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An Augmented Data Envelopment Analysis Approach for Designing a Health Service Network

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Abstract

Background and Objectives: Health centers are taken into consideration as the most important sectors due to providing health care services to the people. Therefore, there is a need for a performance evaluation system to evaluate efficiency and effectiveness of health centers' human resource, running processes, and programs to improve their competitive power.

Methods: To measure the efficiency and productivity of decision making units (DMUs), data envelopment analysis (DEA), which is a nonparametric technique, is considered as the most common tool and can be applied to compare the performance of health centers. However, being DMUs homogenous is one of the underlying assumptions of DEA which prevent us from devising this technique because health centers provide different services, and thus, they are incommensurable. To overcome this barrier, a novel DEA technique is developed to select the best locations for health centers of Iran's healthcare system.

Findings: A practical case of health service network for urban residents' health center (towns) in Fars province incorporated into the proposed technique. The candidate locations for health centers were ranked in terms of efficiency using novel DEA technique, and then, the sensitivity analysis was conducted on final results.

Conclusions: The obtained results imply the high performance of the proposed technique in the ranking of efficient health centers in health care systems. Moreover, this technique introduces a comprehensive performance evaluation tool for health centers and also aids managers and decision-makers to more accurately plan for selecting the best candidate location for health centers along with saving the resources.

Keywords: Health service network design, Healthcare systems, Health centers, Data envelopment analysis.

Background and Objectives

"Reducing health inequalities" as the strategic goal of health systems could not be achieved unless making the health services accessible and available to all communities. In the most cases, a general health care system, either in developing countries or in the developed ones, consists of the three-tier hierarchical system including primary health centers (PHCs), regional health centers (RHCs), and district health centers (DHCs). Giving first aid, primary care, or preventive health services to people is the responsibility of PHCs. RHCs such as clinics are in charge of those services that don't be provided at the first tier like therapeutic and limited curative services. Lastly, giving some specialized care services is the responsibility of DHCs like specialty hospitals.[1,2] Figure 1 depicts the structure of the health service network.

As health centers account for the main parts of expenditure of healthcare systems throughout the world, the efficiency of these centers should be improved. In this regard, it should be noted that measuring the efficiency of health centers is not trivial. In the existing literature, the preferred method to measure and analyze the performance of some similar units like healthcare centers are data envelopment analysis (DEA) and other related techniques like Malmquist indices and distance functions for analysis. The main purpose of DEA is to find the best practice of decision making units (DMUs) as an efficient unit that envelops all inefficient DMUs. Measuring the distance to the optimal frontier, the efficiency value of each DMU can be achieved. Almost all DEA models associate with estimating a technical efficiency score, bearing in mind that the optimal resource allocation is not part of the measure.

A system is called technically efficient when it achieves the highest level out of the theoretical production

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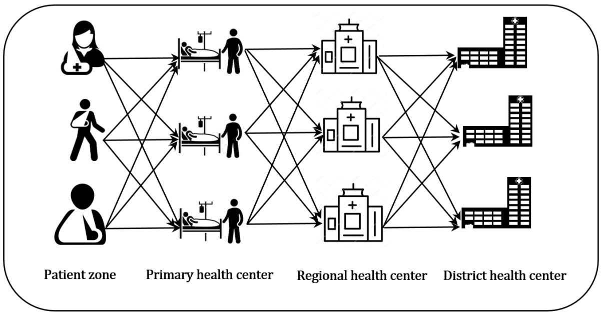

Figure 1. A Schematic View of The Health Service Network.

possibilities. As DEA is considered a nonparametric approach, it needs no specific production function. In other words, the processes within DMUs are assumed as a black-box while all particular inputs are transformed into the characterized outputs over the production process. Consequently, there is a need to know all inputs and outputs, that is, why the DEA technique is a common application to assume multiple inputs and outputs concurrently over the evaluating process of units. In this regard, this paper aims to develop and apply a novel DEA technique to evaluate the efficiency of health centers. Moreover, this paper contributes to the related literature by integrating the standard and inverted DEA model to investigate and evaluate the technical efficiency of a pool of potential locations for PHCs as well as RHCs and DHCs. The main contributions of this study are as follows:

- Presenting a novel health network design consisting of PHCs, RHCs, and DHCs;
- Tailoring an augmented DEA model to selecting best locations for PHCs, RHCs, and DHCs based on their performance efficiency;
- Applying the model and solution method by using a real case in Fars province in Iran to investigate their practicality in the real world.

The rest of the study is arranged as follows. The related study in literature review section. Method section provides the research methodology (DEA method), and a real-world case study is incorporated into the developed method. Finally, the obtained results and conclusion of the research, as well as suggested fields for future research, are presented in the results section and the conclusions and future research section, respectively.

Literature Review

In this section, a background of related literature is reviewed by two major aspects of the current research: health service network and DEA method in health services. These studies are reviewed in two sections: Health Service Network and DEA in Healthcare.

