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Smart growth and transit-oriented development planning in site selection for a new metro transit station in Taipei, Taiwan

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ABSTRACT

In recent years, the application of transit-oriented development (TOD) concept to urban development has been proposed based on the planning principles of smart growth and sustainable development. The development of appropriate design techniques for the surrounded built environment of TOD has become increasingly important as TOD concepts apply to urban development. The available evidence lends itself to the argument that a combined design strategies and TOD patterns planning approach that promotes the quality of urban built environment will help create active, healthier, and more livable communities. This is an essential element of this research. The TOD design strategies can be proposed by utilizing the supply side prediction methodologies of planning. There has also been an increasing interest in the urban built environment design in the past decade. This interest is motivated by the possibility that design policies associated with the built environment can be used to control, manage, and shape individual activity and behavior. This paper first studies and classifies smart growth principles based on literature review. Then the individual expert's judgments are obtained and utilized to evaluate the relative importance of smart growth principles. Next, the site selection for a new metro transit station in Taipei (Taiwan) is conducted to show the application of our proposed methodological approach. A combined Fuzzy Analytic Hierarchy Process (FAHP) and Data Envelopment Analysis (DEA) model with assurance region approach is applied to select the most suitable station from a given set of possible station sites. Both the selected station and the proposed methodological approach are provided to the public sector.

Introduction

To understand how transportation investments can be consistent with the principles and practices of land-use planning is important to researchers, professionals, and community organizations in the field of urban sustainability. Since the 20th century, the automobile has become the primary mode of transportation. This expansion has brought freedom of movement. It nonetheless has caused urban sprawl which increases travel distance and lowers energy-use efficiency. In order to discourage sprawl and to promote energy efficient development patterns, smart growth principles have been applied to integrate land use and transportation planning. Meanwhile sustainable development, with its dual emphasis on the most recent concerns—development and environment—further promotes the use of transit-oriented development (TOD) as a novel approach to development that focuses land uses around a transit station or within a transit corridor. Most site selection research has therefore focused on facility location efficiency (e.g., Min, 1994; Neufville, 1990; Neufville & Keeney, 1972; Paelinck, 1977); however, research has not provided satisfactory answers for the problem of inefficient decision-making units (DMUs) and a prior specification of input and output weights.

Accordingly, this paper develops an integrated approach to show how the site selection problem found in less-effective DMUs can be solved analytically and how the analyzing procedure requires no prior articulation of preference information. Taking facility location investigation of a new metro transit station in Taipei City (Taiwan) as an example, this paper presents an effective solution approach for the site selection problem. Also, under the proposed approach, the selection process can integrate smart growth principles into a TOD planning in order to evaluate and select a location that provides the greatest potential to serve transit riders in. Taiwan is a small island with a high population density. Due to geographical constraints, only one-third of its land can be used to accommodate people and their activities. Taiwan therefore

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faces inefficient urban spatial development patterns. As such, Taipei City, the capital of Taiwan, has encountered serious consequences of urban sprawl. Motor vehicle engine exhaust, particularly from motor scooters, was a main source of air pollution before the implementation of an integrated multi-modal transit system in early 1990s. Currently, the public transit utilization rate reaches about 37%. To further increase the public transit ridership, the Taipei City Government is expanding the transit network and; hence, new metro transit stations are needed. The Government requests that the station location decision is made based on a selected expert panel. Also, the decision-making process must incorporate both TOD planning and smart growth principles as well as be rational, transparent, and understandable.

In an effort to meet these requirements, this paper introduces a decision-making model for reaching a group decision. The model is based on a combined Fuzzy Analytic Hierarchical Process (FAHP) and Data Envelopment Analysis with Probabilistic Assurance Region (DEA/AR) approach. Past studies have constructed models in combining the DEA model with the traditional AHP for solving site selection problems (e.g., Shang & Sueyoshi, 1995; Yoshiharu & Kaoru, 2003). This paper reinforces previous studies by incorporating fuzzy logic into the AHP method. In doing so, we are able to deal with approximate (rather than fixed and exact) expert judgment when assessing the relative importance of smart growth principles. Also, we treat the planning principles of smart growth as the criteria for evaluating a given set of point sites. These criteria are: (1) multiple criteria: qualitative and quantitative; (2) tangible and intangible factors in a hierarchical manner; (3) internal and external constrains (i.e., weaknesses and strengths of each possible site) imposed on the evaluation process.

Material and methods

Site selection research

The facility location problem was first investigated by Weber in 1989 (Brandeau & Chiu, 1989). Weber solves the problem concerning optimal placement of a single facility in order to minimize the total travel distance between the facility and a set of spatially distributed customers. Partovi (2006) further presents a strategic solution to the facility location problem. In the Partovi's model, a combined quality function deployment and analytic network process approach is used to consider external and internal criteria that sustain competitive advantage. Facility site selection involves measuring the needs of a new project against the merits of potential locations. The decision process includes a process of identifying, analyzing, evaluating, and selecting one site from a given set of point sites in light of a given objective. The facility site selection therefore is a multi-criteria decision-making which comprises quantitative and qualitative criteria (Ashrafzadeh, Farimah, & Zare, 2012). Such a decision can be of great importance to companies because a facility construction plan is a long-term commitment. It is usually non-reversible and involves huge costs. This is particularly true for the transportation facilities construction planning.

