Healthcare Facility Location: A DEA Approach

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The purpose of the current paper is to apply Data Envelopment Analysis (DEA) to the healthcare facility location problem. First, facility location models used in healthcare facility location planning as well as location objectives and potential problems are examined. Subsequently, a published research study is used to identify demographic factors considered in the selection of candidate towns for the location of a healthcare facility, and to classify these factors into inputs and outputs. A DEA model was developed and solved for each one of the towns in the study, and the results compared to those obtained through the study's proposed factor-weighted approach. Results were analyzed to recognize the DEA approach's strengths over the published study's results.

INTRODUCTION

The International Facility Management Association (IFMA) (www.ifma.org) defines a strategic facility plan (SFP) as a two-to-five-year plan that comprehensively articulates the type, quantity, and location of spaces required to support an organization's business objectives. Also known as location analysis, facility location decisions play a critical role both in the strategic design of systems for a large variety of both public and private organizations and in specifying the optimum location options for various types of facilities (Ahmadi-Javid, Seyedi, & Syam, 2016; Terouhid, Ries, & Fard, 2012). Due to the long-term commitment of both monetary and human resources, the location decision will have a profound effect on different aspects of a company (Epping, 1982). The first theoretical study on location facilities was by Weber in 1909 (Ahmadi-Javid et al., 2016). Since Weber's seminal work various research and applications have been developed and conducted on the topic.

Location decision makers have customarily focused on the economic aspects of locating facilities (Terouhid et al., 2012). Traditionally, the challenge of facility location was to locate one or several new facilities regarding existing facilities and customers in order to optimize some economic measure (Dzator, M. & Dzator, J., 2016). Poorly located facilities or an improper number of facilities can greatly increase capital and inventory costs while an optimum location may offer a competitive advantage (Ahmadi-Javid et al., 2016; Terouhid et al., 2012). Recently, however, there has been a growing interest in sustainable development and a corresponding paradigm shift that views the location decision as having not only economic but also environmental and social consequences.

Facility location modeling takes on an even greater importance when applied to the siting of healthcare facilities since the implications of poor location decisions extend well beyond the cost and customer service considerations in healthcare. If too few facilities are utilized and/or if they are not strategically located, increases in both morbidity and death from disease can result (Daskin & Dean, 2004; Ahmadi-Javid et al., 2016).

Context

Healthcare costs have increased dramatically in most developed economies over the last few decades and it is widely believed that the inefficiency of healthcare institutions, at least in part, has contributed to these rising costs (Worthington, 2004). As a result of globally pervasive trends such as decreasing birth rates, increase in the average life expectancy resulting in the associated growth in elderly population, and increasing environmental problems such as sound and air pollution, healthcare facility locations have become noticeably more critical and important to society (Ahmadi-Javid et al., 2016).

In recent years, the healthcare market in the US has been wrestling with cost containment due to annual healthcare costs that, until recently, have far exceeded the consumer price index. This has resulted in healthcare costs escalating to more than 17% of the gross national product, per the World Bank, (http://data.worldbank.org/indicator/SH.XPD.TOTL.ZS), double that of any other developed country. At this rate, the cost of healthcare in the US is not sustainable. In addition, the market is redefining itself following passage of the Patient Protection and Affordable Care Act (ACA) legislation of March 2010. The ACA, while increasing the number of insured patients, is also reducing the level of reimbursements provided to hospitals and providers; this further exacerbates the pressure to reduce the costs of providing care. The aforementioned, along with turbulent market conditions have forced the healthcare sector to re-examine its business and operational practices. Strategic planning decisions have been reframed in the light of the current lagging economy, an increased demand for services, new global competition and impending legislation reform (Hoadley, Jorgensen, Masters, Tuma, & Wuff, 2010). Facility location planning decisions are no exception and one now finds market analysis, operational review and financial feasibility analysis included in hospital and other healthcare facility plans with the goal of attaining a competitive advantage (Hoadley et al., 2010).

