Journal of Industrial and Systems Engineering
Vol. 14, No. 4, pp. 138-157
Autumn (November) 2022

A data envelopment analysis approach to evaluate efficiencies in organ allocation problem: A case study

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Abstract

Data envelopment analysis (DEA) is a data-oriented approach to assess the performance of a set of entities known as decision-making units (DMUs), which transform multiple inputs into multiple outputs. On the other hand, the transplantation of organs is one of the most complex and challenging treatments in medicine, and organ allocation is the most important decision throughout the organ transplantation operation. Due to the enormous disparity between organ availability and demand, many individuals die while waiting for organ transplants despite major medical and technological improvements. Furthermore, kidney is the most commonly transplanted organ in the transplantation supply chain all over the world which is investigated in this paper. This research presents a two-stage network DEA model for assessing the efficiency of related DMUs. The main advantage of this study is considering network DEA with internal structures instead of black box DEA models in organ allocation problems. It should be noted that black box DEA models fail to present sufficient data for identifying the inefficiency of DMUs. In addition, it is unclear what occurs within the black box DEA models, and internal relations are not investigated. Finally, a real case study related to the organ allocation problem is presented, and the findings indicate that the proposed method in this study is strongly effective and outperforms the current kidney allocation system in Iran.

Keywords: Data envelopment analysis, organ transplantation, organ allocation, two-stage network DEA, supply chain

1- Introduction

Organ transplantation is one of the most challenging medical procedures in medicine. This surgery involves a recipient receiving an organ from a donor to replace a damaged or missing organ with a new one (WHO, 2022). In the past 50 years, technological and medical developments have made organ transplantation one of the most effective treatment alternatives. It is considered the only treatment for end-stage organ failure, including the kidneys, heart, lungs, and liver (Bouwman et al., 2013). The fundamental difference between this therapy and others is that organ transplantation requires both a donor and a receiver. The transplantation procedure has successfully transplanted the liver, kidney, heart, thymus, and intestine. In the organ transplantation supply chain, kidney is the most often transplanted organ, followed by the liver and the heart (Bartling et al., 2020). Consequently, in this research, kidney has been investigated as the most demanding organ worldwide.

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Besides, the matching process in the organ transplantation supply chain is the most significant and challenging procurement choice since it determines who lives and who dies. The need for an effective matching procedure has motivated academic researchers to focus on designing and evaluating allocation methods (Zenios, 2006).

DEA models can be one of the most appropriate models for evaluating the organ-patient efficiencies (Kao, 2017; Marinho & Araújo, 2021). DEA is a data-driven method to evaluate the performance of a set of entities known as decision-making units (DMUs), which transform multiple inputs into multiple outputs (Cooper et al., 2011; Omrani et al., 2022; Peykani et al., 2022; Sadjadi et al., 2011). DEA is a non-parametric approach for measuring the efficiency of DMUs that does not need a production function (Apornak et al., 2021; Hamid et al., 2018; Liu et al., 2016; Moazeni et al., 2022; Peykani et al., 2018). Regarding the related literature, organ allocation systems especially in DEA models, have been considered as a whole unit or black box with no information about internal components. Black boxes DEA models fail to present sufficient data for identifying the inefficiency of DMUs (Henriques et al., 2020). Moreover, it is unclear what occurs within the black box DEA models, and internal relations are not investigated (Tavana et al., 2018). For instance, according to (Ahmadvand & Pishvaee, 2018a), by examining the kidney allocation system, each organ-patient pair was considered as a DMU, and all procedures were considered in only one step. But in reality, the kidney allocation system consists of internal structures. It should be mentioned that in this study, internal structures are carefully investigated, and the entire organ allocation structures are not considered in black box mode. This structure is known as the two-stage DEA network (Cook & Zhu, 2014). To the best of our knowledge, this structure has not been used in the organ allocation system, which is one of the contributions of this study.

For the first time, Farrel (1957) presented a non-parametric approach for efficiency measurement, which included one input and one output. After that, Charnes et al. (1978) proposed a mathematical model to evaluate the relative efficiency of a homogeneous group of DMUs such as hospitals, schools, and shopping centers. The model presented in their study was the first DEA model, which was named as CCR model. Ahmadvand and Pishvaee (2018a) developed a credibility-based fuzzy common weights DEA model for kidney allocation problem, and utilized the common weight approach for all decision-making units. The developed model was capable of dealing with uncertainty associated with transplantation factors in the Iran kidney allocation system and all processes were considered in only one step as a black box DEA model. Marinho and Araújo (2021) provided a DEA considering the bootstrap technique to assess organ transplantation efficiency. The bootstrap approaches utilized provide for calculating a confidence interval related to DEA scores and allow higher robustness. The importance of randomness, bias in DEA models, and measurement errors were considered, and they found that correcting DEA conventional scores is important.

For managing related activities in the organ transplantation procedure, various national and international organizations have been established in several countries. Eurotransplant in Europe (De Boer et al., 2021), United Network for Organ Sharing (UNOS) in the USA (UNOS, 2022), and Iranian Network for Organ Procurement and Transplantation (IRNOPT) in Iran (Kargar et al., 2020) are examples of organ transplantation organizations. These non-profit organizations are responsible for identifying and assessing brain death situations, obtaining donor permission, and procuring organs (UNOS, 2022). In this study, initial qualified organ-patient pairs are indicated by IRNOPT experts, and after that DEA model is used to calculate the organ-patient pairs' efficiencies.

Moreover, despite the fact that organ transplantation can save hundreds of lives and improve quality of life, it faces numerous obstacles. The significant mismatch between organ supply and demand is a challenging obstacle that must be overcome (UNOS, 2022). Unfortunately, in the United States, about 8,000 people die annually because they do not receive the organs they need in time. (OPTN, 2022). In Iran, 7 to 10 people die each day because of the lack of suitable organs (IRNOPT, 2022). By examining data from other nations, it is evident that the number of organs in the global organ transplant system will not be sufficient to meet the demand from patients on waiting lists (Aubert et al., 2021). This demonstrates that the organ allocation procedure requires careful planning and analysis.

On the other side, there are two organizational approaches for organs and recipients, namely centralized and hierarchical (Kargar et al., 2020). The first method includes conducting a centralized search of a national waitlist by organ type. In the second method, candidates from the same location have higher organ donation priority than other candidates. When an organ becomes accessible under these circumstances, it is first distributed locally, then regionally, and finally nationally. It should be emphasized that the process for organ allocation in this study is based on a centralized system.

The main motivation of the presented article is to propose a novel method utilizing the DEA approach for evaluating the efficiency of organ-patient pairs and considering internal structures based on a centralized system for the kidney allocation system. According to the literature (Ahmadvand & Pishvaee, 2018b; Marinho & Araújo, 2021), organ allocation systems (especially in DEA models) have been considered as a black box or whole unit, with no information about internal components. It should be mentioned that the black boxes DEA models fail to present sufficient data for identifying inefficiency. Furthermore, it is unclear what occurs within the black box DEA models and internal relations and structures are not investigated. On the other hand, investigating a real case study to indicate the proposed approach's applicability is also considered in this paper.

To summarize, a novel two-stage network DEA model in kidney allocation problem by considering internal structures is developed in this study to evaluate the efficiency of organ-patient pairs. The rest of this paper is organized as follows: In section 2, a comprehensive literature review is presented. Problem description and formulations for kidney allocation problem are provided in section 3. In section 4, results and case study are described. In section 5, managerial insights are provided. Finally, conclusions and future research directions are given in section 6.