Locations of transportation facilities can strongly influence capital and operating costs. The amount of research effort has been spent on facility site selection (Neufville, 1990; Neufville & Keeney, 1972; Paelinck, 1977). For example, Neufville and Keeney (1972) develop a multi-attribute utility function to evaluate two alternative airport sites near Mexico City. The authors consider the impacts over time when evaluating these two sites. However, their analysis neither assesses potential economic benefits that are associated with each site nor is validated by the sensitivity analysis. Min (1994) then proposes an AHP model that considers cost-benefit trade-offs and validates his model result by conducting a sensitivity analysis; but, as argued by DeWispelare and Sage (1981), the AHP measures are not capable of assessing the location planner's dynamic utility functions. Thus, in order to overcome these modeling problems, Shang and Sueyoshi (1995) integrate the AHP result (based on the expert's subjective judgment) into a DEA model in order to select a flexible manufacturing system. Yoshiharu and Kaoru (2003) also apply a similar approach to explore the relocation of Japanese government organizations outside Tokyo City.

Many studies (e.g., Belton, 1992; Belton & Vickers, 1993; Cook & Kress, 1990; Cook, Kress, & Seiford, 1992; Doyle & Green, 1993; Stewart, 1994, 1996) highlight the relationship between DEA and Multi-Criteria Decision Analysis (MCDA) because, similar to many approaches to multiple criteria analysis, DEA incorporates a process of assigning weights to criteria. In this study, we obtain the ranking result through a weight assignment technique that sets a relative degree of importance for each study criterion. The ranking method has been widely used as an aid to decision making in MCDA studies; in particular, a study (such as the current work) needs to assess the relative importance of a set of elements (or alternatives) with either single or multiple criteria. Various ranking methodologies ranging from the utility theory to the AHP method have been proposed in the literature (see Fishburn, 1988; Keeney, 1982; Keeney & Raiffa, 1976; Sinuany-Stern & Mehrez, 1987). Particularly, the AHP method, introduced by Saaty (1980), is a subjective method because evaluators assign a weight to a criterion based on their own subjective judgment. It is useful for quantifying subjective (or qualitative) judgment. It generates a weight for each decision criterion and determines the relative importance degree of each alternative. Yang, Su, and Hsu (2000) use AHP to generate objective weights against a set of qualitative layout evaluation criteria and determine the relative importance of multiple-objective layout design alternatives, which are adopted directly from the study of Muther (1973). However, the AHP is efficient neither in evaluating a large number of alternatives nor in selecting performance frontiers.

The DEA method assumes equally proportional improvements of all inputs (or outputs). But, this assumption becomes invalid when a preference structure over the improvement of inputs (or outputs) is present when evaluating inefficient DMUs. The unrestricted weight means that some of the inputs (or outputs) may be assigned a weight of zero, especially if DMUs are doing poorly in a particular dimension. This assumption is definitely not true in the present study, in which all the variables contribute in some way to the overall efficiency. To address the DMU inefficiency problem, the AHP method manages inputs and restricts weights, so that these restricted weights can be more feasible. That is, in a combined DEA and AHP approach, the AHP is used first to prioritize and derive weights for predefined criteria. Derived weights were then used to establish the constraints of the DEA model. Such combined approach presents a thorough decision-making process. The subjective approach used in AHP determines weights that reflect evaluators' subjective judgments, while the objective approach used in DEA determines weights based on mathematical modeling. By combining AHP and DEA, we eliminate most of the drawbacks associated with individual methodologies, and thereby yield a more accurate and justifiable result.

In addition, Charnes, Cooper, and Rhodes (1979) point out that the process to generate weights in a traditional DEA model requires improvements in order to increase model efficiency. Accordingly, studies have proposed approaches, such as CCR (Charnes, Cooper & Rhodes)/AR and BCC/AR, in the DEA literature (e.g., Cooper, Seiford, & Tone, 2000; Dyson & Thanassoulis, 1988; Thompson, Singleton, Thrall, & Smith, 1986). These studies suggest that the Data Envelopment Analysis with Probabilistic Assurance Regions (DEA/AR) method can effectively solve the issues caused by free running of input (and output) weights, and hence improve the efficiency of the DEA model.

In the current work, we attempt to solve a site selection problem by utilizing the Fuzzy AHP as the assurance region's weights assignment and feeds into a DEA planning. Past studies have constructed models in combining the DEA model with the traditional AHP for solving site selection problems (e.g., Shang & Sueyoshi, 1995; Yoshiharu & Kaoru, 2003). To the best knowledge of authors, there is no other literature proposes such integrated approach.

Smart growth principles

Smart growth was launched from a community of environmentalists, citizen groups, transportation planners, and policy makers (Geller, 2003). It is an urban planning and transportation approach that concentrates growth in compact walkable urban centers to avoid sprawl. It can be applied to solve planning and design problems (e.g., mixed-use infill development), to accelerate land use efficiency, and to manage growth (e.g., human population control). It also advocates compact, transit-oriented, walkable, bicycle-friendly land use (e.g., neighborhood schools, complete streets), and mixed-use development with a range of housing choices (Harris, 2012). To implement the smart growth concept, a private engagement is required to reduce wasteful public subsidies of sprawling development (Glendening, 1997).