HEALTHCARE FACILITY LOCATION RESEARCH

Facility location is a critical factor when making strategic plans for healthcare programs. The first facility location model for healthcare systems was proposed by Hakimi (1964) and since that time there has been an active research stream in this area. Afshari and Ping (2014) advanced eight challenges of facility location for healthcare services:

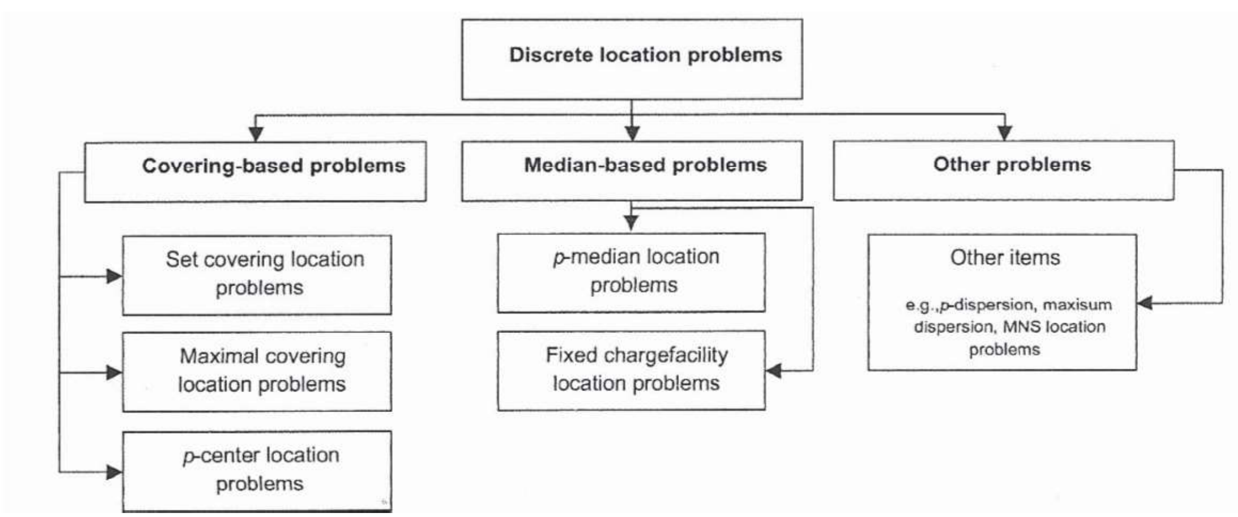
1. difficulties for patients to access healthcare facilities
2. investigating the number of healthcare facilities to cover all patients
3. difficulty of covering all patients' healthcare needs within specified number of healthcare facilities
4. optimizing access to healthcare services to patients with the longest distance
5. dealing with uncertainties in covering patients with healthcare services
6. dealing with varying demands for healthcare services
7. designing a network with various services, various levels and facility types
8. making the decision for the best order and location of healthcare facilities for a combination of challenges.

Ahmadi-Javid, Savedi, and Siddharta, (2016) summarized the literature of the HCF location perspectives from 2000 to 2015 with the following results: (Gould & Leinbach, 1966; Ahmadi-Javid et al., 2016) made one of the first location-allocation studies of healthcare facilities in Guatemala. Rahman and Smith (1999) reviewed location-allocation models used in development planning of health services in developing nations. This resulted in the researchers classifying the studies into four types: (1) determining a number of optimal sites, (2) the location of new optimal sites, (3) evaluating past location decisions, (4) improvement of existing location patterns. Brotcoren, Laporte, and Semet (2003) examined the progression of ambulance location and relocation models over three decades. Daskin and Dean (2004) viewed the location of HCLs from modeling perspective, categorizing HCL models into accessibility, adaptability, and availability models. Li, Zhao, Zhi, & Wyatt (2011) studied methods for locating emergency response facilities. Rias and Viana (2011) looked at applications of operations research in healthcare planning and healthcare management and logistics. Wang (2012) presented a literature review viewing measurement, optimization and impact as issues in inequality in healthcare. Gutiérrez and Vidal (2013) propose a three-dimension framework for home healthcare logistics. Ingolfsson, Budge, and Erkut (2008) provides an overview on planning and management of emergency medical services (Gould & Leinbach, 1966; Günnes & Nickel,2015) provide a short review of public facility location, ambulance planning and hospital layout. Ahmadi-Jivad et al. (2016) refer to the above articles and, given that each article covers a part of healthcare services, use this as proof that the Operations Research discipline lacks a comprehensive review of facility location in healthcare.