The Literature of the Health Service Network

Generally, a health service network includes three-tier which addresses various levels of health services to patients[1]: PHCs that is in charge of providing the primary health services, the first aid cases, and the preventive health services,[2] RHCs that is responsible for some curative and therapeutic process, and[3] general or specialized DHCs that provides more specialized and curative services. In this regard, common service providers are not much cost to be established owing to being visited frequently along with attracting short trips; while specialized and professional service providers are almost very costly to be constructed due to being referred less frequently along with attracting long trips.[3] Designing a healthcare network, the number of healthcare centers to be founded, and their best-fit location is assumed among the key strategic decisions.[4]

At any rate, taking several qualitative and quantitative factors into account, the best-fit location of healthcare facilities should be identified. In this relation, many various location-allocation mathematical models have been proposed in healthcare systems; that is the location-allocation of health service providers for nomadic populations,[5] highly developed cities,[6] city areas,[7] rural areas,[8] primary care providers,[9] preventive healthcare facilities,[10] clinics,[11] community healthcare facilities,[12] public hospitals,[13] perinatal facilities,[14] specialty care providers,[15,16] and long-term care providers.[17]

However, since the network structure of health services is a hierarchy, it seems better to use hierarchical location-allocation models. In these models, along with designing the optimal network, the interactions between different health care facilities belonging to the different echelon of the network should also be taken into consideration. Among the healthcare literature, a three-level hierarchical model has proposed by Galvão et al.[18] In this model, the location of basic units, maternity homes and neonatal clinics, the flow of mothers from demand zones to healthcare facilities and between a group of healthcare facilities have been investigated. In the continuation of this study, Galvão et al[14] have extended this model by considering load balancing as well as the equitable distribution between existing facilities as the main concerns of the model.

Yasenovskiy and Hodgson[3] have developed a mathematical model for a three-level hierarchical system to determine the optimal location of healthcare providers as well as the optimal allocation of demand zone. The levels of their model include the medical centers, the local health centers, and community health centers.

In a bi-objective optimization model, Mitropoulos et al[19] have provided an optimization programming for locating primary healthcare centers aiming to (1) minimizing the distance between patients and health care facilities, and (2) trying to equitably distribute the healthcare facilities among the population. In a bi-level hierarchical multi-service model, Mestre et al[20] have found the best location of two kinds of healthcare centers, i.e., central hospitals and district hospitals. Besides, aiming to minimize the total travel time in the healthcare network, the optimal ascendant and descendent flows associated with two-way referrals of patients in the hospital and the optimal capacity of each facility are the other decision variables of the proposed model. Mitropoulos et al[21] have also developed an optimization model in which the best location of healthcare facilities is determined, and which facilities should be expanded, upgraded, or closed, as well as which ones should give the basic vital services to the people, are specified. Mestre et al[22] have proposed two stochastic location-allocation optimization models to tackle the inherent uncertainty of parameters in the (re)organization of the two-tier hierarchical healthcare network, including the district and central hospitals. For more information about the supply chain in healthcare, the interested readers are referred to Hosseini-Motlagh et al,[23] Cheraghi et al,[24] Issabakhsh et al,[25] Samani,[26-28] Bashiri et al.[29, 30]

The Literature of DEA in Healthcare

DEA has been considered as one of the most prevailing techniques to measure the efficiency of DMUs, such as similar healthcare centers. For the first time, by Charnes et al[31] have introduced the DEA technique, and then, Banker et al[32] have extended this method to measure and assess the efficiency of homogenous units. Much research on efficiency estimating of hospitals was reported in the related literature.[33] In this research, various versions of DEA models have been utilized to evaluate the efficiency of hospitals. Review research about the use of DEA for productivity and efficiency measurements in healthcare were conducted by Hollingsworth et al.[34] Using both mathematical programming frontier approach and econometric techniques, Worthington[35] have examined the efficiency measurement for healthcare services. To investigate the efficiency of Turkey' healthcare systems, Ersoy et al[36] have devised the DEA method to evaluate the technical efficiency of 573 hospitals in Turkey. They have found that less than 10% of Turkish hospitals efficiently operate in comparison to others. In this DEA model, the inputs were number of beds, number of specialists, and number of primary care physicians, and surgical operations, inpatient discharges, and outpatient visits were considered as the outputs of the model.

In comprehensive research in 2002, the performance of hospitals belonged to the Iranian Social Security Organization (SSO) are evaluated by Hajialiafzali et al[37] devising the DEA method. They have found that 26 hospitals out of 53 operate efficiently. Moreover, regarding the super efficiency DEA method developed by Andersen and Peterson,[38] they have applied this model to rank the total hospitals in terms of efficiency. Additionally, they have adopted an average number of staff beds, full-time equivalent (FTE) medical doctors, the total number of FTE nurses, the total number of another person in FTE as the inputs of their model. On the other hand, the total number of medical intervention and the number of major surgeries and were considered as outputs. From a different perspective, Lee et al[39] have investigated the relationship between technical efficiency and the hospital ownerships in Florida for 4 years. In their study, considering hospital size, a number of staff, service complexity, and expenses for the medical suppliers as the inputs and number of FTE trainees, the Medicare case-mix adjusted number of discharges, and number of outpatient as the outputs of a DEA model, they have measured the technical efficiency for each hospital. The results have shown that non-profit hospitals were more efficient compared to profit ones, and also, the teaching hospitals operated more efficient than non-teaching hospitals. In research on healthcare facilities in East Spain, a system to evaluate the efficiency of healthcare facilities has been designed by Caballer-Tarazona et al.[40] They have evaluated the performance of three healthcare service units so that their method benefits the evaluation process of both hospitals' managers and health administration controlling hospitals. The obtained results have implied that the efficiency of the healthcare service units was above the mean. In an analogous study, Dotoli et al[41] have chosen similar inputs but some surgeries and days of hospitalization were assumed as outputs.