Currently there is no one single definition of smart growth that satisfies everyone, and many people have their own (Miller & Hoel, 2002). Barbara McCann, the Executive Director of Smart Growth America, states that smart growth is so many different things. It is not only just transportation but also a mindset towards creating a more holistic community. We have talked about quality of life. ‘What has been more fundamental to quality of life than physical health?’ (Geller, 2003: 1411). In contrast, the National Association of Home Builders (2012) explains it from a developers' perspective. The organization defines smart growth as “development that provides a wide range of different housing choices.” That is, it is defined as the development that provides: (1) a firm, comprehensive, open and locally-based planning, (2) a more effective, innovative and market-sensitive way of utilizing land areas, and (3) housing units according to economic and population projections. Though no two organizations give the same definition, the planning principles which are publicized by the Smart Growth Network have gained widespread recognition. These principles are presented in Table 1.

Smart growth has rapidly gained popularity over the last two decades because it is a type of development that has the following characteristics (Duany & Plater-Zyberk, 1992; Song & Knaap, 2003):

(1) a street network circulation design that utilizes shorter street lengths in a grid-like pattern to promote better traffic flow
(2) higher density residential uses surrounding retail, recreational, and governmental uses
(3) more mixture of land uses that reduce the number of vehicle trips
(4) better accessibility to retail and transit that improves quality of life
(5) pedestrian-friendly neighborhoods

Nonetheless, the application of its planning principles to community development projects has encountered implementation challenges. These challenges are brought up by individuals and organizations concerned with property rights, home building, the automobile industry, and agriculture (Knaap & Talen, 2005). Such opposition has inhibited the ability of urban planners, government officials, environmentalists and real estate developers who promote smart growth to achieve initial project objectives (Downs, 2005).

The planning principles of smart growth are still relatively new and even the term “smart growth” is a highly visible concept in public policy debates. It is touted as a framework for helping communities achieve a better, more equitable and affordable built environment. Edwards and Haines (2007) evaluate the use of principles in a local comprehensive plan. The authors conclude that smart growth is most often narrowly described in terms of encouraging communities to support compact, mixed use, pedestrian-friendly, and ecologically sound development directed to existing built areas. Ye, Mandpe, and Meyer (2005) also note that, beyond the categories of resource preservation and community development, most dimensions of smart growth definition are urban focused. These studies suggest that the smart growth paradigm needs more careful attention if it is to be successfully promoted to all communities. Many of the needs of rural communities seem to be left out of the standard definitions of smart growth and the array of policies to advance better planning.

Despite many economic and political challenges faced by land planners and growth management advocates, there is much to be optimistic about its initiatives towards the planning and developing of communities. According to Chapin (2012), smart growth is an opportunity towards achieving desirable development outcomes.

Table 1
Smart growth principles.

Principle	Description
Mix Land Uses (C1)	- Supporting the integration of mixed land uses in communities as a critical component of achieving better place to live.
Infill Development of Existing Communities (C2)	- Directing development towards existing communities already served by infrastructure, seeking to utilize resources that existing neighborhoods offer, and conserving open space and irreplaceable natural resources on the urban fringe.
Preserve Open Space and Critical Environmental Areas (C3)	- Open space preservation supports smart growth goals by bolstering local economies, preserving critical environmental areas, improving our community's quality of life, and guiding new growth into existing communities.
Compact Building (C4)	- Providing a means for communities to incorporate more compact building design as an alternative to conventional, land-consumptive development.
Variety of Housing Choices (C5)	- Providing a range of housing types, sizes, and prices.
Walkable Neighborhoods (C6)	- Creating walkable communities to live, work, learn, worship, and play.
Variety of Transportation Choices (C7)	- Providing a wider range of transportation options in an effort to improve beleaguered current systems.
Community-stakeholder partnership (C8)	- Encouraging community and stakeholder to jointly making development decisions.
Cost Effective Development (C9)	- Embracing the private sector to help make development decisions to be predictable, fair, and cost effective.

Source: The official website of Smart Growth Network, http://www.smartgrowth.org/network.php.

Methodology approach

The Taipei City Government gathered six experts working in empirical economics and law fields, decision-making research, civil engineering department, environment related institutions, and assessment. These experts were responsible for finding a decision-making model and selecting the best location for a new metro train station in Taipei. Moreover, the selection process must incorporate both the TOD planning and the smart growth principles.

Accordingly, experts first identified seven possible transit station sites based on the 5-D TOD characteristics. Then a consensus-making model based on a combination of FAHP and DEA/AR was adopted in order to form a group consensus decision. As with other typical urban problems, multiple criteria (both quantitative and qualitative) are used to compare the seven possible sites. And, we treated the nine smart growth principles listed in Table 1 of the previous section as the criteria in the model. Experts, individually and independently, reported their rating of each possible site by assigning each a cardinal number score. Thus the higher the score, the better the evaluation is. The evaluation result is a matrix with seven columns (i.e., possible transit station sites) and nine rows (i.e., criteria or smart growth principles).

Next, in the selection process, was to synthesize the seven evaluations in order to reach consensus. There are several ways to do so. In this study, we use a combined methodological approach which is suitable for facility location selection. The proposed approach comprises FAHP and DEA/AR. The DEA/AR model was used to assess the strength and weakness of seven possible station sites. Taking into account all these factors, a reasonable conclusion was sought for the group decision-making process.