Facility Location Models Used in HealthCare

One of the best-known categories of recognized problems in healthcare settings is location problems. In general, these problems can be either continuous or discrete. Continuous location problems concern the facilities location anywhere in the proposed region. Discrete problems refer to demand points which apply only to the candidate location. Daskin and Dean (2004) classified the discrete location problems into three broad categories: covering-based problems, median-based problems, and other problems. Ahmadi-Javid et al. (2016) modified Daskin's classification, presented in Figure 1.

FIGURE 1
A CLASSIFICATION OF DISCRETE LOCATION PROBLEMS



These three location models-- the set covering model, maximal covering model, and P-median model-- summarize the fundamental objectives of healthcare facility location and underlie most of the facility location models used in healthcare. The set covering model and the p-center model treat healthcare service as a binary---a demand node is either covered or not covered. All three models are in the class of discrete facility location models, as opposed to the class of continuous location models (Daskin & Dean, 2004). Therefore, in these models it can be assumed that there is a finite set of possible locations or nodes where facilities can be sited. Accordingly, a location may be represented by several hundred or even several thousand nodes (Valipour, Nedjati, & Kazemi, 2013). These models are discussed briefly below:

The set covering model. The set covering model, also known as the location set covering problem, seeks to locate the minimum number or cost of facilities needed to cover all demands within a specified time or distance. This model seeks to locate the minimum number of facilities required to 'cover' all demand or population in an area (Dzator, M. & Dzator J., 2016).

The maximal covering location model is one of the most common models employed in healthcare planning. First proposed by Church & Revelle (Valipour et al., 2013) the objective of the maximal covering location model is to locate a predetermined number of facilities to maximize the demand or population that is covered (Dzator, M. & Dzator, J., 2016). This model relaxes the condition that all demands must be served within the covering standard, maximizes the number of covered demands using a fixed number of facilities and minimizes the maximum distance (Daskin & Dean, 2004). According to Valipour, Nedjati and Kazemi (2013) a population is covered if at least one facility is located with a pre-defined distance identified as the coverage radius.

The P-median model. The P-median model drops the notion of coverage and minimizes the demand-weighted total distance between demand nodes and the nearest facilities. The model assesses the average distance that a client has to travel to receive service or the average distance that a provider must travel to reach his/her clients (Daskin & Dean, 2004).

Although healthcare facilities should be located as to best respond to the needs of its target public(s), there are constraints that must also be complied with. The major constraints of location literature as it applies to healthcare facilities are accessibility, adaptability and availability (Daskin & Dean, 2004).

Accessibility models are typically straightforward extensions or applications of one of the basic location models. The goals of accessibility models are generally to maximize coverage or to minimize average distance in order to assess the ability of patients or clients to reach the healthcare facility, or in emergency services, the ability of healthcare providers to reach patients (Daskin & Dean, 2004). Accessibility models also attempt to find facility locations that perform well with respect to static inputs. In particular, demand, cost and travel distance or travel time data are generally assumed to be fixed and non-random in this class of models. Thus, the models are often relatively straightforward extensions of the classic models above.

Adaptability models reflect long-term uncertainty, recognizing that future conditions are difficult, if not impossible to predict. These models attempt to find solutions that perform well across a range of future scenarios. Generally, a single set of locations must be identified for all scenarios, but the assignment of demands to facilities can be scenario-dependent. Typical objectives include optimizing the expected system performance, minimizing the worst-case performance and minimizing the maximum regret. Regret measures the difference in performance of the system for a given scenario between the compromise solution and the solution that would have been optimal for the specified scenario (Daskin & Dean, 2004).

Availability models attempt to account for the short-term unavailability of facility locations that result from facilities being busy. Models of facility availability are most applicable to emergency service systems, such as ambulances (Daskin & Dean, 2004).