In an analogous study in Iran, the technical efficiency of 28 similar types of health centers (public and private hospitals) have been measured by Shahhoseini et al[42] with the difference that the inputs were the number of active beds, number of nurses, number of physicians, and number of other professionals. In a distinct study, using a dataset for 11 consecutive years, the relationship between technical efficiency and hospital specialization have been analyzed by Lindlbauer and Schreyogg.[43] The obtained results implied that efficiency has a negative relationship with case-mix specialization, whereas medical specialization has a direct impact on technical efficiency. During 2005–2009, Fragkiadakis et al[44] have evaluated the economic efficiency, as well as operational, for 87 Greek public hospitals using DEA method. They have also obtained the efficiency trends over time, along with the factors that can interpret the results of efficiency evaluation. In another study, considering the geographical location in performance evaluation, a multi-group DEA model has been proposed by Rezaee and Karimdadi.[45] In this model, some operational beds, the total number of personnel, and the number of medical equipment were assumed as inputs, and the bed-day and bed occupancy rate, the number of inpatients, the number of outpatients, and the number of special patients were considered as outputs.

In the literature of DEA, cross-efficiency has been broadly used in the research. For example, in a region of Southern Italy, the performance of hospitals has been evaluated using fuzzy cross-efficiency DEA model by Costantino et al.[46] In this model, triangular fuzzy numbers are considered to imbed the uncertainty in data, and then by compromising between objectives, a triangular fuzzy efficiency for each hospital through a cross-evaluation has been estimated. Finally, to obtain the rank of hospitals, results were de-fuzzified. In an innovative study in an Italian region, Dotoli et al[41] have proposed an innovative cross-efficiency DEA method to assess the efficiency of DMUs under fuzzy uncertainty and then applied the proposed method to performance evaluation of healthcare systems. Ruiz and Sirvent[47] have provided a fuzzy cross-efficiency evaluation based on possibility measure. The proposed method can be utilized for fuzzy inputs and convex outputs. Moreover, to tackle the alternate optimal results for the weights, they have also developed benevolent and aggressive fuzzy formulations. In the previous works, some papers focused on the generating weights in cross-efficiency DEA model.

In another research, Hatam[48] presented a technique of DEA and it is used for evaluating the efficiency of 18 general hospitals affiliated to social security organization in Iran. Yazdian Hossein Abadi et al[50] implemented resource allocation to improve the efficiency of the hospital. Their model was a goal programming model to calculate common weights that followed minimum common weight deviation from the values calculated by the DEA's primary. Authors considered 30 hospitals with 2 outputs and 4 inputs, for allocating the resources. Adjusted admissions and outpatient visits were the outputs and bed, the number of services provided by hospitals, total hours worked per week and operational expenses were inputs. Kiadaliri et al[49] reviewed studies that calculated hospitals technical efficiency in Iran and quantified the model specifications impact on the reported efficiency scores by using meta-regression analysis.

In the reviewed works, researchers have tried to generate weights in cross-efficiency DEA model. However, Lam[51] have proposed a novel approach by applying mixed-integer linear programming, super-efficiency DEA model, and discriminant analysis to obtain suitable weight sets to be used in cross-evaluation computing. In a review study, Wu et al[52] have investigated the cross-efficiency DEA technique eliminating the assumption of average cross-efficiency scores, and to obtain weights for ultimate cross-efficiency scores, they have devised the Shannon entropy. Another cross-efficiency DEA model has been provided by Wu et al[53] for goal setting of all DMUs. In this model, some secondary goal models were considered to obtain weights assuming both desirable and undesirable cross-efficiency goals for each DMUs. The obtained results demonstrated that the cross-efficiency goals could be reachable and also improved for the DMUs. Wu et al[54] have developed a cross-efficiency DEA method regarding improving in Pareto frontier by integrating cross-efficiency Pareto improvement and Pareto optimality estimation models. Their adopted approach was applicable for generating a common set of weights for inputs as well as outputs and then, based on obtained weights, calculating efficiency of all DMUs.

For more information about DEA in healthcare, the interested readers are referred to Haeri et al,[55] Rezaee et al,[56] Peykani et al.[57-59]

Methods

Non-parametric methods such as DEA are considered as a prevailing technique to evaluate technical (technological) efficiency. Behind the concept of DEA, technical efficiency indicates that in a given level of outputs, it tried to minimize the number of inputs. In this section, to evaluate the technical efficiency for a pool of potential locations for PHCs as well as RHCs and DHCs, a DEA method is devised due to incorporating the relationship investigation between inputs and outputs into the model. In this respect, each location alternative assumed as a DMU to be ranked in terms of technical efficiency. The merit of this method is that it requires neither pre-specified weights of inputs and outputs nor their normalized values. Indeed, in the DEA methods, the weights play the role of decision variables and are allowed to take values which the efficiency scores be maximized. However, even though this flexibility allows the DEA method to specify inefficient DMUs, in case of classic production frontier, DEA method cannot discriminate the efficient DMUs on the efficient frontier that they operate in the same performance and efficiency score.

To overcome this drawback, two linear optimization models are simultaneously solved which modify the DEA method. The modified DEA method consists of the standard model of DEA and the inverted model, which are proposed by Charnes et al,[31] respectively. The standard model achieves efficient frontier whereas the inverted model seeks to reach the anti-efficient frontier (see Figure 2).

As can be seen, the upper (green) frontier (i.e., efficient frontier) includes best practice DMUs (J and I), and the bottom (red) frontier (i.e., anti-efficient frontier) envelopes those of the worst practice (M and N). At any rate, DMUs L and P attend in both frontiers which can be assumed neither as the best-practice nor the worst-practice DMUs. In continuation of this section, the explained modified DEA is devised to evaluate the efficiency of each potential location. To this goal in the following, the standard and inverted DEA are introduced.