2- Literature review

Organ transplantation network design involves long-term, mid-term, and short-term planning level decisions (Ahmadvand & Pishvaee, 2018b). Long-term decisions include the location and allocation of facilities (Bruni et al., 2006; Savaşer et al., 2019; Zahiri, Tavakkoli-Moghaddam, Mohammadi, et al., 2014), the interaction between transplant centers, facilities, and transplantation organizations (Beliën et al., 2013), and the local design of organ transplantation networks (Demirci et al., 2012; Kong et al., 2010; Stahl et al., 2005). Moreover, mid-term and short-term decisions are related to transportation planning for patients, organs, staff scheduling, and organ allocation (Ahmadvand & Pishvaee, 2018a). Regarding the controversies surrounding the availability of numerous alternatives and the optimal allocation system, organ allocation approaches and their related strategies have developed significantly in recent years (Alagoz et al., 2009).

Akan (2008) provided a multiclass fluid model for the liver allocation problem. The model considered that patients might reject some organs, and overloaded queues were also involved. Organs wasted because of patients' rejection and overall quality-adjusted life years (QALY) was optimized for analyzing the efficiency. In another study, Akan et al. (2012) developed a multiclass fluid model for the liver organ transplantation waiting list, which includes the patient's health situation by permitting them to change between classes. The main purpose was to maximize total QALY and minimize overall patient deaths number. Results indicated that the model's performance was better than the UNOS organ allocation system.

Alagoz et al. (2004) presented a Markov decision procedure for the optimal transplant time for a live donor. Along with the quality-adjusted life expectancy measure, researchers optimized the patients' overall reward, and patient health status described the state of the process. They utilized a value iteration approach for solving the problem. In another research, Alagoz et al. (2007) examined the possibility of accepting a provided liver organ of a specific quality. They developed a model with a discrete time situation and an unlimited horizon that the process is determined by the patient's health condition. Lastly, a policy iteration approach was utilized to solve the Markov decision process.

Beliën et al. (2013) suggested a mixed-integer linear programming model for minimizing the waiting time between when an organ becomes available in hospitals as supply points and when it is transplanted in transplant centers as demand points. Zahiri et al. (2014) presented a multi-period location-allocation model for organ transplantation centers. A bi-objective stochastic optimization method was used to minimize the overall time and cost, as well as the organ transplantation operation waiting time, while identifying the objectives for organs and solving medium and small-sized problems. Gentry et al. (2015) proposed a binary integer programming model to reduce the differences in liver availability among regions by dividing donor service districts into four and eight shared areas. Al-Ebbini et al. (2016) proposed a fuzzy logic model for a lung allocation system. The main goal was to identify suitable patients for lung transplantation. Their system represents a more accurate and time-efficient tool for lung allocation problem.

Zenios et al. (2000) presented a dynamic resource kidney allocation problem with objective of minimizing waiting times, and transplantation's likelihood linear function for different types of patients and maximizing the quality-adjusted life expectancy. Besides, a simulation model was utilized, and findings indicated that a dynamic approach could decrease average waiting time and increase the quality-adjusted life expectancy. Su and Zenios (2005) developed a sequential stochastic assignment model for kidney allocation problem. The main goal was to maximize the total expected reward by selecting an optimal organ allocation policy. One year later, Su and Zenios (2006) presented a model with transplantation queues for kidney allocation problem to examine the impact of information asymmetries on the allocation system. In their developed model, each kidney would be allocated to only one recipient based on its particular type. Bertsimas et al. (2013) provided a method for determining the optimal scoring weights utilized in the kidney allocation problem. Their method creates a point system based upon the chosen scoring components that promote medical efficiency, for instance, life years gained from transplant, while enforcing chosen fairness limits. They input fairness criteria, various score components, and transplantation data toward a mixed integer non-linear programming model and utilize linear regression to find weights of scoring. Their approach allows decision-makers to dynamically adjust the scoring rules and analyze the related results using a simulation model which is utilized by organ procurement and transplantation network in the USA.

Savaşer et al. (2019) investigated Turkey's organ transplantation system and developed mixed-integer programming models for maximizing potential-weighted intra-regional organ transplantation flow by analyzing various transportation modes and taking clustering structures for the matchmaking process into account. Further, to deal with uncertainty, a simulation model was utilized to evaluate the performance of the results. At last, findings revealed that re-clustering could enhance the organ allocation system in Turkey.

Kargar et al. (2020) investigated the organ transplantation problem considering epistemic uncertainty. Their model was a mixed-integer non-linear possibilistic programming for the liver allocation problem, and triangular possibility distribution was applied. The developed model minimized the time and transportation cost and maximized the survival rate. Results showed that the suggested model performed much better than the IRNOPT allocation system. Rouhani and Amin (2022) utilized a novel robust convex optimization method for designing an efficient organ transplantation network. They presented a multi-objective model, and the main goal was to maximize the geographical parity in the demand and supply uncertainty situation and minimize costs and total time. Furthermore, the augmented ε-constraint method was utilized to solve the model, and a real case study in Iran showed the model's performance. Goli et al. (2022) developed a possibilistic programming model and simulation-oriented solution approach for organ transplantation, allocation, location, and distribution. The presented model involving the fuzzy uncertainty of transportation time and demand, minimizes total costs. Additionally, findings demonstrated that the viability rate in the developed organ transplantation supply chain is lower than the satisfaction rate of patients.

The summary of reviewed papers can be seen in Table 1. The main contributions of this research compared to previous studies are summarized as follows:

- Proposing a two-stage network DEA model in kidney allocation problem by investigating internal organ allocation system structure and relationships.
- Utilizing an additive decomposition approach for the developed two-stage structure.
- Investigating a real case study for evaluating the applicability of the presented approach.

Table 1. Organ allocation problem related articles

Author	Organ	Modeling approach	Solution approach	Objective Function	Case study	Internal structures
Zenios et al. (2000)	Kidney	Fluid Model	Policy Improvement Algorithm	WT, LT, QALY	USA	×
Alagoz et al. (2004)	Liver	Markov Decision Process	Value Iteration Algorithm	QALE	USA	×
Su and Zenios (2005)	Kidney	Sequential Assignment Match Process	Dynamic Programming	TER	USA	×
Bruni et al. (2006)	Liver	Mixed Integer Linear Programming	Exact	WT, TD	Italy	×
Su and Zenios (2006)	Kidney	Sequential Assignment Match Process	Achievable Region	QALY, EQ, TTT	USA	×
Alagoz et al. (2007)	Liver	Markov Decision Process	Policy Iteration Algorithm	TEDR	USA	×
Akan et al. (2008)	Liver	Fluid Model	Heuristic	NWO, QALY	USA	×
Kong et al. (2010)	Liver	Mixed Integer Linear Programming	Heuristic	TE, GP	USA	×
Akan et al. (2012)	Liver	Fluid Model	Heuristic	QALY, NPDWT	USA	×
Beliën et al. (2013)	Multiple	Mixed Integer Linear Programming	Exact	TTT	Belgium	×
Bertsimas et al. (2013)	Kidney	Mixed Integer Non-Linear Programming	Linear Regression	LYFT	USA	×
Zahiri et al. (2014)	Multiple	Mixed Integer Non-Linear Programming	Meta Heuristic	TTC	Iran	×
Gentry et al. (2015)	Liver	Integer Programming	Exact	NML	USA	×
Ahmadvand and Pishvaee (2018)	Kidney	DEA	Credibility Common Weight DEA	LYFT, WT, TTT	Iran	×
Savaşer et al. (2018)	Multiple	Integer Programming	Exact	PWIRF	Turkey	×
Kargar et al. (2020)	Liver	Mixed Integer Non-Linear Programming	Fuzzy Goal Programming	TTCO, SR	Iran	×
Marinho and Araújo (2021)	Multiple	DEA	Bootstrap Bias-Corrected	TE	Brazil	×
Rouhani and Amin (2022)	Multiple	Mixed Integer Linear Programming	Exact	TTT, TTCO, GP	Iran	×
Goli et al. (2022)	Multiple	Mixed Integer Linear Programming	Robust Possibilistic Programming	TC	-	×
This study (2023)	Kidney	DEA	Exact	WT, QALY, LYFT	Iran	✓