Healthcare Facility Location Objectives

There is not a single solution that can be applied in every situation as each location decision problem is unique. Intolerable expanses and delay in the realization of healthcare facilities due to the lack of transparency and efficiency in decision making processes often occur. Negative impacts can occur which affect the efficiency of medical service, the physical, psychological and social wellness of the users, visual problems, reduced air quality, noise and economic issues. As healthcare costs have increased financial investment issues have become more important and there has been a greater demand for either maintaining or improving the quality of medical services.

In the past when deciding where to locate healthcare facilities researchers often considered the improvement of only a single objective sufficient to make the determination. Recently, many scholars are treating the problem of where to locate a healthcare facility as a multi-objective problem (Zhang, Cao, Liu, & Huang, 2016). According to Li, Zhao, Zhu, & Wyatt (2011) issues in facility location include proximity to customers, business climate, total costs, infrastructure, quality of labor, suppliers, other facilities and environmental regulation. Other objectives considered have included accessibility (Hodgart, 1978; Langford & Higgs, 2006; Murawski & Church, 2009), cost (Landa-Torres, Manjarres, Salcedo-Sanz, Del Ser, & Gil-Lopez, 2013), cost and equity of accessibility (Ngui & Apparicio, 2011), participation (Gu, Wang, & McGregor, 2010; Li, Zhao, Zhu, & Wyatt, 2011; Zhang, Cao, Liu, Huang, 2016), flexibility in service location selection (Saaty, 1980), number of people within an acceptable travel distance of at least one facility (Gu et al., 2010; Shariff, Moin, & Omar, 2012) reducing cost and increasing utilization criteria (Dokmeci, 1979) influence of distance, transport and accessibility (1990s) cost minimization, demand oriented, profit maximization and environmental concerns (Current, Min, & Schilling, 1990).

Regional Healthcare Facility Location Decisions

A major issue in defining locations for regional healthcare facilities is to guarantee that the most isolated local inhabitants are able to access the facility within an acceptable time frame, particularly in more urgent cases, but also in situations that require frequent visits (Goncalves, Ferreira & Condessa, 2014). A regional healthcare facility should be located as to best respond to the needs of its target public. The emergency medical services act of 1973 stipulated that 95% of service requests had to be served within 30 minutes in a rural area and within 10 minutes in an urban area. As such, Federal legislation has encouraged the use of accessibility models such as the maximal covering model (Goncalves et al., 2014). Generally speaking, individuals able to choose do travel to the health facility that is closest to home. However, they may also opt for a different location, for which the time-distance or cost-distance is lower due to an adequate infrastructure network and/or good public transportation systems (Goncalves et al., 2014).

Location has been found to affect the performance of healthcare facilities, although the variety of services offered at a given site can moderate the effect of location (Mitropoulos, P. et al., 2013). Accordingly, when planning for the siting of a regional healthcare facility, decision makers must utilize a strategy that considers not only the location site but also the effect of services offered within the network of healthcare facilities (Goncalves et al., 2014).

USE OF DEA IN HEALTHCARE FACILITY LOCATION DECISIONS

Data Envelopment Analysis (DEA) is an application of the linear optimization technique and was developed by Charnes et al. (1978) to measure the relative efficiencies of alternatives which involve multiple, incommensurate inputs and outputs. These alternatives are referred to as decision-making units (DMUs). DEA has found a variety of applications in several areas and has been used to measure the performance of physician practices, component suppliers, school districts, banks, hospitals, robots, courts etc. Lall and Teyarachakul (2006), Thanassoulis et al. (1978), Boussofiane et al. (1991) and several other papers addressed the fact that information obtained from DEA assessment can be used to discover which DMUs can be classified as efficient or inefficient, identify possible good operational practices and explore the possibility of setting targets for inefficient units. Banker and Morey (1986) presented the DEA formulation to evaluate the efficiency of DMUs when some of the inputs and outputs are exogenously fixed and beyond the control of the DMUs. Recently, DEA has been integrated with the multiple-objective linear programming (MOLP) as an interactive approach to a resource-allocation problem in organizations with a centralized decision-making environment. Golany (1988) proposed the use of preference information when setting the performance targets in the context of DEA. Sutton and Green (2002) used the DEA notion to evaluate decision choices. They suggested the modified DEA to find weights which show the performance of options and to provide a framework to elicit and use information exogenous to the decision alternatives. The efficiency score of each DMU is determined by the weighted sum of outputs divided by the weighted sum of inputs. Charnes et al. (1978) recognized the difficulty in seeking common weights because each DMU may value inputs and output differently; they proposed to use a set of weights that give the highest possible relative efficiency scores.