Standard DEA Model

The following notations are used for the formulation of the DEA models:

a	Index of DMUs; $a=\{1,2,\ldots,A\}$
b	Index of inputs; $b=\{1,2,\ldots,B\}$
c	Index of outputs; $c=\{1,2,\ldots,C\}$
y_{ba}	Parameter attributed to the input b of DMU a
x_{ca}	Parameter attributed to the output c of DMU a
ω_k .	Free decision variable; representing the measure of efficiency for the investigated DMU k
μ_a	Positive decision variable; representing the weight of DMU a

The standard DEA model is formulated as follows:

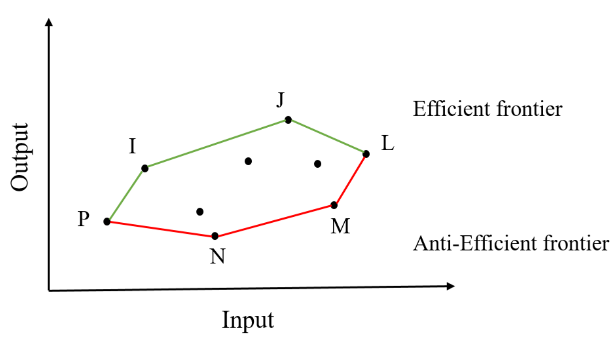

Figure 2. The Schematic Demonstration of the Efficient and Anti-Efficient Frontiers.

$$\min q_{uk}^* = \omega_k$$

$$\sum_a y_{ba} \times \mu_a \le \omega_k \times y_{dl} \qquad \forall b \qquad (1)$$

$$\sum_a x_{ca} \times \mu_a \ge x_{cl} \qquad \forall c$$

Inverted DEA Model

Employing the mentioned notations, the inverted DEA formulation is presented in the model (2).

$$\max q_{vk}^* = \omega_k$$

$$\sum_a y_{ba} \times \mu_a \ge \omega_k \times y_{bk} \qquad \forall b \qquad (2)$$

$$\sum_a x_{ca} \times \mu_a \le x_{ck} \qquad \forall c$$

Regarding models (1) and (2), q_{uk}^* and q_{vk}^* reflect the efficiency scores of the standard and inverted DEA models, respectively. It is worthy to note that q_{uk}^* and q_{vk}^* take values within intervals (0,1] and $[1,+\infty)$, respectively. Therefore, to have the same scale for q_{vk}^* and q_{uk}^*, the efficiency score of the inverted model is transformed to $1-\frac{1}{q_{vk}^*}$, and then, the final efficiency score can be obtained by: $qi_k^* = \alpha * q_{uk}^* + (1-\alpha) * \left(1-\frac{1}{q_{vk}^*}\right)$ where (α) and $(1-\alpha)$ are considered the weight for inputs and outputs, respectively. Values for α is determined by decision-makers. In other words, by determining the value for α, more (or less) importance can be attached to the standard DEA model from 0.5 to higher, e.g., 0.6, 0.7, 0.8 and 0.9, (or lower, e.g., 0.1, 0.2, 0.3 and 0.4) values to measure the efficiency for changes in value of *(α)*. However, equal importance (α = 0.5) for the inputs and outputs are considered and implied this value in formulations (1) and (2) in its convenience form as $qi_k^* = \frac{q_{uk}^* + \left(1-\frac{1}{q_{vk}^*}\right)}{2}$. qi_k^* is called the aggregated indicator for each DMU which can be utilized as follows by classifying the possible values into three ranges:

1. It is less than or equal to $\frac{q_{uk}^*}{2}$ provided that DMU *k* belongs only to the anti-efficient frontier when $q_{vk}^* = 1$ (e.g., DMUs N and M).
2. It equals to $\frac{1}{2}$ provided that DMU *k* belongs to the efficient and also anti-efficient frontiers when $q_{uk}^* = 1$ and $q_{vk}^* = 1$ (e.g., DMUs L . and P).
3. It is greater than $\frac{1}{2}$ provided that DMU k belongs only to the efficient frontier when $q_{uk}^* = 1$ and

$q_{vk}^{*} \in (1, +\infty)$, (e.g., DMUs I and J). In this case, DMU k operates highly efficient and is in the best performance.

The Criteria

In this sub-section, some criteria are introduced to back the decision about the location of health care centers regarding the method mentioned above. The criteria are divided into two divisions: inputs (negative criteria) and outputs (positive criteria). Regarding the concept of DEA, the criteria that should be decreased are considered as inputs, and contrarily, the criteria that should be increased assumed as outputs. The candidate locations for health centers (i.e., PHCs, RHCs, and DHCs) have behaved as DMUs. As the responsibilities of each health care different as well as numerous, the most important criteria are taken into consideration for each one.

In the present study, the candidate locations for PHCs, RHCs, and DHCs are considered to be the DMUs and the input and output factors for each health center are driven according to the experts' knowledge and viewpoint. We measured the traffic as an input indicator based on the average time between each health (PHC, RHC, and DHC) facility, and the average time spent to get to the health center. The pollution is measured according to the pollution rate of each location. The natural disaster occurrence is estimated with respect to the number of faults close to a candidate location. The available places for establishing each health centers are measured based on the number of available places to establish a health facility in each district. The population density is calculated based on the population around a candidate location for health facilities. The mentioned criteria are defined as follows (Table 1):

A Practical Case Study

In this section, a practical case study is applied to the proposed method, to show the application in designing the healthcare service network for urban residents' health center (towns) in Fars province. This province, with 122 608 km^2 of area, is one of the important regions in the country that requires special attention to move toward a sustainable development using a comprehensive plan. In this respect, it should be noted healthcare and medical conditional not only affect the province development, but also play a significant role to improve the public health welfare in general. The goal of this study is to investigate the healthcare and medical system in Fars province to improve the healthcare system by providing a robust and reliable design/plan.