There are several practical issues associated with using the proposed approach for selecting a feasible facility location. These issues include: (1) a multi-stage procedure for applying a FAHP-like method to analyze criteria weights, which were assigned by experts; (2) the use of strength and weakness scores in the DEA method to characterize the possible point sites. These issues are addressed in the following sub-section.

Multi-stage use of a FAHP-like method

In applying the Fuzzy AHP, the number of paired comparisons arising from n criteria may be inconveniently large and the question arises whether it is possible to economize in the number of comparisons made. In an effort to overcome this shortage, a multi-stage modeling process was used.

In the first stage, experts assigned weights to criteria using either the FAHP method or their own subjective judgments. In the former, the FAHP method allows incomplete pairwise comparisons if experts had little or no confidence in comparing criteria and skipped some comparisons. In the end of this stage, seven sets of weights on nine criteria were gathered. In the second stage, the distribution of weighted scores was shown to each expert. They therefore learnt where they were in the distribution and had the opportunity to modify their weights. This process was continued until a convergence was reached. In the third stage, we consider the sensitivity analysis required to generate a final decision. First, the sensitivities of selected criteria scores are analyzed. Some criteria, such as Variety of Transportation Choices (C7), always have uncertainties embedded in their weighted scores even if experts rate them. Thus the sensitivity of results *vis-à-vis* these scores should be examined. The robustness of solutions should also be verified. Secondly, the sensitivity of criteria weights should be analyzed when discussing the *vis-à-vis* scores of model results.

In addition to this traditional way of assigning weights, the concept of weight restriction has been adopted in research, and several weight restriction methods have been generated. The most popular one is assurance region (AR) (e.g., Kao & Hung, 2008; Sun, 2004). Through the ARs obtained by prior information, DEA models can handle cases in which weights are subjected to predetermined relationships. When management is concerned with the degree to which the goals are met, then by setting the inputs of each DMU as one to neglect the difference and influence of inputs, the measurement result obtained is referred to as relative effectiveness (Lin, 2010). The AR weight restriction method used to evaluate efficiency measures is sensitive to the values of lower and upper bounds (L_{ij} and U_{ij}), which restrict the ratio of weights (u_i and u_j). That is, $L_{ij} \le u_i/u_j \le U_{ij}$. These values are derived from the minimum and maximum ratios estimated by experts. If an expert's ratio estimation differs substantially from that of the others and yielding “too small L_{ij}” or “too large U_{ij}”, we can neglect such extreme lower or upper bound. In doing so, we reduce the interval that the ratio can be accepted as allowable. Note that this rule is similar to the one which is used to score a gymnast in the Olympic Game in order to avoid a “home-town decision.”

Moreover, we defined “tightening the lower/upper bounds” in this study. In our station location selection problem, there are seven possible sites, seven outputs and nine criteria. We also assumed that the number of inputs is one. These numbers suggest that we lack the degrees of freedom for discriminating efficiency among the seven possible sites. A rule of thumb is as follows:

$$n \ge \max\{m \times s, 3(m + s)\}$$

where n = number of alternatives, m = number of inputs, and s = number of outputs (Cooper, Seiford, & Tone, 1999: 252). A straightforward application of the rule of thumb indicates that we are severely disadvantaged with regard to discrimination. Thompson et al. (1986) introduce a AR restriction method in order to obtain sharper discrimination in the station-selection process for the Super Collider project. Although AR constraints contribute to narrowing the production possibility set and to strengthening the discrimination power of the site selection problem, there may still remain cases where we cannot discern significant differences in efficiency. In such cases, we are obliged to tighten the upper and lower bounds of the assurance region.

The best site selection for a new metro transit station examined in this study is based on experts' evaluations and consists of rational, transparent, and easy to understand. In an effort to meet these requirements, we propose a consensus-making model based on a combination of Fuzzy AHP and DEA with Assurance Region.

Fuzzy analytic hierarchy process (FAHP)

In the following, we first outline the extent analysis method on fuzzy AHP and then the method is applied to a metro train station selection problem. Let $X = (x_1, x_2,\ldots, x_n)$ be an object set, and $U = (u_1, u_2,\ldots, u_m)$ be a goal set. According to the method of Chang's (1992) extent analysis, each object is taken and extent analysis for each goal, g_i; is performed, respectively. Therefore, m extent analysis values for each object can be obtained, with the following signs (Kahraman, Cebeci, & Ruan, 2004):

$$\mathrm{M}^1_{\mathrm{g_i}}, \quad \mathrm{M}^2_{\mathrm{g_i}}, \ldots, \mathrm{M}^{\mathrm{m}}_{\mathrm{g_i}}, \ldots \quad i = 1, 2, \ldots, n,$$

where all the $\mathrm{M}^{\mathrm{j}}_{\mathrm{g_i}}$ (j = 1, 2,…, m) are $\mathrm{TFN_s}$.