The fractional form of DEA, which maximize the efficiency h0 of the j0 DMU is defined as follows:

$$\text{Max} \qquad h_0 = \frac{\sum_{r=1}^{t} u_r y_{rj_0}}{\sum_{i=1}^{m} v_i x_{ij_0}}$$

$$\text{s.t.} \qquad \frac{\sum_{r=1}^{t} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \qquad j = 1\ldots, j_0 \ldots, n$$

$$u_r \geq \varepsilon \qquad r = 1\ldots t,$$

$$v_i \geq \varepsilon \qquad i = 1\ldots m, \qquad \text{(Model M1)}$$

where

y_{rj} = the amount of the r th output from unit j,
u_r = the weight given to the r th output,
x_{ij} = the amount of the i th input to the unit j,
v_i = the weight given to the i th input, and
ε = a very small positive number

Charnes and Cooper (1962) provide approaches to convert Model M1 into a linear programming model by setting the denominator in the objective function to some arbitrary constant and moving the denominator in the first constraints to the right-hand side of the constraint. For computational convenience, the DEA linear programming model is converted into a dual model as follows:

$$\text{Max} \qquad Z_0 - \varepsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{t} s_r^+ \right)$$

$$\text{s.t.} \qquad Z_0\, x_{ij_0} - \sum_{j=1}^{n} x_{ij}\lambda_j - s_i^- = 0 \qquad i = 1\ldots m$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{rj_0} \qquad r = 1\ldots t$$

$$\lambda_j,\ s_i^-,\ s_r^+ \geq 0 \qquad \text{(Model M2)}$$

where λ_j, s_i^-, s_r^+ are the dual variables.

There are alternatives to measure the efficiency of a DMU. One may use either the input-reducing efficiency or an output-increasing efficiency measure. Both model M1 and M2 measure output-increasing efficiency. In measuring the input-reducing efficiency, the relative efficiency of a DMU (for example DMU j_0) is evaluated by finding the best practice DMU's minimum effort required to produce the same amount of outputs as DMU j_0 does. In other words, how much effort it takes for the best practice DMU (reference DMU) to produce as much outputs as DMU j_0. We consider the application of DEA to project selection; the choices of DMU become project alternatives. For simplicity, we apply model M1 to select the best project candidate.

APPLICATION OF DEA IN HEALTHCARE FACILITY LOCATION DECISIONS

Healthcare systems are one of the most studied systems in the literature. According to Hollingsworth (2008) DEA has been the most frequently used technique for measuring efficiency and, since the introduction of DEA, researchers have been using the methodology for researching problems in health systems, including location decisions. For example, Mitropoulos,P. et. al., (2013) use DEA to determine which HC facilities provide basic vital services, their efficiency ratings, and consolidation recommendations. DEA has also been used together with other methodologies by several researchers in order to solve location planning problems. See for example, Mitropoulos, P. et al., (2013), Li et. al. (2013) Farahani, R. Z., SteadieSefi, M., & Asgari, N. (2010); Klimberg & Ratick (2008), Guo (2009); Thomas et.al. (2002); Narasimhan et. al. (2005).

As described in the previous section, DEA assesses the relative efficiency of DMUs by obtaining the maximum of a ratio of weighted outputs to weighted inputs. In this paper, the selection criteria for competing healthcare facility locations were the inputs and outputs in the model. Data from a previous study on the Healthcare Facility Location problem (Blum, 2014) as it pertains to Community Health Centers (CHC), was used to illustrate how the DEA approach may be applied.