As can be observed in Figure 3, Fars province is composed of 29 towns (nodes) with a total population of 4 851 274, each of which is assumed as a patient zone as well as the initial potential location for establishing a PHC. Additionally, for establishing RHCs, towns Marvdasht, Abadeh, Estahban, Abadeh, Kovar, Estahban, Bovanat, Arsanjan, Khonj and Pasargad have been selected as the initial candidate locations and for establishing DHCs towns Marvdasht, Abadeh, Estahban, Bovanat, and Khonj have been chosen, given that the population and geographical location of each town is taken into account as important factors for selecting the potential locations.

Table 2 shows the population and geographic coordinates of each town (i.e., patient zone).

Results

In this section, using a modified DEA model regarding the criteria introduce earlier in methods section, the efficiency of each potential location for health centers is evaluated. Additionally, Tables 3-5 demonstrate the means, standard deviations, and the range of changes for inputs and outputs. To obtain the efficiency, models (1) and (2) should be solved for each DMU (i.e., each town), for each health center (i.e., PHCs, RHCs, and DHCs), to know the best alternative locations for establishing the mentioned centers. Solving the DEA models, efficiency score (q_{uk}^{*}) and anti-efficiency score (q_{vk}^{*}) are obtained, and then, to determine the final efficiency score for each potential location, the aggregated indicator (qi_{k}^{*}) is calculated.

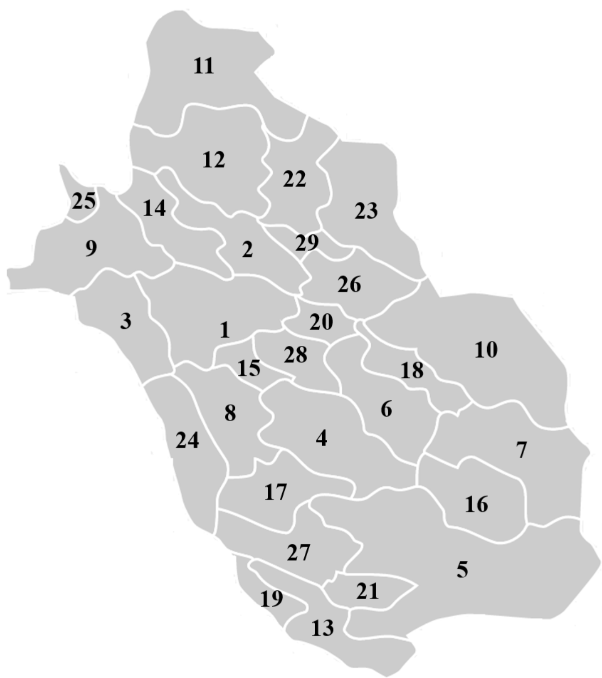

Figure 3. The Boundary of the Patient Zones.

Table 1. The Mentioned Criteria

Criteria	Reason
Traffic	As the availability of patients to the health centers is of great importance, locations with less traffic are more desirable. Hence, this criterion is considered as an input for primary, regional, and DHCs.
Pollution	In terms of hygiene and sanitation, locations with less pollution are better due to health safety. Additionally, the treatment may take a long time, and thus, it is more desirable that the patients give treatment in a location with less pollution and risk. Therefore, this criterion is assumed as input for primary, regional, and DHCs.
Population density	The high population density is more desirable due to the concentration of people to receive health services. Therefore, this criterion is assumed as an output for primary, regional, and DHCs.
Natural disasters incidence	A location with a high rate of disaster striking is hazardous for primary, regional, and DHCs and decrease the efficiency due to disruption. Given this assumption, this criterion is considered as an input.
Appropriate workplace	The environment conditions like temperature, light, humidity levels, etc., need to be under control for staff and patient convenience. Hence, this criterion is considered as an output for primary, regional, and DHCs.
Skilled staff	Giving high-quality services and products to patients requires a sufficient number of trained and well-versed staff in health centers. As this criterion has a direct relation to the increase in efficiency, this criterion is considered as an output factor for primary, regional, and DHCs.

Table 2. Population and Geographic Coordinates of Each Patient Zone

Patient Zone	Town Name	Population	PHC candidate	RHC Candidate	DHC Candidate
1	Shiraz	1869001	√		
2	Marvdasht	323434	√	√	√
3	Kazeron	266217	√		
4	Jahrom	228532	√		
5	Larestan	213930	√	√	
6	Fasa	205187	√		
7	Darab	201489	√		
8	Firozabad	121417	√	√	
9	Mamasani	117527	√		
10	Neiriz	113291	√		
11	Abadeh	100831	√	√	√
12	Eghlid	93763	√		
13	Lamerd	91782	√		
14	Sepidan	91049	√		
15	Kovar	83882	√	√	
16	Zarindasht	73199	√		
17	Ghir o Karzin	71202	√		
18	Estahban	68850	√	√	√
19	Mohr	64827	√		
20	Khorameh	54864	√		
21	Gerash	53907	√		
22	Khoram bid	50522	√		
23	Bovanat	50418	√	√	√
24	Farashband	45459	√		
25	Rostam	44386	√		
26	Arsanjan	43725	√	√	
27	Khonj	41359	√	√	√
28	Sarvestan	38114	√	√	
29	Pasargad	30118	√	√	