Steps of the Chang's extent analysis can be given as in the following:

Step 1: The value off fuzzy synthetic extent with respect to the *i*th object is defined as

$$S_i = \sum_{j=1}^{m} M_{g_i}^{j} \otimes \left[\sum_{j=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j} \right]^{-1} \tag{1}$$

To obtain $\sum_{j=1}^{m} M_{g_i}^{j}$, perform the fuzzy addition operation of m extent analysis values for a particular matrix such that

$$\sum_{j=i}^{m} M_{g_i}^{j} = \left(\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j \right) \tag{2}$$

and to obtain $[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{g_i}^{j}]^{-1}$, perform the fuzzy addition operation of$M_{g_i}^{j}$ $(j = 1, 2, \ldots, m)$ values such that

$$\sum_{i=1}^{n} \sum_{j=i}^{m} M_{g_i}^{j} = \left(\sum_{i=1}^{n} l_i, \sum_{i=1}^{n} m_i, \sum_{i=1}^{n} u_i \right) \tag{3}$$

and then compute the inverse of the vector in Eq. (3) such that

$$\left[\sum_{j=1}^{n} \sum_{j=1}^{m} M_{g_i}^{j} \right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i} \right) \tag{4}$$

Step 2: The degree of possibility of $M_2 = (l_2, m_2, u_2) \geq M_1 = (l_1, m_1, u_1)$ is defined as

$$V(M_2 \geq M_1) = \sup_{y \geq x} \left[\min\left(\mu_{M_1}(x), \mu_{M_2}(y) \right) \right] \tag{5}$$

and can be equivalently expressed as follows:

$$\begin{aligned} V(M_2 \geq M_1) &= hgt(M_1 \cap M_2) = \mu_{M_2}(d) \\ &= \begin{cases} 1, & \text{if } m_2 \geq m_1 \\ 0, & \text{if } l_1 \geq u_2 \\ \dfrac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)}, & \text{otherwise} \end{cases} \end{aligned} \tag{6}$$

where d is the ordinate of the highest intersection point *D* between μ_{M_1} and μ_{M_2}.(see Fig. 1). To compare M_1 and M_2, we need both the values of V $(M_1 \geq M_2)$ and V $(M_2 \geq M_1)$.

Step 3: The degree possibility for a convex fuzzy number to be greater than *k* convex fuzzy numbers M_i $(i = 1, 2, \ldots, k)$ can be defined by

$$\begin{aligned} &V(M \geq M_1, M_2, \ldots, M_k) \\ &\quad = V[(M \geq M_1) \text{ and } (M \geq M_2) \text{ and} \ldots \text{ and} (M \geq M_k)] \\ &\quad = \min V(M \geq Mi), \quad i = 1, 2, 3, \ldots, k. \end{aligned} \tag{7}$$

Assume that

$$d'(A_i) = \min V(S_i \geq S_k) \tag{8}$$

for k=1, 2,…, n; $\mathbf{k} \neq \mathbf{i}$. Then the weight vector is given by

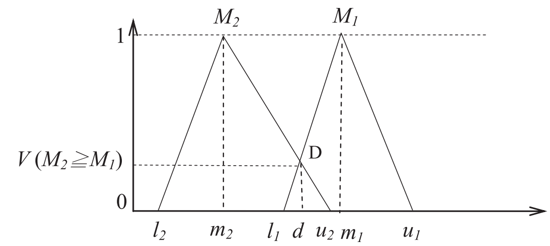

Fig. 1. The interaction between M_1 and M_2.

$$W' = (d'(A_1), d'(A_2), \ldots, d'(A_n))^T \tag{9}$$

where A_i $(i = 1, 2, \ldots, n)$ are *n* elements.

Step 4: Via normalization, the normalized weight vectors are

$$W = (d(A_1), d(A_2), \ldots, d(A_n))^T \tag{10}$$

where *W* is a non-fuzzy number.

Data envelopment analysis (DEA)

DEA is a method for estimating the efficiency of units where it is difficult to identify absolute measures of efficiency (Charnes, Cooper, & Rhodes, 1978). A typical application is the comparison of different distribution centers in a wholesale network in which the mixture of products distributed by different DMUs varies widely. If we consider a case with only one input but two heterogenous outputs, the DEA can be easily visualized. If we calculate the output for each input unit, the outputs for each DMU can be plotted on a two-dimensional graph. The envelope enclosing data points is similar to an optimal mix of output, which is achieved by using the most efficient DMUs in the system.

The DEA method has been applied to various areas of knowledge, such as rating and benchmarking of providers across the health system, educational assessment, production engineering, management and economics (Anderson, 2002). Although these systems are very difficult to visualize, the advantage of using DEA is to deal with systems with multiple inputs and outputs. By comparing each unit to all other similar units, the need to unify inputs and outputs to a single scale or to weight the relative importance of inputs and outputs can be avoided. For example, Ganley and Cubbin (1992) develop common weights for all units by maximizing their sum of efficiency ratios. Sinuany-Stern, Mehrez, and Barboy (1994) use linear discriminant analysis to rank units based on their pre-given DEA dichotomy classification. Friedman and Sinuany-Stern (1997) use canonical correlation analysis (CCA/DEA) to fully rank units based on common weights. Sinuany-Stern and Friedman (1998a, 1998b) develop the discriminant analysis of ratios (DR/DEA) rather than the traditional linear discriminant analysis. Oral, Kettani, and Lang (1991) use a cross-efficiency matrix to select R&D projects. Sinuany-Stern and Friedman (1998a, 1998b) use cross-efficiency matrix to rank units.

Nonetheless, none of the aforementioned methods provides an ultimately good model for fully ranking units in the DEA context because they have their own limitations (Friedman & Sinuany-Stern, 1998). Some methods are based on subjective data and others are limited to part of the units. In the current work, we attempt to fully rank scale units by applying the AHP technique within the DEA context. The AHP performs pairwise comparisons between criteria and between units, and then ranks units overall.