Objective Function: WT: Minimize Waiting Time, LT: Minimize Likelihood of Transplantation, QALY: Maximize Quality Adjusted Life Years, QALE: Maximize Quality Adjusted Life Expectancy, TER: Maximize Total Expected Reward, TE: Maximize Transplant Efficiency, GP: Maximize Geographic Parity, TD: Minimize Travel Distance, EQ: Maximize Equity, TTT: Minimize Total Transportation Time, TEDR: Maximize Total Expected Discounted Reward, NOW: Minimize Number of Wasted Organs, NPDWT: Minimize Number of Patients Deaths while Waiting for Transplantation, LYFT: Maximize Life Years From Transplant, TTC: Minimize Total Time and Cost, NML: Minimize Number of Misdirected Livers, PWIRF: Maximize Potential Weighted Intra-Regional Flow, TTCO: Minimize Total Transportation Cost, SR: Maximize Survival Rate, TC: Minimize Total Cost, NML: Minimize Number of Misdirected Livers,

3- Problem description and formulation

This section describes the kidney allocation problem and presents the network DEA model

3-1- Problem description

The matchmaking procedure is the process of finding the best organ-patient pair for each kidney that appears in the organ transplantation supply chain. In other words, this process is the procedure of selecting the ideal recipient for an organ entering the organ transplantation network system (Kargar et al., 2020). In Iran, a non-profit organization is responsible for organ procurement (Ahmadvand & Pishvaee, 2018a). In a point-based allocation system, which is the current allocation system in Iran, compatible recipients are ordered in descending order depending on the total number of points received for a specific criterion. Consequently, various criteria are used to find which recipient is the best for each kidney in the system. Related criteria utilized in this study are as follows:

- Waiting time (WT): This criterion relates to the length of time a patient has been on dialysis, on the waiting list, or attained end-stage kidney disease. The patient's WT is regarded as the most important and key factor in the Iran organ allocation system. In addition, the WT for patients awaiting a kidney transplant who were getting dialysis prior to being listed on the waiting list is computed from the time dialysis treatment began (Ahmadvand & Pishvaee, 2018a).
- Quality-adjusted life years (QALY): If a person has a choice between two or more treatments or interventions (e.g., different types of kidneys), he should choose the one that will result in the greatest number of years of quality life. In fact, the QALY was designed as an output metric that integrates both quality (i.e., illness rate) and quantity (i.e., mortality) (HLA Matching and Antibodies, 1998).
- Life years from transplant (LYFT): This criterion is defined as the difference between a candidate's median expected survival with a kidney donation from a specific donor and their median expected survival without a transplant. On the basis of each candidate's medical and demographic information, projected lifespans with and without a kidney transplant are calculated. The donor kidney's qualities are also factored into survival after a kidney transplant (Wolfe et al., 2008).

When a kidney enters the organ transplantation system, numerous patients will be considered for transplantation based on the initial recommendations of experts, and there will be multiple initial qualified organ-patient pairs for each kidney. Due to the unique qualities of each kidney, only a limited number of individuals will be eligible to receive it. In addition to the patient's health situation, specialists at this stage also assess the patient's perspective of pleasure in accepting or rejecting the proposed organ based on their medical history. Thus, considering transplant specialists' experience, the initial qualifying organ-patient couples for each kidney have been identified, and the efficiency of each pair has been evaluated utilizing the presented two-stage network DEA model. It should be mentioned that the initial pairings are the only viable pairs for calculating efficiency. This does not indicate that the organ will be assigned to the patient before applying the developed DEA model. In summary, each of the qualified patient-organ pairs for each kidney which were identified by organ transplantation experts, are DMUs in the presented problem.

The existing kidney allocation mechanism in Iran has numerous flaws. First, the existing approach lacks post-transplant outcome measuring criteria such as LYFT and QALY. Therefore, some patients should not receive a kidney that will last as long as they need, and they have been returned to the waiting list (IRNOPT, 2022). On the other side, the most significant criterion in Iran's organ allocation system for assigning organs to the patient is WT which needs to be a better measure for evaluating the best possible organ-patient pair for each organ. Thus, in this study, to solve current issues in Iran's organ allocation system, measures such as WT, QALY, and LYFT are investigated together in a two-stage data envelopment model, and internal structures are also considered. Regarding the assumptions in this study, WT measure is considered for the first stage, QALY measure as the intermediate measure from the first stage to the second stage, and LYFT as the system's final output. In the following section, the structure of the two-stage network data envelopment analysis model is described in detail.

3-2- Model structure and formulation

The two-stage structure is a popular network structure that has received lots of attention in the network DEA literature (Peykani et al., 2021). According to figure 1, there are n homogeneous decision-making units DMU_j $(j = 1, \dots, n)$ which in the first stage I inputs x_{ij} $(i = 1, \dots, I)$ enter the system, and D outputs z_{dj} $(d = 1, \dots, D)$ come out. The outputs of the first stage, which are known as intermediate criteria, are entered as input to the second stage, and finally R outputs y_{rj} $(r = 1, \dots, R)$ come out. In addition, the non-negative weights u_i $(i = 1, \dots, I)$, v_d $(d = 1, \dots, D)$, and π_r $(r = 1, \dots, R)$ are assigned to the x_{ij} $(i = 1, \dots, I)$, z_{dj} $(d = 1, \dots, D)$, and y_{rj} $(r = 1, \dots, R)$, respectively.

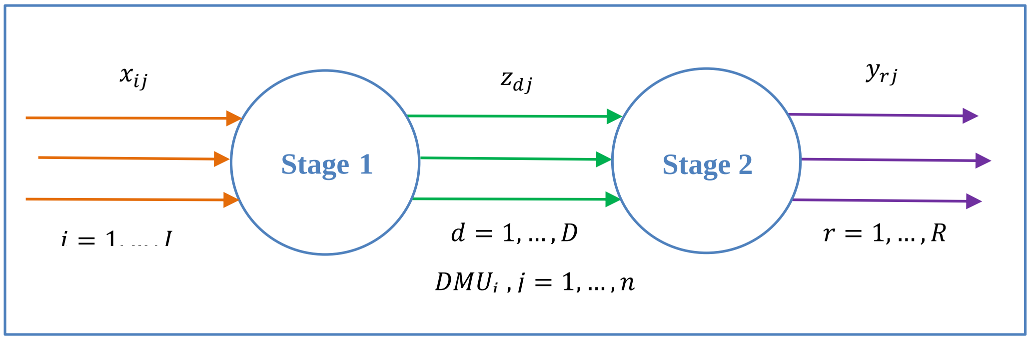

Fig. 1. Two-stage network DEA model structure for the organ allocation problem

There are several modeling methodologies used in network DEA research, like additive decomposition (Chen et al., 2009), multiple decomposition (Kao & Hwang, 2008), and game theory (Liang et al., 2008). Regarding the popularity of the additive method for evaluating the performance of DMUs (Kao, 2017), and the capability of using this approach for a general two-stage network structure with intermediate criteria, this approach is used. Following is a description of the modeling process utilizing the additive decomposition approach for the presented two-stage structure. Considering figure 1, the efficiency value of the first stage for the investigated DMU (DMU_k) can be determined by model (1):

$$
\begin{aligned}
&\psi_k^{stage1} = Max \frac{\sum_{d=1}^{D} v_d z_{dk}}{\sum_{i=1}^{I} u_i x_{ik}} \\
&S.t. \\
&\frac{\sum_{d=1}^{D} v_d z_{dj}}{\sum_{i=1}^{I} u_i x_{ij}} \le 1, \quad \forall j \\
&u_i, v_d \ge 0, \quad \forall i, d
\end{aligned}
\tag{1}
$$