Table 3. Inputs and outputs properties; PHCs

	Input/Output	Average	Standard Deviation	Min	Max	Maximum Correlation
Primary health center	Traffic	53.06	20.89	20	87	0.03
	Pollution	57.58	29.16	14	100	0.03
	Population density	19.20	6.00	10	30	0.04
	Natural disasters incidence	2.68	0.95	1	4	-0.01
	Appropriate workplace	3.31	1.28	1	5	0.04
	Skilled staff	56.13	22.66	23	97	0.06

Table 4. Inputs and Outputs Properties; RHCs

	Input/Output	Average	Standard Deviation	Min	Max	Maximum Correlation
Regional health center	Traffic	49.80	20.24	20	84	-0.23
	Pollution	60.70	32.18	14	100	-0.23
	Population density	19.70	7.14	10	28	0.38
	Natural disasters incidence	2.80	0.87	1	4	-0.13
	Appropriate workplace	3.70	1.10	2	5	0.38
	Skilled staff	57.90	21.26	26	95	0.33

Table 5. Inputs and Outputs Properties; DHCs

	Input/Output	Average	Standard Deviation	Min	Max	Maximum Correlation
DHC	Traffic	61.20	17.83	42	84	0.65
	Pollution	60.40	33.29	14	90	-0.49
	Population density	22.20	6.04	11	28	0.33
	Natural disasters incidence	2.20	0.74	1	3	-0.49
	Appropriate workplace	4.0	1.09	2	5	0.33
	Skilled staff	55	24.37	26	95	0.11-

Towns with acceptable efficiency score are considered as potential locations to establish the health centers. In this regard, the ‘acceptable’ level is determined based on managerial views and belongs to those potential locations which their aggregated indicator is greater than 0.5 (i.e., $qi_k^* > 0.5$). Tables 6-8 show the efficiency, anti-efficiency, and final aggregated efficiency for each PHC, RHC, and DHC, respectively. Eventually, the mentioned regions are ranked based on aggregated efficiency values. Figure 4 shows a schematic demonstration of locations for establishing PHCs, RHCs, DHCs.

The highlighted towns in grey color in Tables 6-8 are capable of establishing the desired facilities since they have reached the minimum acceptable score. Therefore, these locations can be introduced as potential sets in the proposed DEA method. As this method omits the undesirable locations (i.e., those with $qi_k^* < 0.5$), the complexity decreases in case of a large number of potential location (i.e., DMUs) that unnecessary investigations are reduced (i.e., DMUs), and thus, the practicality of proposed method is improved due to closeness to real-world applications.

Sensitivity Analysis

In this section, the sensitivity analysis of the obtained results is conducted. Herein, regarding the final efficiency score, that is $qi_k^* = \alpha * q_{uk}^* + (1-\alpha) * \left(1 - \frac{1}{q_{vk}^*}\right)$, the analysis is performed on parameter α . As can be observed in Table 9, raising the level of α from 0.5 to 0.6, the final locations for establishing PHC increase from 15 to 18 (Shiraz, Ghir o Karzin, and Estahban are added to established locations when the level of α arrived to 0.6). Similarly, raising the level of α to 0.7, 0.8, and 0.9, final locations for PHC increase to 21, 23, and 25, respectively. So, with increasing the α from 0.6 to 0.7, 0.8, 0.9; Larestan, Eghlid, and Khoram bid, Jahrom and Rostama, Gerash and Bovanat are established, respectively. Table 10 shows the increase in the level of α and corresponding changes in the number of final locations for RHC. As can be seen, the number of selected location for establishing RHC is 6 and 9 at the level of 0.6 and 0.7 for the parameter α, respectively. In other word, Larestan, Bovanat, and Khonj are established with raising the level of α as RHCs. Moreover, raising the level of parameter α, all candidate locations are chosen for establishing RHC. In our study,

Table 6. The summary of results for the districts to identify the most efficient locations for PHCs

DMU	Town	[illegible]	[illegible]	[illegible]	Ranking
1	Shiraz	0.642	1.529	0.494	16
2	Marvdasht	1.000	1.003	0.502	13
3	Kazeron	0.812	1.796	0.628	9
4	Jahrom	0.615	1.126	0.364	21
5	Larestan	0.672	1.212	0.424	19
6	Fasa	0.966	1.462	0.641	7
7	Darab	1.000	1.641	0.695	6
8	Firozabad	0.886	1.181	0.520	12
9	Mamasani	0.799	1.847	0.629	8
10	Neiriz	0.489	1.000	0.244	27
11	Abadeh	1.000	1.855	0.730	3
12	Eghlid	0.726	1.000	0.363	22
13	Lamerd	1.000	1.000	0.500	14
14	Sepidan	1.000	2.333	0.786	1
15	Kovar	0.499	1.000	0.250	26
16	Zarindasht	1.000	1.653	0.698	5
17	Ghir o Karzin	0.897	1.000	0.449	18
18	Estahban	0.788	1.214	0.482	17
19	Mohr	0.940	1.416	0.617	10
20	Khorameh	1.000	1.801	0.722	4
21	Gerash	0.562	1.000	0.281	25
22	Khoram bid	0.751	1.000	0.376	20
23	Bovanat	0.621	1.000	0.311	24
24	Farashband	0.477	1.000	0.238	28
25	Rostam	0.697	1.000	0.348	23
26	Arsanjan	1.000	1.885	0.735	2
27	Khonj	0.719	1.389	0.500	15
28	Sarvestan	0.437	1.000	0.218	29
29	Pasargad	1.000	1.170	0.573	11