That is, based on the subjective weights given by evaluators, we construct a pairwise matrix for each comparison between any two variables. And the eigenvector of the maximal eigenvalue of each matrix is used for ranking units. Because the AHP model consists of more than one level, a hierarchical composition is used to weight eigenvectors based on criteria weights. The sum is taken from all weighted eigenvector entries corresponding to those in lower levels, which results in a global priority vector for the lowest level in the hierarchy. The global priorities are essentially the result of distributing the weights of the hierarchy from one level to the level below.

The DEA is a nonparametric approach that does not require any assumption about functional forms of the production function. In the simplest case, efficiency is defined as the output-to-input ratio (Y/X). And DEA usually deals with a unit (k) that has multiple inputs (X_{ik} where $i = 1,\ldots, m$) and multiple outputs (Y_{rk}, where $r = 1,\ldots, s$), which can be integrated into an efficiency measure; that is, the weighted sum of the outputs is divided by the weighted sum of the inputs $h_k = \sum u_r Y_{rk}/\sum v_i X_{ik}$. This definition requires a set of factor weights u_r and v_i.

Unlike MCDA models, which usually rank elements on multiple criteria (inputs and outputs) and usually provide common weights, DEA does not use common weights. In the DEA, the values of weights differ from unit to unit. And, it is this flexibility in the choice of weights that characterizes the DEA model. Such variability is the strength of DEA because DEA is directed to frontiers rather than central tendencies. Instead of trying to fit a regression plane through the center of the data, DEA floats a piecewise linear surface (i.e., the efficient frontier) to rest on top of the observations. That is, DEA chooses a set of weights that assigns the highest possible efficiency score for each study unit (Sinuany-Stern, Mehrez, & Hadad, 2000). Thus, in our study, it is assumed that weights can vary from station to station in accordance with the smart growth principles which we select for characterizing the study stations.

To evaluate the positives of station j_0, the weights (u_i) in Eq. (1) are chosen so that they maximize θj_0 under the conditions that same weights are applied when evaluating all other stations and that the objective station is compared to these stations (Charnes et al., 1978; Cooper et al., 1999). The above statements also explain how the concept of AHP is incorporated into the DEA/AR model.

A recent paper by Wang, Parkan, and Luo (2007) shows and proposes an LP method for Generating the most Favorable Weights (LP-GFW) from pairwise comparison matrices, which incorporate the variable weight concept of DEA into the AHP priority scheme in order to generate the most favorable weights for the study criteria and alternatives based on a crisp pairwise comparison matrix. The LP-GFW method differs from the LP-based approach presented by Chandran, Golden, and Wasil (2005): the former uses variable weights for each criterion (or alternative) and consists of n LP models, while the latter uses fixed weights and is comprised of a two-stage-goal programming model.

This paper is an attempt to fully rank scale units in the DEA context, utilizing one of the more popular MCDM methods—the AHP (see Saaty, 1980). Whereas the assurance region (AR) model of Data envelopment analysis (DEA) is useful in resolving the measurement of location efficiency because its calculations are nonparametric; it can handle more than one output; and it does not require an explicit a priori determination of relationships between outputs and inputs (as is required for conventional estimation of efficiency using production functions). The AR approach overcomes the issues caused by free running of input and output weights in basic DEA models. In the current work, we draw some policy implications for transportation locations and suggest directions for future research. In an effort to meet these requirements, this paper introduces a decision-making model for reaching a group decision. The proposed model is based on a combined Fuzzy Analytic Hierarchical Process (FAHP) and Data Envelopment Analysis with Probabilistic Assurance Region (DEA/AR) approach.

Moreover, in order to evaluate the strength of a possible station site j_0, the weights (u_i) in Eq. (1) are chosen so that weights are maximized under the following two conditions: (1) the same weights are applied in evaluating all other possible sites, and (2) the objective station site is compared relative to all other possible station sites, a principle in accord with DEA (Charnes et al. 1978; Cooper et al. 1999). This also explains how the AHP can be incorporated into the DEA/AR. Given the score matrix $S = (S_{ij})$, we evaluate the total score of station $j = j_0$ using a weighted sum of S_{ij_0} as

$$\theta_{j_0} = \sum_i u_i S_{ij_0} \tag{1}$$

with a non-negative weight set (u_i).

For the DEA/AR model, we evaluate each possible station site against the other possible site in terms of strengths and weaknesses. This DEA evaluation principle can be formulated as follows:

$$\text{Max} \quad \theta_{j_0} = \sum_i u_i S_{ij_0}, \tag{2}$$

subject to

$$\sum_i u_i S_{ij_0} \le 1 \quad (\forall j), \tag{3}$$

$$u_i \ge 0 \quad (\forall j). \tag{4}$$

Note that the DEA is directed towards effectiveness rather than efficiency since the site selection problem in this study is not a resource utilization problem. To achieve targeted goals is the purpose of this study. The initial goals, stated broadly, are made sufficiently precise with accompanying criteria for evaluation so that (a) proposed actions can be evaluated more accurately and that (b), once the proposed actions are implemented, any accomplishment (or lack thereof) can be subsequently identified and evaluated (see Cooper et al., 1999: 66, for additional discussion).