Subsequently, the efficiency value of the second stage for the investigated DMU (DMU_k) can be determined by using model (2):

$$\psi_k^{stage2} = Max \frac{\sum_{r=1}^{R} \pi_r y_{rk}}{\sum_{d=1}^{D} v_d z_{dk}}$$

$$S.t.$$

$$\frac{\sum_{r=1}^{R} \pi_r y_{rj}}{\sum_{d=1}^{D} v_d z_{dj}} \leq 1, \quad \forall j \tag{2}$$

$$\pi_r, v_d \geq 0, \quad \forall r, d$$

According to the study by Chen et al. (2009), the total efficiency of the general two-stage procedure can be determined by using equation (3):

$$\begin{aligned} \psi_k^{total} &= \varphi_1\left(\psi_k^{stage1}\right) + \varphi_2\left(\psi_k^{stage2}\right) \\ &= \varphi_1\left(\frac{\sum_{d=1}^{D} v_d z_{dk}}{\sum_{i=1}^{I} u_i x_{ik}}\right) + \varphi_2\left(\frac{\sum_{r=1}^{R} \pi_r y_{rk}}{\sum_{d=1}^{D} v_d z_{dk}}\right) \end{aligned} \tag{3}$$

It should be mentioned that in equation (3), φ_1 and φ_2 are user-specified weights so that $\varphi_1 + \varphi_2 = 1$. To be more specific, φ_1 demonstrates the importance of the first stage performance, while φ_2 demonstrates the importance of the second stage performance in the total system performance. Consequently, the total efficiency value of DMU_k is determined by using model (4):

$$\psi_k^{total} = Max\, \varphi_1\left(\frac{\sum_{d=1}^{D} v_d z_{dk}}{\sum_{i=1}^{I} u_i x_{ik}}\right) + \varphi_2\left(\frac{\sum_{r=1}^{R} \pi_r y_{rk}}{\sum_{d=1}^{D} v_d z_{dk}}\right)$$

$$S.t.$$

$$\frac{\sum_{d=1}^{D} v_d z_{dj}}{\sum_{i=1}^{I} u_i x_{ij}} \leq 1, \quad \forall j \tag{4}$$

$$\frac{\sum_{r=1}^{R} \pi_r y_{rj}}{\sum_{d=1}^{D} v_d z_{dj}} \leq 1, \quad \forall j$$

$$u_i, v_d, \pi_r \geq 0, \quad \forall i, d, r$$

Accordingly, model (4) cannot be transformed to linear programming by using Charnes and Cooper (Peykani et al., 2021) transformation. Subsequently, according to Chen et al. (2009) research, the suggested φ_1 and φ_2 are determined by equations (5) and (6), respectively:

$$\varphi_1 = \frac{\sum_{i=1}^{I} u_i x_{ik}}{\sum_{i=1}^{I} u_i x_{ik} + \sum_{d=1}^{D} v_d z_{dk}} \tag{5}$$

$$\varphi_2 = \frac{\sum_{d=1}^{D} v_d z_{dk}}{\sum_{i=1}^{I} u_i x_{ik} + \sum_{d=1}^{D} v_d z_{dk}} \tag{6}$$

Therefore, by utilizing equations (5) and (6), model (4) will be transformed to model (7):

$$\psi_k^{total} = Max \frac{\sum_{d=1}^{D} v_d z_{dk} + \sum_{r=1}^{R} \pi_r y_{rk}}{\sum_{i=1}^{I} u_i x_{ik} + \sum_{d=1}^{D} v_d z_{dk}}$$

$$S.t.$$

$$\frac{\sum_{d=1}^{D} v_d z_{dj}}{\sum_{i=1}^{I} u_i x_{ij}} \leq 1, \quad \forall j \tag{7}$$

$$\frac{\sum_{r=1}^{R} \pi_r y_{rj}}{\sum_{d=1}^{D} v_d z_{dj}} \leq 1, \quad \forall j$$

$$u_i, v_d, \pi_r \geq 0, \quad \forall i, d, r$$

Model (7) is now transformed into a linear programming model (8) using the transformation of Charnes and Cooper (Peykani et al., 2021):

$$\psi_k^{total} = Max \sum_{d=1}^{D} \vartheta_d z_{dk} + \sum_{r=1}^{R} \tau_r y_{rk}$$

$$S.t.$$

$$\sum_{i=1}^{I} \mu_i x_{ik} + \sum_{d=1}^{D} \vartheta_d z_{dk} = 1$$

$$\sum_{d=1}^{D} \vartheta_d z_{dj} - \sum_{i=1}^{I} \mu_i x_{ij} \leq 0, \quad \forall j \tag{8}$$

$$\sum_{r=1}^{R} \tau_r y_{rj} - \sum_{d=1}^{D} \vartheta_d z_{dj} \leq 0, \quad \forall j$$

$$\mu_i, \vartheta_d, \tau_r \geq 0, \quad \forall i, d, r$$

It should be mentioned that optimal multipliers derived from model (8) may not be unique, so the total efficiency decomposition described in equation (3) could not be unique. Kao and Hwang (2009) presented an approach to find the set of multipliers that provides maximum efficiency for the first stage or second stage while remaining the total efficiency value constant. Thus, by assuming that in the organ allocation problem, the importance of the first stage has a higher priority than the second stage, ψ_k^{stage1} will be determined by utilizing model (9) while $\psi_k^{total^*}$ optimal value is derived from model (8):

$$
\begin{aligned}
&\psi_k^{stage1} = Max \frac{\sum_{d=1}^{D} v_d z_{dk}}{\sum_{i=1}^{I} u_i x_{ik}} \\
&S.t. \\
&\frac{\sum_{d=1}^{D} v_d z_{dj}}{\sum_{i=1}^{I} u_i x_{ij}} \leq 1, \ \ \forall j \\
&\frac{\sum_{r=1}^{R} \pi_r y_{rj}}{\sum_{d=1}^{D} v_d z_{dj}} \leq 1, \ \ \forall j \\
&\frac{\sum_{d=1}^{D} v_d z_{dk} + \sum_{r=1}^{R} \pi_r y_{rk}}{\sum_{i=1}^{I} u_i x_{ik} + \sum_{d=1}^{D} v_d z_{dk}} = \psi_k^{total^*} \\
&u_i, v_d, \pi_r \geq 0, \ \ \forall i, d, r
\end{aligned}
\tag{9}
$$

Model (9) is a linear fractional programming model, so by utilizing Charnes and Cooper transformation, this model is equal to model (10) as follows:

$$
\begin{aligned}
&\psi_k^{stage1} = Max \sum_{d=1}^{D} \vartheta_d z_{dk} \\
&S.t. \\
&\sum_{i=1}^{I} \mu_i x_{ik} = 1 \\
&\sum_{d=1}^{D} \vartheta_d z_{dj} - \sum_{i=1}^{I} \mu_i x_{ij} \leq 0, \ \ \forall j \\
&\sum_{r=1}^{R} \tau_r y_{rj} - \sum_{d=1}^{D} \vartheta_d z_{dj} \leq 0, \ \ \forall j \\
&\sum_{d=1}^{D} \vartheta_d z_{dk} + \sum_{r=1}^{R} \tau_r y_{rk} - \psi_k^{total^*} \sum_{d=1}^{D} \vartheta_d z_{dk} = \psi_k^{total^*} \\
&\mu_i, \vartheta_d, \tau_r \geq 0, \ \ \forall i, d, r
\end{aligned}
\tag{10}
$$

Eventually, by using model (10) the value of $\psi_k^{stage1^*}$ is calculated, and the efficiency value of the second stage is determined utilizing equation (11):

$$
\psi_k^{stage2^*} = \frac{\psi_k^{total^*} - {\varphi_1}^* \psi_k^{stage1^*}}{{\varphi_2}^*} \tag{11}
$$

It should be noted that ${\varphi_1}^*$ and ${\varphi_2}^*$ are in fact the optimal weights acquired from model (8) utilizing equations (5) and (6).

