comparisons of the technical efficiency of the hospital sector: panel data analysis of OECD countries using parametric and non-parametric approaches”. *Health policy*, *112*(1-2), pp.70-79 (2013).

[15] Leleu, H., Moises, J. and Valdmanis, V.G. “How do payer mix and technical inefficiency affect hospital profit? ”.A weighted DEA approach. *Operations Research for Health Care*, *3*(4), pp.231-237 (2014).

[16] Popescu, C., Asandului, L. and Fatulescu, P. “A data envelopment analysis for evaluating Romania's health system”. *Procedia-Social and Behavioral Sciences*, *109*, pp.1185-1189 (2014).

[17] Asandului, L., Roman, M. and Fatulescu, P. "The efficiency of healthcare systems in Europe: A data envelopment analysis approach". *Procedia Economics and Finance*, *10*, pp.261-268 (2014).

[18] Al-Refaie, A., Fouad, R.H. and Li, M.H. "Applying simulation and DEA to improve performance of emergency department in a Jordanian hospital". *Simulation Modelling Practice and Theory*, *41*, pp.59-72 (2014).

[19] Chowdhury, H. and Zelenyuk, V. "Performance of hospital services in Ontario: DEA with truncated regression approach". *Omega*, *63*, pp.111-122 (2016).

[20] Campos, M.S., Fernández-Montes, and A., Gavilan, J.M. "Public resource usage in health systems: a data envelopment analysis of the efficiency of health systems of autonomous communities in Spain". *Public health*, *138*, pp.33-40 (2016).

[21] Johannessen, K.A., Kittelsen, S.A. and Hagen, T.P. "Assessing physician productivity following Norwegian hospital reform: A panel and data envelopment analysis". *Social Science & Medicine*, *175*, pp.117-126 (2017).

[22] Khushalani, J. and Ozcan, Y.A. "Are hospitals producing quality care efficiently? An analysis using Dynamic Network Data Envelopment Analysis (DEA)". *Socio-Economic Planning Sciences*, *60*, pp.15-23 (2017).

[23] Patra, A. and Ray, P.K. "Measurement of efficiency and productivity growth of hospital systems: a Indian case study ". In *Healthcare Systems Management: Methodologies and Applications* (pp. 13-22). Springer, Singapore (2018).

[24] Şahin, B. and İlgün, G. "Assessment of the efficiency of dental services in Turkey". *Health Policy and Technology*, *7*(2), pp.173-181 (2018).

[25] Haghighi, S.M. and Torabi, S.A. "A novel mixed sustainability-resilience framework for evaluating hospital information systems". *International journal of medical informatics*, *118*, pp.16-28 (2018).

[26] Peykani, P., Mohammadi, E., Emrouznejad, A. et al. "Fuzzy data envelopment analysis: An adjustable approach". *Expert Systems with Applications*, *136*, pp.439-452 (2019).

[27] Thorsen, M.L., Thorsen, A. and McGarvey, R. "Operational efficiency, patient composition and regional context of US health centers: Associations with access to early prenatal care and low birth weight". *Social Science & Medicine*, *226*, pp.143-152 (2019).

[28] Abolghasem, S., Toloo, M. and Amézquita, S. "A dataset of healthcare systems for cross-efficiency evaluation in the presence of flexible measure". *Data in brief*, *25*, p.104239 (2019).

[29] Chawla, R., Goswami, B. and Singh, B. "Evaluating laboratory performance with quality indicators". *Laboratory Medicine*, *41*(5), pp.297-300 (2010).

[30] Bakar, A.H.A., Hakim, I.L. and Chong, S.C. "Measuring supply chain performance among public hospital laboratories". *International journal of productivity and performance management* (2010).

[31] Gumus, A.T. "Evaluation of hazardous waste transportation firms by using a two step fuzzy-AHP and TOPSIS methodology". *Expert systems with applications*, *36*(2), pp.4067-4074 (2009).

[32] Lin, M.C., Wang, C.C. and Chen, M.S. "Using AHP and TOPSIS approaches in customer-driven product design process". *Computers in industry*, *59*(1), pp.17-31 92008).

[33] Chen, C.T., 2000. "Extensions of the TOPSIS for group decision-making under fuzzy environment". *Fuzzy sets and systems*, *114*(1), pp.1-9.

[34] Aviles-Sacoto, S., Cook, W. D. and Imanirad, R. "Two-stage network DEA: when intermediate measures can be treated as outputs from the second stage". *Journal of the Operational Research Society*, *66(11)*, 1868-1877 (2015).

[35] Kao, C., and Hwang, S. N. "Efficiency decomposition in two-stage data envelopment analysis: An application to non-life insurance companies in Taiwan", *European journal of operational research*, *185(1)*, 418-429 (2008).

[36] Charnes, A., and Cooper, W. W. "Programming with linear fractional functional", *Naval Research logistics quarterly*, *9(3-4)*, 181-186 (1962).