In the aforementioned study, the organization *Family Healthcare Center* proposed location criteria that were deemed as important characteristics from the competing healthcare facilities (CHCs). The criteria considered for potential locations were: population, 3-year population percent growth, percent individuals below poverty level, median household income, percent of population insured, and medically underserved areas score (MUA). Note that the units of measure of these criteria vary from units for population to $ for median household income to percentages for population growth and population insured. The DEA approach allows for the simultaneous use of data ***as it comes*** regardless of how different the units of measure of the output and input criteria under consideration are. *Family Healthcare Center* used these criteria to illustrate a proposed selection procedure. Criteria was weighted on a 0-100 percent scale in consultation with executive leadership, and scores for locations were assigned on a 0-100 scale after converting raw input data proportionally. In the study, ten potential locations considered in the study were: Detroit Lakes, Dilworth, Breckenridge, Pelican Rapids, Rothsay, Elizabeth, Erhard, Wolverton and Kent, all in Minnesota, and Hillsboro in North Dakota. The population, the 3-year population percentage growth, percentage of individuals below the poverty level, and the medically underserved areas score served as output variables. The median household income and the percent of population insured were treated as input variables.

Data for these locations and overall scores may be found in **Table 1** (Blum, 2014). From **Table 1** it can be observed that the cities of Pelican Rapids (score: 69.32) and Wolverton (score: 57.56), both in Minnesota, are the more attractive locations based on the combination of the six established criteria and their assigned subjective weights. A decision to be made on the basis of these results could elicit the open question of how the results would change for variations on the weights assigned to the six criteria which, as indicated, are subjective in nature. The DEA approach would make this a moot point as the technique optimizes the weights associated with each criterion for each individual candidate location.

TABLE 1
FHC LOCATION SELECTION DATA

Location Grading Rubric				56501	56529	56520	56572	58045	56579	56533	56534	56594	56553
Factor		**Direction**	**Weight**	**Detroit Lakes, MN**	**Dilworth, MN**	**Breckenridge, MN**	**Pelican Rapids, MN**	**Hillsboro, ND**	**Rothsay, MN**	**Elizabeth, MN**	**Erhard, MN**	**Wolverton, MN**	**Kent, MN**
Town Demographics	**Variable**												
Population w/in 10 Mile Radius (2010 Census)	Output X1	↑	10%	20317	156557	11932	7898	2398	2074	15967	7269	1906	4110
3 Year Population Growth	Output X2	↑	10%	3.85	2.49	-0.59	-0.04	0.37	-1.01	0.578	0.6757	0.0000	0.0000
% of Individuals Below Poverty Level	Output X3	↑	30%	13.5	11.9	8	27.5	11	11	10	10	27.9	5
MUA Score	Output X4	↑	10%	54.7	53.5	59.2	58.6	60.6	58.6	58.6	58.6	59.2	59.2
Median Household Income	Input X5	↓	30%	39,846	46,005	49,500	33,796	43,173	44,375	41,442	37,955	46,750	52,679
% of Population Insured (Private & Public)	Input X6	↓	10%	91	89.2	93.4	91.8	92.6	83.2	83.3	90.5	69.8	64.2
Score			100%	44.72	37.75	18.46	69.32	35.29	31.66	38.6	40.98	57.56	20.26

DATA ENVELOPMENT ANALYSIS RESULTS

For illustration and comparison purposes, the same criteria and data used by *Family Healthcare Center* in their study and contained in Table 1 was used in our DEA model application. Relevant results from a DEA application are dependent upon the ratio of the number of input and output variables to the number of Decision Making Units, in our case the number of competing locations. A rule of thumb for this ratio is given by Banker et al. (1986) as: $s + m < n/3$, where s is the number of inputs, m is the number of outputs and n is the number of DMUs. While our DEA application does not meet this rule of thumb, we decided to preserve the six criteria and all raw data from the reference study sacrificing the robustness of the results in favor of a hopefully clearer illustration of the use and potential benefits of the DEA approach.

As previously stated, the output variables considered for this DEA application were the population, 3-year population percent growth, percent of individuals below poverty level, and MUA score. The input variables were the household income and percent population insured. The DMUs considered were the same ten potential locations considered in the reference *Family Healthcare Center* study.