Table 7. The Summary of Results for the Districts to Identify the Most Efficient Locations for RHCs

DMU	Town	[illegible]	[illegible]	[illegible]	Ranking
2	Marvdasht	1.000	1.000	0.500	4
5	Larestan	0.796	1.000	0.398	7
8	Mamasani	1.000	1.000	0.500	3
11	Abadeh	1.000	1.330	0.624	1
15	Kovar	0.660	1.000	0.330	10
18	Estahban	1.000	1.000	0.500	5
23	Bovanat	0.758	1.000	0.379	8
26	Arsanjan	1.000	1.192	0.581	2
27	Khonj	0.748	1.000	0.374	9
29	Pasargad	1.000	1.000	0.500	6

Table 8. Results Summary of the Districts to Identify the Most Efficient Locations for DHCs

DMU	Town	[illegible]	[illegible]	[illegible]	Ranking
2	Marvdasht	1.000	1.000	0.500	2
11	Abadeh	1.000	1.119	0.553	1
18	Estahban	1.000	1.000	0.500	3
23	Bovanat	0.761	1.000	0.380	5
27	Khonj	0.929	1.000	0.465	4

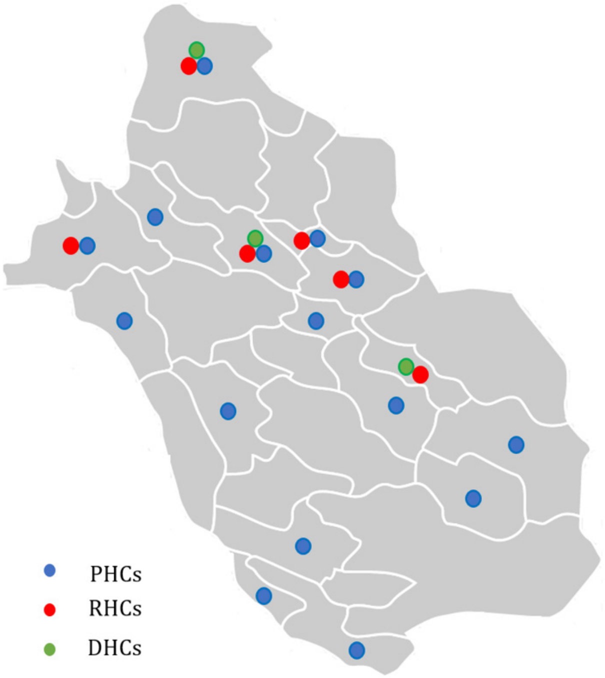

Figure 4. The Final Location for Establishing PHCs, RHCs, and DHCs.

Table 9. Sensitivity Analysis on α Parameter to Selecting PHCs

DMU	Town	$\alpha = 0.5$	$\alpha = 0.6$	$\alpha = 0.7$	$\alpha = 0.8$	$\alpha = 0.9$
1	Shiraz	0.494	0.523	0.553	0.583	0.612
2	Marvdasht	0.502	0.601	0.701	0.801	0.900
3	Kazeron	0.628	0.664	0.701	0.738	0.775
4	Jahrom	0.364	0.413	0.464	0.514	0.565
5	Larestan	0.424	0.473	0.523	0.573	0.622
6	Fasa	0.641	0.706	0.771	0.836	0.901
7	Darab	0.695	0.756	0.817	0.878	0.939
8	Firozabad	0.520	0.592	0.666	0.739	0.813
9	Mamasani	0.629	0.662	0.697	0.731	0.765
10	Neiriz	0.244	0.293	0.342	0.391	0.440
11	Abadeh	0.730	0.784	0.838	0.892	0.946
12	Eghlid	0.363	0.435	0.508	0.581	0.653
13	Lamerd	0.500	0.600	0.700	0.800	0.900
14	Sepidan	0.786	0.828	0.871	0.914	0.957
15	Kovar	0.250	0.299	0.349	0.399	0.449
16	Zarindasht	0.698	0.758	0.819	0.879	0.940
17	Ghir o Karzin	0.449	0.538	0.628	0.718	0.807
18	Estahban	0.482	0.543	0.604	0.666	0.727
19	Mohr	0.617	0.681	0.746	0.811	0.875
20	Khorameh	0.722	0.777	0.833	0.889	0.944
21	Gerash	0.281	0.337	0.393	0.450	0.506
22	Khoram bid	0.376	0.450	0.526	0.601	0.676
23	Bovanat	0.311	0.372	0.435	0.497	0.559
24	Farashband	0.238	0.286	0.334	0.382	0.429
25	Rostam	0.348	0.418	0.488	0.558	0.627
26	Arsanjan	0.735	0.787	0.841	0.894	0.947
27	Khonj	0.500	0.543	0.587	0.631	0.675
28	Sarvestan	0.218	0.262	0.306	0.350	0.393
29	Pasargad	0.573	0.658	0.744	0.829	0.915

the input-oriented model (traffic, pollution and natural disasters incidence) is important than the output-oriented model (population density, appropriate workplace, and skilled staff) so we recommended the output-oriented model in the health services network. However, the model can calculate the trade-off between input and output with changing in the level of α. For the sake of simplicity, we considered equal importance (α =0.5) for the inputs and outputs and applied the above formulation in its simple form. Without loss of generality, in the above formulation, we can give more importance to the standard DEA model by changing α from 0.5 to higher, e.g., 0.6, 0.7, 0.8 and 0.9 (rResults are shown in Tables 9, 10 and 11), values to show that the input-oriented model is important with raising the level of α. On the contrary, decreasing the level of α, outputs that include population density, appropriate workplace, and skilled staff are important and the number of locations decreases. Table 10 also shows how changes in the level of parameter α affect the number of final location for establishing DHC. Raising the level of parameter α to 0.6, 4 locations out of 5 candidate locations are chosen to establish DHC. In other word, Khonj is established with 0.1 change in the level of α as DHC. Additionally, when the level of α exceeds 0.6, all candidate locations are selected for establishing DHC. Figure 5 shows the graphical demonstration of selected locations for establishing PHC, RHC, and DHC under different level of α.