4- Results and case study

In this section, a real case study is presented to demonstrate the performance of the DEA mathematical approach. As mentioned before, kidney is the most commonly transplanted organ all over the world, and in Iran, statistics also indicate that the great majority of annual transplants involve this organ. Notably, almost 76% of all transplants performed in Iran through the end of 2021 are related to kidneys (IRNOPT, 2022).

Moreover, IRNOPT is responsible for organ allocation and related matters in Iran. It coordinates transplantation procedures using numerous local OPUs. A director is charged with interacting with IRNOPT on behalf of each unit. These non-profit organizations are responsible for diagnosing and identifying brain-dead patients, gaining consent for organ donation, and purchasing organs. In addition, when an organ appears available, the local OPU checks the waiting list for a suitable recipient. It should be noted that transplantation specialists gave the first qualified organ-patient pairs for each kidney in this study, and then the efficiency of each qualified pair had been determined utilizing the presented approach.

For each kidney entered into the organ transplantation system, the presented approach calculates the efficiency of the qualified organ-patient pairs provided by transplantation specialists. Required data for donated kidneys and patients were obtained from the Iran ministry of health and medical education, including 35 kidneys and 710 patients waiting to receive a suitable kidney. It should be considered that, DMUs are initial qualified organ-patient pairs in the developed model for each kidney. Therefore, Due to each organ-patient pair unique characteristics, the number of DMUs is different and varies between 10 and 73. It means that for one specific kidney, there are only 10 qualified patients who can receive the kidney; for another specific kidney, this number is 73 patients and for other kidneys this number is between 10 and 73 because of each organ-patient pair unique characteristics and features, this number is different for each of them. Besides, all calculations are conducted by GAMS 24.1 software on a COREi7 PC with 16 GB of RAM. The statistical information about input, intermediate, and output criteria used in the presented model are shown in table 2.

Table 2. Statistical information about input, intermediate, and output criteria.

Type	Stage	Variable	Unit	Min	Max	Average
Input	1	WT	years	0.5	13	5.31
Intermediate	from 1 to 2	QALY	years	1.75	8.25	4.72
Output	2	LYFT	years	1.5	13.75	7.83

Finally, the presented DEA model is solved for all of the 35 kidneys. The values of efficiencies are assessed, and the related results for 5 kidneys are shown in table 3. It should be mentioned that for summarizing the findings, the results of only 5 kidneys are shown in table 3. As can be seen in the presented table, the number of DMUs from the first kidney to the fifth kidney is 41, 73, 49, 10, and 44, respectively. On the other hand, the selected patient for each kidney is the one with all the efficiencies equal to 1. For example, for the first kidney, the selected patient is the one who is in the DMU_{17}, or for the second kidney, DMU_{32} is the best organ-patient pair for that specific kidney.

Table 3. The first, second and total stage efficiency scores of the presented approach
(K-No.1 means Kidney Number 1, which is the first kidney investigated in DEA model)

K-No.1	**Efficiency Scores**			**K-No.2**	**Efficiency Scores**			**K-No.2**	**Efficiency Scores**			**K-No.4**	**Efficiency Scores**		
	Stage 1	**Stage 2**	**Total**		**Stage 1**	**Stage 2**	**Total**		**Stage 1**	**Stage 2**	**Total**		**Stage 1**	**Stage 2**	**Total**
DMU$_{1}$	0.496	0.763	0.701	DMU$_{14}$	0.556	0.449	0.491	DMU$_{69}$	0.762	1.000	0.913	DMU$_{1}$	0.941	0.590	0.675
DMU$_{2}$	0.933	0.653	0.793	DMU$_{15}$	0.736	0.921	0.801	DMU$_{70}$	0.521	0.598	0.572	DMU$_{2}$	1.000	1.000	1.000
DMU$_{3}$	0.459	0.763	0.612	DMU$_{16}$	0.455	1.000	0.813	DMU$_{71}$	0.662	0.796	0.707	DMU$_{3}$	0.569	0.255	0.413
DMU$_{4}$	0.837	0.234	0.524	DMU$_{17}$	0.567	0.715	0.671	DMU$_{72}$	0.586	0.982	0.871	DMU$_{4}$	0.851	0.236	0.741
DMU$_{5}$	0.322	0.445	0.347	DMU$_{18}$	0.273	0.337	0.303	DMU$_{73}$	0.631	0.936	0.901	DMU$_{5}$	0.422	0.328	0.369
DMU$_{6}$	0.198	0.542	0.445	DMU$_{19}$	0.836	0.643	0.712	**K-No.3**				DMU$_{6}$	0.270	0.487	0.401
DMU$_{7}$	0.819	0.793	0.802	DMU$_{20}$	0.588	0.643	0.602	DMU$_{1}$	0.389	0.662	0.583	DMU$_{7}$	0.065	0.718	0.589
DMU$_{8}$	0.419	0.286	0.376	DMU$_{21}$	0.792	0.442	0.662	DMU$_{2}$	0.862	0.483	0.671	DMU$_{8}$	0.608	0.821	0.751
DMU$_{9}$	0.969	0.815	0.856	DMU$_{22}$	0.231	0.575	0.401	DMU$_{3}$	0.131	0.289	0.201	DMU$_{9}$	0.356	0.581	0.519
DMU$_{10}$	0.731	0.603	0.658	DMU$_{23}$	0.379	0.626	0.523	DMU$_{4}$	0.022	0.696	0.430	DMU$_{10}$	0.574	0.504	0.567
DMU$_{11}$	0.822	0.789	0.801	DMU$_{24}$	0.450	0.631	0.600	DMU$_{5}$	0.663	0.484	0.532	**K-No.5**			
DMU$_{12}$	0.519	0.264	0.412	DMU$_{25}$	0.495	0.253	0.354	DMU$_{6}$	0.310	0.414	0.372	DMU$_{1}$	0.896	0.755	0.822
DMU$_{13}$	0.189	0.820	0.669	DMU$_{26}$	1.000	0.927	0.939	DMU$_{7}$	0.568	0.549	0.555	DMU$_{2}$	0.302	0.348	0.319
DMU$_{14}$	0.929	0.881	0.901	DMU$_{27}$	0.969	0.958	0.960	DMU$_{8}$	0.411	0.121	0.301	DMU$_{3}$	0.195	0.375	0.283
DMU$_{15}$	0.125	0.634	0.471	DMU$_{28}$	0.735	0.373	0.548	DMU$_{9}$	0.983	0.881	0.899	DMU$_{4}$	0.448	0.702	0.614
DMU$_{16}$	0.851	0.482	0.698	DMU$_{29}$	0.818	0.856	0.835	DMU$_{10}$	0.566	0.853	0.763	DMU$_{5}$	0.578	0.170	0.492
DMU$_{17}$	1.000	1.000	1.000	DMU$_{30}$	0.536	0.398	0.501	DMU$_{11}$	0.533	0.684	0.579	DMU$_{6}$	0.057	0.643	0.441
DMU$_{18}$	0.198	0.792	0.458	DMU$_{31}$	0.254	0.292	0.272	DMU$_{12}$	0.122	0.456	0.331	DMU$_{7}$	0.715	0.694	0.706
DMU$_{19}$	0.833	0.206	0.672	DMU$_{32}$	1.000	1.000	1.000	DMU$_{13}$	0.323	0.735	0.654	DMU$_{8}$	0.584	0.729	0.686
DMU$_{20}$	0.368	0.486	0.394	DMU$_{33}$	0.739	0.057	0.433	DMU$_{14}$	0.015	0.365	0.272	DMU$_{9}$	0.767	0.112	0.620
DMU$_{21}$	0.896	0.441	0.698	DMU$_{34}$	0.194	0.434	0.301	DMU$_{15}$	0.450	0.585	0.592	DMU$_{10}$	0.376	0.466	0.400
DMU$_{22}$	0.622	0.396	0.517	DMU$_{35}$	0.403	0.050	0.335	DMU$_{16}$	0.649	1.000	0.910	DMU$_{11}$	0.592	0.482	0.518
DMU$_{23}$	0.352	0.602	0.512	DMU$_{36}$	0.470	0.406	0.461	DMU$_{17}$	0.167	0.418	0.312	DMU$_{12}$	0.455	0.519	0.501
DMU$_{24}$	0.583	0.217	0.415	DMU$_{37}$	0.766	0.325	0.548	DMU$_{18}$	0.271	0.655	0.463	DMU$_{13}$	0.317	0.991	0.710
DMU$_{25}$	0.672	0.122	0.463	DMU$_{38}$	0.802	0.886	0.832	DMU$_{19}$	0.360	0.087	0.264	DMU$_{14}$	0.172	0.198	0.188
DMU$_{26}$	0.638	0.753	0.701	DMU$_{39}$	0.204	0.738	0.513	DMU$_{20}$	0.516	0.832	0.713	DMU$_{15}$	0.551	0.980	0.901
DMU$_{27}$	0.274	0.486	0.375	DMU$_{40}$	0.259	0.805	0.629	DMU$_{21}$	0.921	1.000	0.963	DMU$_{16}$	0.869	0.908	0.889
DMU$_{28}$	0.838	1.000	0.958	DMU$_{41}$	0.133	0.708	0.541	DMU$_{22}$	0.409	0.416	0.412	DMU$_{17}$	0.334	0.145	0.270