Figures

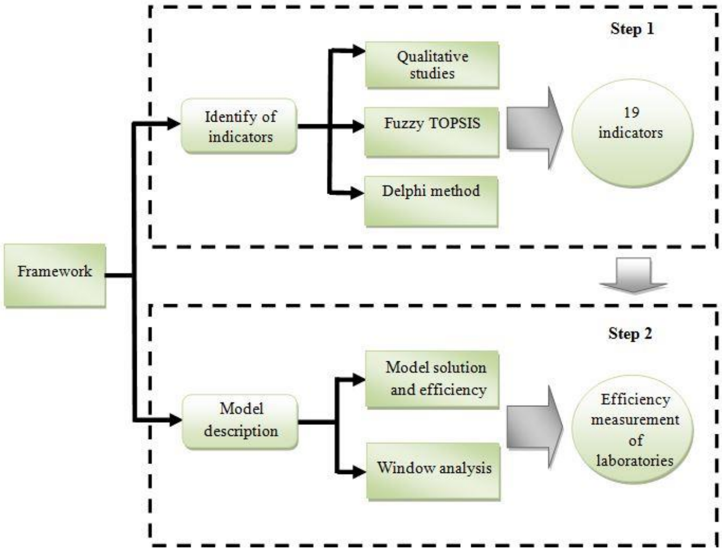

Fig.1 Steps of Methodology

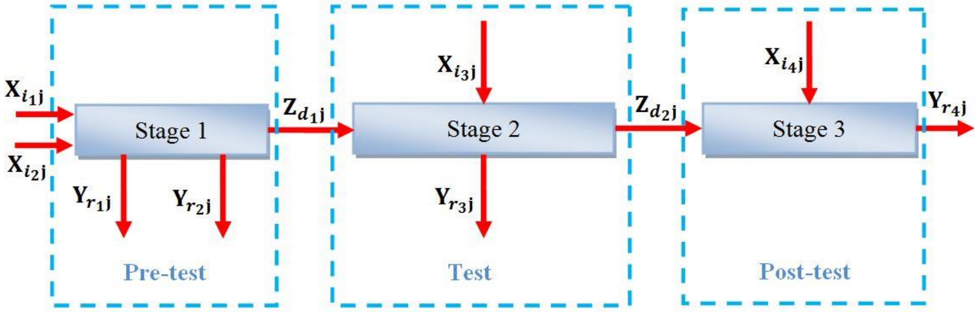

Fig.2 A three stage series

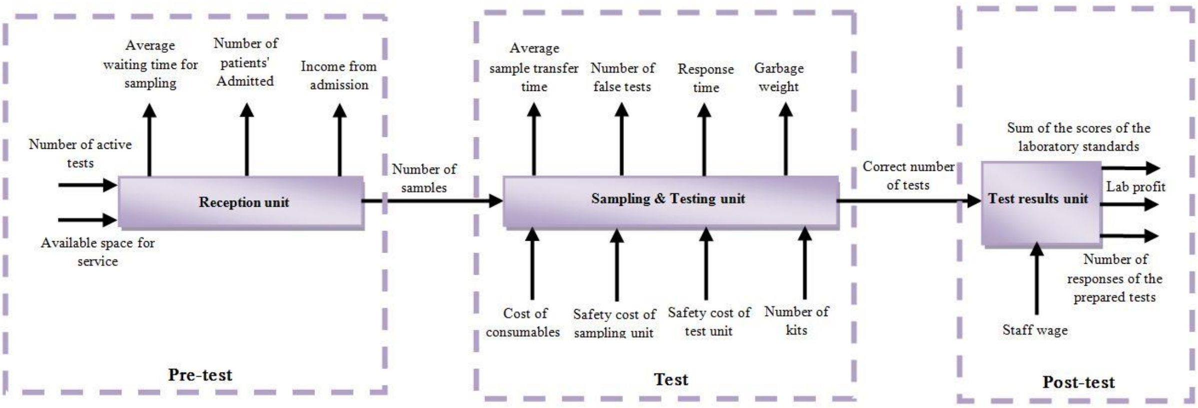

Fig. 3 Three-stage network of a medical diagnostic laboratory

Tables

Table1. Indicators effective in evaluating the performance of medical diagnostic laboratories

Row	Indicator
1	Sum of the scores of the laboratory standards
2	Garbage weight
3	Average sample transfer time
4	Number of patients' admitted
5	Number of active experiments
6	Correct number of tests
7	Test response time
8	Number of false tests
9	Available space for service
10	Average waiting time for sampling
11	Cost of consumables
12	Staff wage
13	Number of responses of the prepared tests
14	Safety cost of test unit
15	Number of kits
16	Safety cost of sampling unit
17	Lab profit
18	Income from admission
19	Cost of laboratory space and land value
20	Number of samples
21	Cost of staff welfare

Table2. Triangular Fuzzy Numbers of Linguistic variables

Linguistic variables	Triangular fuzzy number	Defuzzification value
Very low effect	(1, 1, 3)	0.75
Low effect	(1, 3, 5)	0.5625
Medium effect	(3, 5, 7)	0.3125
High effect	(5, 7, 9)	0.0625
Very high effect	(7, 9, 9)	0.0625