Conclusions and Future Research

In the complexity of real-world cases, employing system engineering models can help to provide both qualified and cost-efficient healthcare services. In this regard, operations research science is considered as one of the most common tools in the healthcare context. In this study, through investigating a case of Fars province, an augmented version of DEA was developed to evaluate potential locations for establishing health care centers and then identify the most efficient one. This method can greatly help managers and researchers to assess the performance of alternatives in the wide variety of multi-criteria decision-making problems. The obtained results showed that the developed method is practical and

Table 10. Sensitivity Analysis on α Parameter to Selecting RHCs

DMU	Town	$\alpha = 0.5$	$\alpha = 0.6$	$\alpha = 0.7$	$\alpha = 0.8$	$\alpha = 0.9$
2	Marvdasht	0.500	0.600	0.700	0.800	0.900
5	Larestan	0.398	0.478	0.557	0.637	0.716
8	Mamasani	0.500	0.600	0.700	0.800	0.900
11	Abadeh	0.624	0.699	0.774	0.850	0.925
15	Kovar	0.330	0.396	0.462	0.528	0.594
18	Estahban	0.500	0.600	0.700	0.800	0.900
23	Bovanat	0.379	0.455	0.531	0.606	0.682
26	Arsanjan	0.581	0.664	0.748	0.832	0.916
27	Khonj	0.374	0.449	0.524	0.598	0.673
29	Pasargad	0.500	0.600	0.700	0.800	0.900

Table 11. Sensitivity analysis on α parameter to selecting DHCs

DMU	Town	$\alpha = 0.5$	$\alpha = 0.6$	$\alpha = 0.7$	$\alpha = 0.8$	$\alpha = 0.9$
2	Marvdasht	0.500	0.600	0.700	0.800	0.900
11	Abadeh	0.553	0.643	0.732	0.821	0.911
18	Estahban	0.500	0.600	0.700	0.800	0.900
23	Bovanat	0.380	0.457	0.533	0.609	0.685
27	Khonj	0.465	0.557	0.650	0.743	0.836

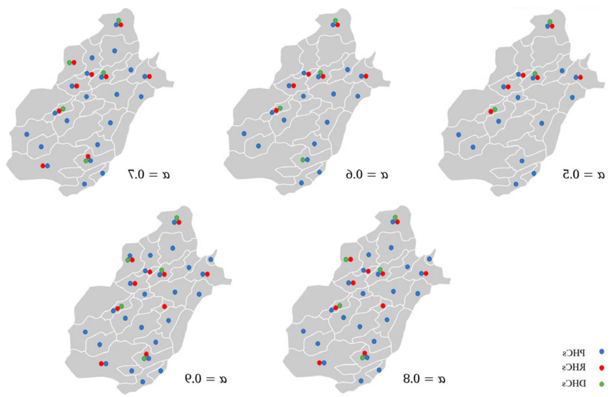

Figure 5. The Final Location for PHCs, RHCs, DHCs Under Different Level of α.

suitable for fully ranking of DMUs, herein the potential location for establishing healthcare centers. It should be noted although this method was applied to a healthcare location problem, it can easily be devised in any problems which deal with evaluating alternatives.

Regarding the proposed method in this study, some research directions can be followed. To evaluate the performance of the proposed technique, it can be compared with other existing multi-criterion decision-making methods. Moreover, to embed the uncertainty of parameters, the fuzzy number can be used instead of a crisp one, and finally, the obtained results from both model can be compared.

Providing both cost-efficient and qualified healthcare services could be realized through using systems engineering models especially in complex cases. Operations research science is one of the most popular system thinking principles that is a fast-growing area of research in the healthcare context. In this paper, an augmented version of DEA was applied to identify the most efficient alternatives as candidate locations for establishing the health care centers in the case of Fars province. This technique is a useful tool for managers, and researchers, who seek to evaluate alternative performance in various multi-criteria decision making studies. The conclusion of this paper indicates that the proposed approach is effective and suitable for fully ranking of DMUs. Although we used the proposed approach in health centers efficiency, it can easily be applied in any other DEA applications.

There are some research realms to be discovered in the future. The proposed technique can be compared with other multi-criteria decision-making techniques. Also, the fuzzy method can be applied rather than a crisp one, and the obtained results can be compared. Finally, the model can be improved for group decision making incorporating different DMs to the process of decision making. Additionally, considering uncertainty approaches in inputs and output of the model could be tailored to develop the health service network design. In this paper, a medium real data was tailored to evaluate the performance of the model. The future direction could be developed by using data for a larger province.

Authors' Contributions

SHM contributed to study design, data collection and analysis, and manuscript drafting. AZF took part in the interpretation of the results and drafting the manuscript. Both authors read and approved the final manuscript.

Competing Interests

The authors declare no competing interests.

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