Table 3. (Continued)

K-No.1	Efficiency Scores			K-No.2	Efficiency Scores			K-No.3	Efficiency Scores			K-No.5	Efficiency Scores		
	Stage 1	Stage 2	Total		Stage 1	Stage 2	Total		Stage 1	Stage 2	Total		Stage 1	Stage 2	Total
DMU$_{29}$	0.257	0.543	0.356	DMU$_{42}$	0.938	0.413	0.632	DMU$_{23}$	0.393	0.708	0.663	DMU$_{18}$	0.547	0.384	0.417
DMU$_{30}$	0.188	0.443	0.314	DMU$_{43}$	0.492	0.791	0.681	DMU$_{24}$	1.000	1.000	1.000	DMU$_{19}$	0.372	0.744	0.559
DMU$_{31}$	0.963	0.976	0.970	DMU$_{44}$	0.348	0.214	0.296	DMU$_{25}$	0.233	0.983	0.776	DMU$_{20}$	1.000	1.000	1.000
DMU$_{32}$	0.277	0.404	0.317	DMU$_{45}$	0.905	0.377	0.779	DMU$_{26}$	0.524	0.943	0.823	DMU$_{21}$	0.815	0.304	0.706
DMU$_{33}$	0.535	0.587	0.560	DMU$_{46}$	0.104	0.864	0.523	DMU$_{27}$	0.502	0.904	0.892	DMU$_{22}$	0.963	1.000	0.979
DMU$_{34}$	0.343	0.578	0.498	DMU$_{47}$	0.743	0.472	0.661	DMU$_{28}$	0.795	0.657	0.733	DMU$_{23}$	0.289	0.485	0.402
DMU$_{35}$	1.000	0.462	0.891	DMU$_{48}$	0.477	0.511	0.491	DMU$_{29}$	0.111	0.609	0.516	DMU$_{24}$	0.436	0.032	0.312
DMU$_{36}$	0.916	0.612	0.781	DMU$_{49}$	1.000	0.849	0.963	DMU$_{30}$	0.266	0.074	0.156	DMU$_{25}$	0.680	0.244	0.601
DMU$_{37}$	0.552	0.242	0.395	DMU$_{50}$	0.662	0.724	0.692	DMU$_{31}$	0.507	0.750	0.612	DMU$_{26}$	0.384	0.264	0.307
DMU$_{38}$	0.334	0.771	0.573	DMU$_{51}$	0.094	0.955	0.721	DMU$_{32}$	0.315	0.197	0.266	DMU$_{27}$	0.254	0.054	0.186
DMU$_{39}$	0.746	1.000	0.915	DMU$_{52}$	0.855	0.830	0.850	DMU$_{33}$	0.132	0.228	0.201	DMU$_{28}$	0.524	0.977	0.789
DMU$_{40}$	0.885	0.493	0.695	DMU$_{53}$	0.600	0.162	0.492	DMU$_{34}$	0.700	0.560	0.623	DMU$_{29}$	0.766	0.820	0.801
DMU$_{41}$	0.801	0.609	0.722	DMU$_{54}$	0.365	0.988	0.815	DMU$_{35}$	0.497	0.173	0.378	DMU$_{30}$	1.000	0.519	0.823
K-No.2				DMU$_{55}$	0.464	0.911	0.802	DMU$_{36}$	0.792	0.484	0.682	DMU$_{31}$	0.952	0.273	0.702
DMU$_{1}$	0.679	0.816	0.751	DMU$_{56}$	0.459	0.298	0.348	DMU$_{37}$	0.646	0.882	0.702	DMU$_{32}$	0.801	0.274	0.601
DMU$_{2}$	0.551	0.921	0.831	DMU$_{57}$	0.703	0.124	0.661	DMU$_{38}$	0.666	0.145	0.469	DMU$_{33}$	0.581	0.418	0.506
DMU$_{3}$	0.556	0.980	0.846	DMU$_{58}$	0.119	0.386	0.215	DMU$_{39}$	0.114	0.917	0.795	DMU$_{34}$	0.312	0.364	0.343
DMU$_{4}$	0.631	0.480	0.561	DMU$_{59}$	0.863	1.000	0.924	DMU$_{40}$	0.334	0.822	0.731	DMU$_{35}$	0.610	0.665	0.630
DMU$_{5}$	0.525	0.454	0.501	DMU$_{60}$	0.593	0.992	0.754	DMU$_{41}$	0.475	0.407	0.463	DMU$_{36}$	0.721	0.670	0.691
DMU$_{6}$	0.913	0.518	0.781	DMU$_{61}$	0.696	0.089	0.216	DMU$_{42}$	0.276	0.873	0.723	DMU$_{37}$	0.892	0.524	0.710
DMU$_{7}$	0.833	0.404	0.706	DMU$_{62}$	0.792	0.553	0.701	DMU$_{43}$	0.157	0.009	0.101	DMU$_{38}$	0.324	0.441	0.371
DMU$_{8}$	0.361	0.741	0.691	DMU$_{63}$	0.421	0.756	0.614	DMU$_{44}$	0.698	0.892	0.810	DMU$_{39}$	0.440	0.921	0.886
DMU$_{9}$	0.258	0.801	0.645	DMU$_{64}$	0.128	0.359	0.277	DMU$_{45}$	0.507	0.600	0.569	DMU$_{40}$	0.910	0.692	0.703
DMU$_{10}$	0.397	0.610	0.561	DMU$_{65}$	0.157	0.664	0.442	DMU$_{46}$	1.000	0.997	0.998	DMU$_{41}$	0.210	0.392	0.361
DMU$_{11}$	0.464	0.495	0.482	DMU$_{66}$	0.912	0.659	0.876	DMU$_{47}$	0.304	0.984	0.796	DMU$_{42}$	0.721	0.810	0.760
DMU$_{12}$	0.648	0.841	0.701	DMU$_{67}$	0.564	0.821	0.789	DMU$_{48}$	0.040	0.523	0.401	DMU$_{43}$	0.660	0.412	0.520
DMU$_{13}$	0.518	0.384	0.441	DMU$_{68}$	0.771	0.963	0.892	DMU$_{49}$	0.607	0.763	0.706	DMU$_{44}$	0.692	0.372	0.412