Furthermore, the weights assigned to each criterion should reflect the preference of all the evaluators. This can be represented by the DEA model with assurance region. That is, for each pair of criteria i_1, i_2, the ratio u_{i_1}/u_{i_2} must be bounded by $L_{i_1 i_2}$ and $U_{i_1 i_2}$ as

$$L_{i_1 i_2} \le u_{i_1}/u_{i_2} \le U_{i_1 i_2} \tag{5}$$

where the bounds are calculated by using the evaluator's weights (W_{ki}) as

$$L_{i_1 i_2} = \min_k \frac{W_{ki_1}}{W_{ki_2}}, \quad U_{i_1 i_2} = \max_k \frac{W_{ki_1}}{W_{ki_2}}. \tag{6}$$

The most preferable weight set, therefore, is assigned to the targeted station site within the allowable range. However, the same weight is used to evaluate all other possible sites, and the targeted station site is compared against all other possible sites. If the optimal objective value $\theta^*_{j_0}$ satisfies $\theta^*_{j_0} = 1$, the possible station site j_0 can be determined to be the best one. On the other hand, if $\theta^*_{j_0} < 1$, the possible station site j_0 is inferior to the other possible sites with respect to some (or all) criteria.

Results

Site selection for a new metro transit station in Taipei

The expert panel identified seven possible transit station sites based on the 5-D TOD characteristics—i.e., net residential density, jobs/housing diversity, walkable design, distance to rail mass transit station, and destinations—introduced by Cervero and Murakami (2008). As shown in Fig. 2, these possible sites are designated LG02 to LG08. In addition, the figure shows another two sites: LG01 and LG08A. These two sites are not considered as possible station sites because the LG01 site is very close to an existing metro transit station and the LG08A site serves as a metro depot. Hence, they are not evaluated in this study.

The relative importance of smart growth principles

The nine smart growth principles listed in Table 1 are treated as criteria. They are designated C1 to C9. Then each possible station site is to be evaluated using these criteria. The expert panel (comprising six experts) first assigns cardinal scores to each criterion. Then, six sets of scores are averaged for each possible station site. These averaged scores for sites are shown in Table 2. The cardinal score is in a range between 0 and 10, where 0 represents “not important at all” and 10 represents “extremely important.” Also, let us denote the matrix (Table 2) by $S = S_{ij}$, where i (=1,…, 9) is the index for criteria and j (=1,…, 7) for possible station sites.

Experts assign the cardinal scores using their own subjective judgments. According to previous studies, such as Golden, Wasil, Harker, and Eds (1989) and Tone (1989), the AHP method is useful for quantifying these subjective (or qualitative) judgments when it is combined with the fuzzy theory. Table 3 shows the result of fuzzy AHP procedure for the determination of weights, which are estimated by each expert based on each study criterion. For example, expert1 makes pairwise comparisons to obtain weights for the nine study criteria. Moreover, we denote the matrix (Table 3) by W_{ki}, where k is an index of weight for the expert and i for the

Table 2
Cardinal scores (S_{ij}) of seven possible transit station sites.

Criteria i (=1,…, 9)	Possible sites						
	LG02	LG03	LG04	LG05	LG06	LG07	LG08
C1	5.5	6.5	8	6.5	7	7.5	7.5
C2	7	7.5	8	7.5	7.5	9	8.5
C3	6	5	5	6.5	6.5	6	5.5
C4	5.5	7.5	8	7	8.5	8.5	8
C5	5	7	7.5	6.5	6	5.5	5.5
C6	6.5	7	8	8	7	8.5	7
C7	5.5	5	5.5	5.5	5	5	4.5
C8	5	5	6.5	5	6	6	6
C9	7	7.5	8	7	8	8	7.5
Total	*53*	*58*	*64.5*	*59.5*	*61.5*	*64*	*60*

Table 3
The FAHP result: criteria weights (W_{ki}) estimated by six experts.

Criteria i (=1,…, 9)	Experts						
	Expert1	Expert2	Expert3	Expert4	Expert5	Expert6	Average
C1	0.289	0.183	0.273	0.290	0.108	0.093	0.206
C2	0.040	0.167	0.157	0.136	0.264	0.090	0.142
C3	0.060	0.154	0.058	0.033	0.030	0.212	0.091
C4	0.165	0.254	0.128	0.140	0.183	0.084	0.159
C5	0.026	0.037	0.041	0.038	0.018	0.021	0.030
C6	0.018	0.099	0.211	0.153	0.031	0.212	0.121
C7	0.138	0.055	0.084	0.036	0.099	0.212	0.104
C8	0.052	0.027	0.029	0.031	0.060	0.038	0.040
C9	0.212	0.024	0.019	0.143	0.207	0.038	0.107
CR values	*0.09*	*0.05*	*0.04*	*0.06*	*0.08*	*0.02*	–

Note: LG01 and LG08A are not considered as possible transit station sites and, hence, they are not evaluated in this study.

Fig. 2. Seven possible metro transit station sites in Taipei.

criterion. Next in the evaluation process is to reach consensus with each expert having different weights for each of the nine criteria. One feasible way is to use the averaged weights provided in Table 3. Applying such weights to the score matrix $S = (S_{ij})$ leads to a comparison of relative importance among seven possible sites.

The use of average weight, however, implies that there is only one virtual expert's judgment can be representative. Thus the variety of opinions across experts is not taken into account. Given the degree of scatter (see Table 3), such averaged weight system must be used cautiously from a consensus point of view.