Results

Using the latest version of LINGO, efficiency ratios for each of the ten potential locations were calculated. The results may be found in **Table 2**. An examination of **Table 2** indicates that the cities of Detroit Lakes, Dilworth, Pelican Rapids, Wolverton and Kent, exhibit a relative efficiency of 1, meaning that for their respective reported household income and percent population insured levels, no other city showed a better combination of population, 3-year population percent growth, percent individuals below poverty, and MUA scores.

The other five cities under consideration exhibit a relative efficiency value of below 1, indicating that at least one other city shows a better combination of population, 3-year population percent growth, percent individuals below poverty, and MUA scores, for comparable levels of household income and percent population insured values. As an illustration consider the city of Breckenridge. The DEA results suggest that the city of Breckenridge is 14.7% less efficient than its reference set, namely, the cities of Dilworth, Pelican Rapids and Wolverton. An examination of the data associated with Breckenridge and Dilworth reveals that with comparable values of household incomes and percent population insured, Dilworth has a significantly larger population, 3-year population percent growth and percent of individuals below poverty level (all desirable for the purpose of the study) than Breckenridge.

TABLE 2
LOCATION EFFICIENCY RATIOS

Location	**Efficiency Ratios**	**Reference Set**
Detroit Lakes MN	1.0000	-------
Dilworth MN	1.0000	-------
Breckenridge MN	0.8530	Dilworth, Pelican Rapids, Wolverton
Pelican Rapids MN	1.0000	-------
Hillsboro ND	0.938	Detroit Lakes, Pelican Rapids, Wolverton
Rothsay MN	0.935	Pelican Rapids, Wolverton
Elizabeth MN	0.993	Detroit Lakes, Dilworth, Pelican Rapids, Wolverton
Erhard MN	0.984	Detroit Lakes, Pelican Rapids, Wolverton
Wolverton MN	1.0000	-------
Kent MN	1.0000	-------

The DEA approach is helpful in removing the subjectivity associated with the weights assigned to the selection criteria in the reference study. For example, consider the cities of Pelican Rapids and Dilworth, which exhibited scores of 69.32 and 37.75 in the reference study, but an equal efficiency score of 1 in the DEA application. The reference study shows a clearly superior overall score for the city of Pelican Rapids. However, a careful examination of the data shows that for comparable values of household incomes, MUA scores and percent population insured, the city of Pelican Rapids shows a very *favorable* difference in the value of the percent of individuals below poverty level versus that of Dilworth, but, at the same time, it shows a very *unfavorable* difference in the values versus those of Dilworth for population level, and 3-year percent population growth. This puts into question the arguably large difference score between these two cities reported in the reference study.

It follows that the DEA approach allows for the introduction of other relevant factors during the location selection decision process. The cities of Detroit Lakes, Dilworth, Pelican Rapids, Wolverton and Kent, all attained a relative efficiency score of 1 and thus ranked as equally attractive locations for the CHC healthcare facility selection problem. Criteria not deemed important enough to be included among the original six in the reference study, may now be taken into consideration at the discretion of the decision makers.

CONCLUSIONS

In this paper, a DEA approach is proposed as an alternative procedure to assist decision-makers in selecting the best location for a Community Healthcare Facility from several being considered. An actual data set available in the literature was used to illustrate how the DEA approach may be applied and to compare its features with those of an actually-used and fairly common procedure (use of informed weights and scores). In the data set considered, subjective weights were assigned to the various criteria offered by the competing locations. Results from the DEA approach were compared to those from the reference study. The benefits of the DEA approach are that it does not rely on subjective weights and provides a larger set of equally acceptable locations. The DEA approach outcome may be improved by adding more potential locations to the study in order to achieve a greater ratio of Decision Making Units to the total number of relevant variables considered for the location selection. A possible extension opportunity for this paper would be to conduct a sensitivity analysis that would help identify the necessary changes to the various criteria or inputs/outputs of those locations with a reported relative efficiency less than 1, so that they may achieve a relative efficiency of 1. This process would involve further analysis of mathematical programming results.

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