It should be mentioned that for each of the kidneys, only one DMU had the efficiency of the first stage, the second stage, and the total efficiency with a value of 1. Finally, after running the model, the values of the input, intermediate and output parameters of the model in comparison to the IRNOPT system for each of the selected patients for 35 kidneys are shown in figure 2 to figure 4. As it can be seen in figure 2 for the presented approach compared to the IRNOPT method, the waiting time for all selected patients is shorter, meaning that patients will receive the organ they require sooner.

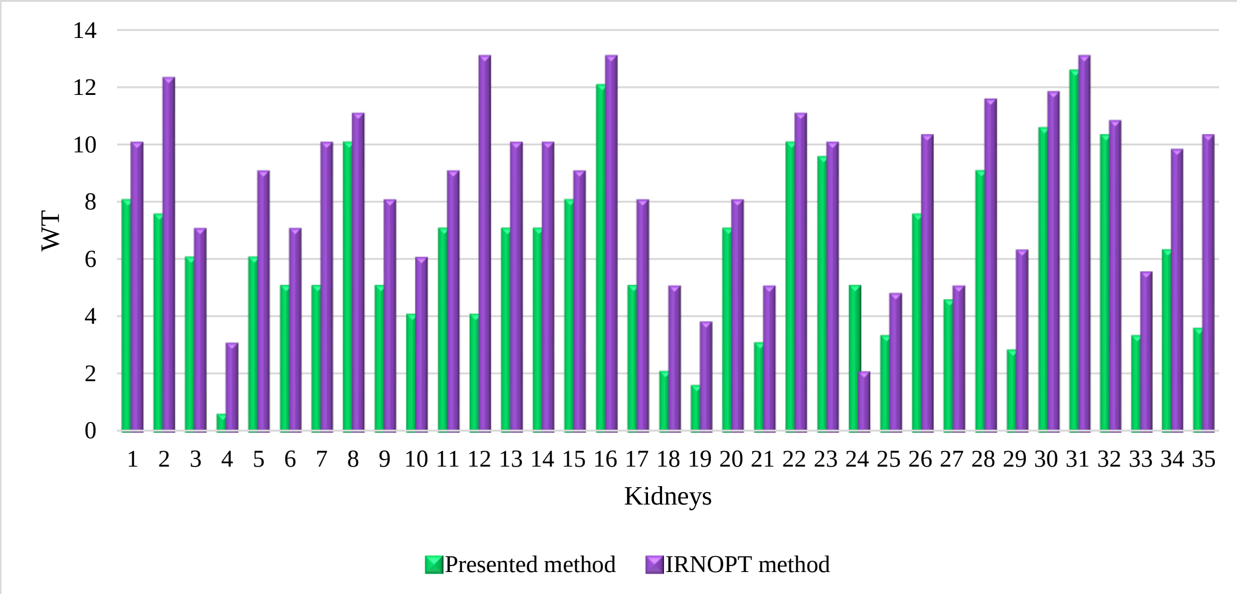

Fig .2. Comparison of the WT parameters of the presented method with the current IRNOPT allocation system

In figure 3, for the developed method compared to the IRNOPT method, the QALY measure for all chosen patients is greater. It means that by using the presented approach in this study, patients will have more quality related to their life.

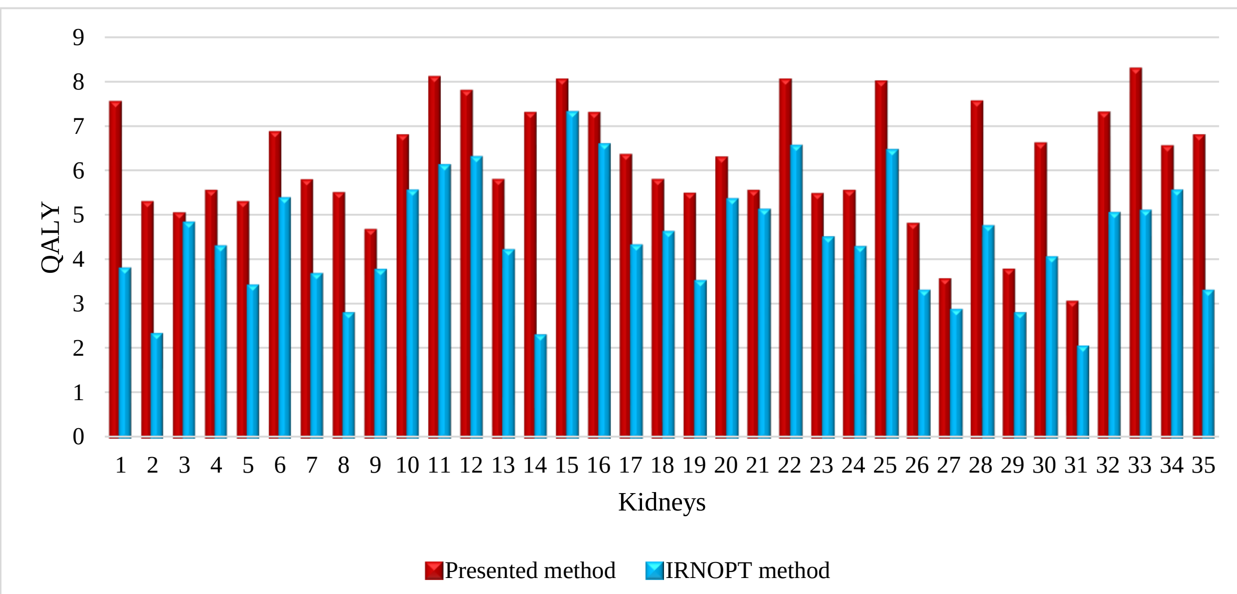

Fig .3. Comparison of the QALY parameters of the presented method with the current IRNOPT allocation system.

In figure 4, for the presented method compared to the IRNOPT method, the LYFT measure for all selected patients is greater. It means that by using developed approach in this study, patients will have more life years from their organ transplants.