Table3: Ranking of indicators

Row	Indicator	The distance to the positive ideal	The distance to the negative ideal	C	Rank
1	Sum of the scores of the laboratory standards	25.085	0.921	0.035	1
2	Cost of laboratory space and land value	25.21	0.808	0.031	2
3	Average sample transfer time	25.243	0.776	0.03	3
4	Garbage weight	25.26	0.758	0.029	4
5	Number of patients' admitted	25.266	0.754	0.029	5
6	Number of active experiments	25.288	0.734	0.028	6
7	Number of false tests	25.302	0.722	0.028	7
8	Number of samples	25.356	0.669	0.026	8
9	Available space for service	25.367	0.658	0.025	9
10	Correct number of tests	25.466	0.644	0.022	10
11	Number of kits	25.480	0.606	0.022	11
12	Average waiting time for sampling	25.501	0.599	0.02	12
13	Staff wage	25.566	0.576	0.019	13
14	Cost of staff welfare	25.599	0.555	0.019	14
15	Test response time	25.607	0.543	0.017	15
16	responses of the prepared tests	25.666	0.520	0.017	16
17	Income from admission	25.676	0.511	0.016	17
18	Cost of consumables	25.702	0.498	0.013	18
19	Safety cost of test unit	25.756	0.477	0.013	19
20	Lab profit	25.768	0.465	0.011	20
21	Safety cost of sampling unit	25.789	0.413	0.011	21

Table 4.The Likert Scale

1	2	3	4	5
Very low effect	Low effect	Medium effect	High effect	Very high effect

Table 5.Effective indicators for the performance evaluation of medical diagnostic laboratories

Row	Indicator
1	Sum of the scores of the laboratory standards
2	Garbage weight
3	Average sample transfer time
4	Number of patients' admitted
5	Number of active experiments
6	Correct number of tests
7	Number of false tests
8	Available pace for service
9	Staff wage
10	Number of kits
11	Income from admission
12	Cost of consumables
13	Safety cost of test unit
14	Safety cost of sampling unit
15	Average waiting time for sampling
16	Test response time
17	Number of responses of the prepared tests
18	Lab profit
19	Number of samples

Table6. Comparison of overall Efficiency and Efficiency of four Stages for 25 medical Diagnostic Laboratories in 2018

Lab	θ^{overall}	$\theta^{Reception\ unit}$	$\theta^{Sampling\ \&\ Testing\ \ unit}$	$\theta^{Test\ results\ unit}$	K_1	K_2
1	0.79044	1	1	0.79044	0	0
2	0.74755	1	1	0.74755	0	0
3	1	1	0.9367	0.9367	0	0
4	0.80058	0.99195	0.53988	0.42874	0	0
5	0.74256	1	1	0.74256	0	0
6	0.87083	1	0.82592	0.71924	0	0
7	0.88457	1	1	0.88457	0	0
8	0.44298	1	0.81647	0.36168	0	0

9	0.67675	0.99738	0.75611	0.51036	0	0
10	0.99999	0.99709	0.43292	0.43166	0	0
11	0.89141	1	0.89103	0.79428	0	0
12	0.62505	0.99599	0.36656	0.2282	0	0
13	1	0.99037	1	0.99037	0	0
14	0.75534	1	0.66139	0.49958	0	0
15	0.92763	1	0.43943	0.40763	0	0
16	0.79536	1	1	0.79536	0	0
17	0.78145	1	0.59759	0.46699	0	0
18	1	0.99216	1	0.99216	0	0
19	0.89967	0.97776	1	0.87966	0	0
20	1	0.99079	0.36925	0.36585	0	0
21	1	0.99236	0.15403	0.15362	0	0
22	1	1	1	1	0	0
23	0.65196	0.99456	0.7256	0.47049	0	0
24	0.69152	0.99348	0.53293	0.36613	0	0
25	0.67739	1	0.41965	0.28427	0	0

Biographies

Niloufar Ghafari Someh is candidate Ph.D. in Industrial Engineering from Science and Research Branch, Islamic Azad University. Her Ph.D. research focuses on Data Envelopment Analysis. Her research interests include Data Envelopment Analysis (DEA), Supply chain management and System optimization.

Mir Saman Pishvaee is an Associate Professor of Industrial Engineering at Iran University of Science and Technology. He received his Ph.D. from University of Tehran in 2012 and initiated his work as a faculty member at SIE since 2013. His research vision is concentrated mainly on Supply chain management and System optimization. He teaches Procurement and Supply Management, Robust Optimization, System analysis and design and Operations Management courses.

Seyed Jafar Sadjadi finished his PhD at the University of Waterloo, Canada. His research interest is focused on solving different classes of optimization problems in industrial engineering areas, such as supply chain management, portfolio optimization, optimal pricing, etc. He has been serving at Iran University of Science and Technology since 2001.

Roya Soltani is currently an assistant professor at the Department of Industrial Engineering, KHATAM University, Tehran, Iran. Her research interests include data envelopment analysis (DEA), decision theory, fuzzy theory, evolutionary algorithms and reliability.