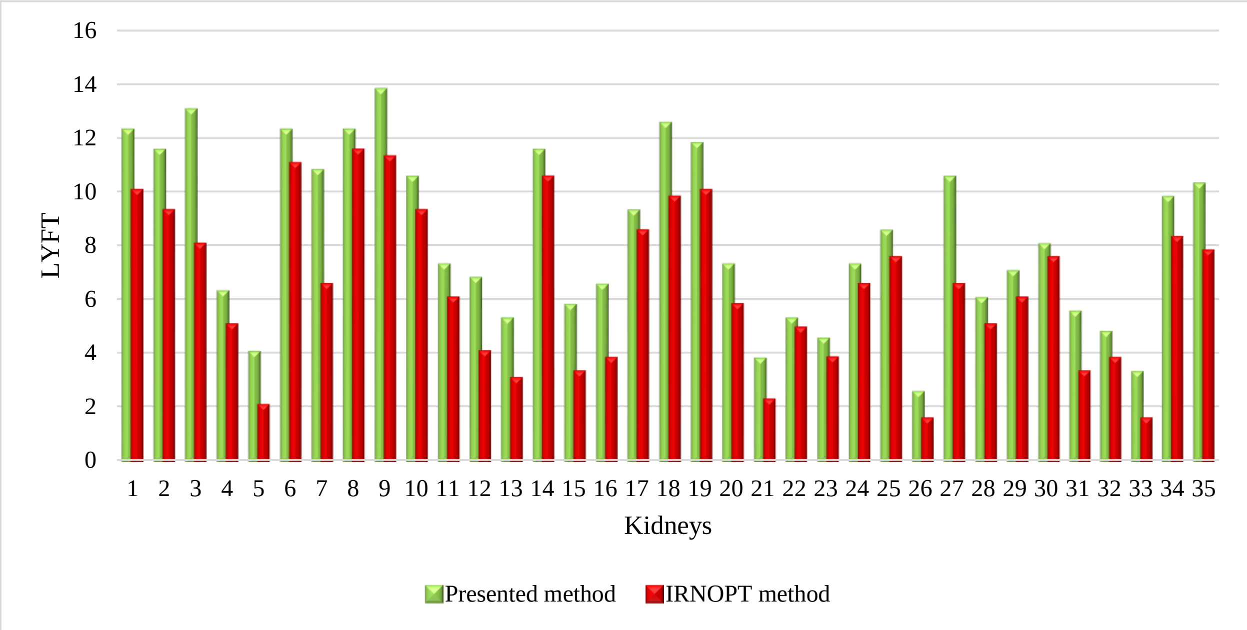

Fig .4. Comparison of the LYFT parameters of the presented method with the current IRNOPT allocation system.

According to the results and the obtained parameters values for the selected organ-patient pairs, the presented DEA approach in this research by considering internal structures outperforms the current allocation system in Iran. Finally, in figure 5, the cumulative results of the WT, QALY, and LYFT measures for all of 35 kidneys are presented. It indicates that cumulative values of the WT, QALY, and LYFT measures have been improved by 36.88%, 39.77%, and 28.06% in the developed approach in this study.

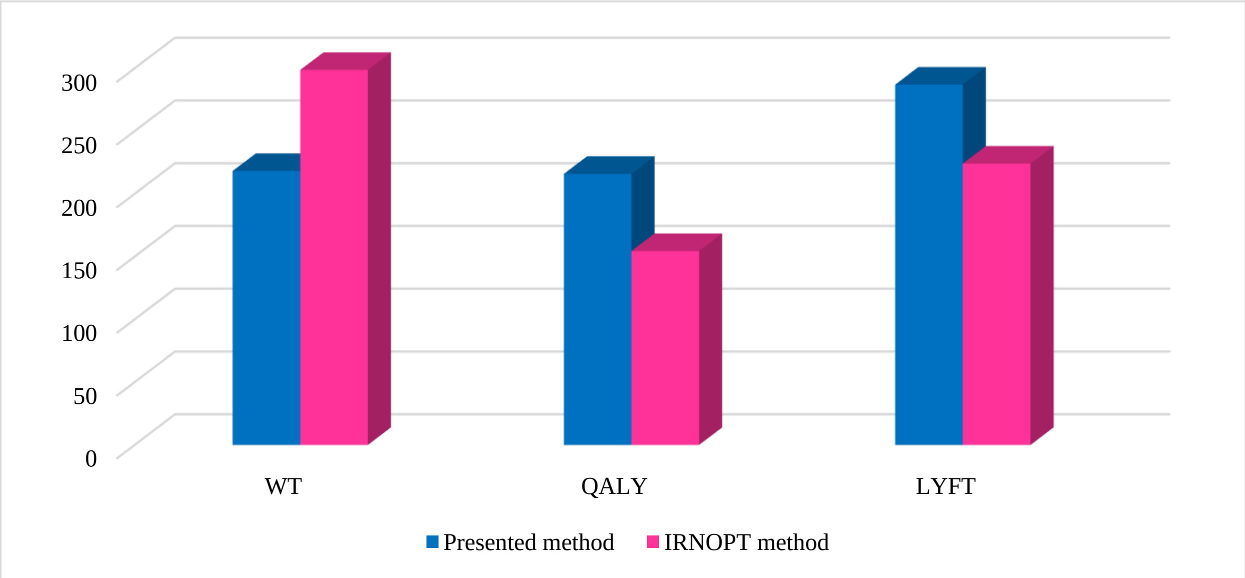

Fig .5. Comparison of the cumulative results of the WT, QALY, and LYFT measures for all of the 35 kidneys in the presented method with the current IRNOPT organ allocation system.

5- Managerial insights

This study provided a DEA approach with internal structures for organ allocation problem. Notably, managerial insights are as follows: (1) results in this study demonstrate that considering internal structures in kidney allocation DEA approach outperforms the black box DEA method (cumulative values of the WT, QALY, and LYFT measures have been improved by 36.88%, 39.77%, and 28.06% in the developed approach in comparison to the IRNOPT approach) because it can investigate more aspects of the organ allocation problem and it is closer to the problem's reality, (2) initial qualified organ-patient pairs were indicated by IRNOPT experts, and after that DEA model was utilized to calculate the organ-patient pairs' efficiencies. Furthermore, as a result of the outstanding performance of the presented model in all of the investigated measures, initial qualified organ-patient pairs can also be selected by the DEA models, (3) considering figure 5 and cumulative results show that the greatest improvement belongs to the QALY measure. It means that the presented approach in this study, in terms of quality, performs better than quantity and decision-makers can use this method if the quality is more important for them in kidney allocation problem and (4) the additive decomposition approach informs decision-makers that this method can be one of the best approaches to deal with network structures in DEA models.

6- Conclusions and future research directions

In healthcare systems, organ transplantation is a complex treatment technique. This treatment differs from others in that it requires both a recipient (a patient who needs an organ to improve their quality of life or to survive) and a donor (a living or dead person who donates organs). Only particular tissues, such as skin, bones, heart, and valves, and specific organ types, such as kidneys, lungs, heart, and liver, are suitable for organ transplantation. Kidney is the most widely transplanted organ followed by liver and heart. In addition, one of the most significant procedures in organ transplantation processes is organ allocation. The procedure of finding the best recipient for the kidney that emerges into the transplantation supply chain system is called the matchmaking procedure or organ allocation. Despite the significant medical advances, due to the enormous disparity among organ supply and demand, a large number of patients die while waiting for organ transplants. Therefore, developing an efficient organ allocation method has a fundamental role in organizing organ demand and supply.

In this research, an organ allocation approach based on a two-stage network DEA model for kidney allocation problem was presented. This approach utilized input, intermediate, and output measures for evaluating efficiencies of qualified organ-patient pairs by considering internal structures instead of black box DEA models. To the best of our knowledge, this is the first study that uses two-stage network DEA models for kidney allocation problem. Finally, findings demonstrate that presented approach in this study outperforms the current organ allocation system in Iran. Finally, future research directions are as follows:

- In this study, WT, QALY, and LYFT were considered as investigated measures in kidney allocation problem. Therefore, other measures or criteria can be investigated in the kidney allocation problem.
- Considering internal structures in DEA models can clarify the relationship between problem parameters and other components in the problem, which can be utilized in other healthcare systems.
- In this research, the two-stage network DEA model was used and as a future direction, other structures can be utilized to model this problem.
- DEA approach showed that this method could have a suitable performance for ranking organ-patient pairs. Moreover, other methods for ranking these pairs can be utilized and compared to the DEA approach.
- Additive decomposition approach in DEA models was used to model the organ allocation problem. Thus, other approaches like the multiplier method can be utilized.

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