As shown in Table 4, LG07 and LG04 are the two possible sites with highest weighted scores. Table 4 also shows the additive weighted scores for seven study station sites, where each station site' score consists of two quantitative numbers resulting from the weighting process and individual cardinal scores (S_{ij}). Then based on the additive summation of weights obtained from the Fuzzy AHP modeling process and the cardinal scores obtained from the expert panel, we calculate an overall score for each study station using a simple additive weight (SAW) process. The result is presented in the Table.

For W_{ki}'s, k is denoted as the index of weight for the evaluator and i for the criterion. And, u_i is denoted as a nonnegative weight set in Eq. (1). It is assumed that weights can vary from station to station in accordance with a set of chosen smart growth principles used for characterizing the study stations. Both W_{ki} and u_i represent the same meaning for the weighting scales. However, W_{ki} represents an index of weight for each evaluator. In addition, by using average weight, only one evaluator's judgment (as supposed to a consensus judgment) can be representative. Another way of looking at the above approach is that weights are common to all study stations. We may call this approach as a fixed weight approach, as contrasted with an variable weight structure. On the other hand, a set of u_i is chosen to maximize θ_{j_0} under the conditions that same weights are applied when evaluating all other stations and that the objective station is compared to these stations. This principle is in accord with the DEA.

Evaluation of the possible site with strength

Eq. (2) is maximized subject to the constraints expressed by Eqs. (3)–(5). The most preferable weight set is assigned to a targeted station site within allowable ranges so that all possible sites are evaluated in terms of their strengths.

From Table 3, we have lower/upper bounds of ratios for each criteria pair shown in Table 5. Treating these bounds as assurance region constraints, the variable weight problem is solved. The resulting optimal scores, ranking, and weights for all possible sites are listed in Table 6. For example, the score for the LG02 site is 0.8734905 and its ranking is 7. Its weights ($u_1^* = 0.014832$; $u_2^* = 0.014158$; $u_3^* = 0.033710$; $u_4^* = 0.013393$; $u_5^* = 0.003348$; $u_6^* = 0.010123$; $u_7^* = 0.033482$; $u_8^* = 0.006000$; $u_9^* = 0.017170$) are optimal under the constraints expressed in Table 5.

Table 6 indicates the relative distances from the efficient frontier. The lower a score, the weaker the strength is for a possible site. In the paragraph that follows, we verify that the optimal weights for all possible station sites shown in the Table also satisfied these weight constraints. The LG02 site is unable to attain a full score of one even when it is assigned the maximum allowable weights. As can be verified, the weights give a full score of one to the LG04 site and the LG07 site, which are called "reference" to the LG02 site and are on the efficient frontier of the decision making unit problem for the site selection. Thus the seven possible sites can be ranked in an order of strength.

Table 4
Additive weighted scores for possible station sites.

	LG02	LG03	LG04	LG05	LG06	LG07	LG08
Score	5.93	6.46	7.19	6.70	6.91	7.28	6.79

Table 5
Upper and lower bounds of ratios.

Ratio	Lower bound	Upper bound	Ratio	Lower bound	Upper bound	Ratio	Lower bound	Upper bound
u1/u2	0.41	7.23	u2/u7	0.29	3.78	u4/u8	2.21	9.41
u1/u3	0.44	8.79	u2/u8	0.77	6.19	u4/u9	0.78	10.58
u1/u4	0.59	2.13	u2/u9	0.19	6.96	u5/u6	0.10	1.44
u1/u5	4.43	11.12	u3/u4	0.16	2.52	u5/u7	0.10	1.06
u1/u6	0.44	16.06	u3/u5	0.87	10.10	u5/u8	0.30	1.41
u1/u7	0.44	8.06	u3/u6	0.22	3.33	u5/u9	0.12	2.16
u1/u8	1.80	9.41	u3/u7	0.30	2.80	u6/u7	0.13	4.25
u1/u9	0.52	14.37	u3/u8	0.50	5.70	u6/u8	0.35	7.28
u2/u3	0.42	8.80	u3/u9	0.14	6.42	u6/u9	0.08	11.11
u2/u4	0.24	1.44	u4/u5	3.12	10.17	u7/u8	1.16	5.58
u2/u5	1.54	14.67	u4/u6	0.40	9.17	u7/u9	0.25	5.58
u2/u6	0.42	8.52	u4/u7	0.40	4.62	u8/u9	0.22	1.53

Evaluation of the possible site with weakness

In the previous section, each possible station site is compared with the two best performers, the LG04 site and the LG07 site. We name this evaluation scheme "evaluation of the possible site with strength" because the comparison is made with respect to the best performers. In this section, each possible station site is compared with respect to the worst performer. Such that the weights are the worst in the sense that the objective function in Eq. (2) is minimized. This principle can thus be formulated as follows:

$$\mathrm{Min}\ \theta_{j_0} = \sum_i u_i S_{ij_0}, \tag{7}$$

subject to

$$\sum_i u_i S_{ij} \geq 1 \quad (\forall j), \tag{8}$$

$$L_{i_1 i_2} \leq u_{i_1}/u_{i_2} \leq U_{i_1 i_2} \quad (\forall (i_1, i_2)), \tag{9}$$

$$u_i \geq 0 \quad (\forall j). \tag{10}$$

By dint of the reversed inequality in Equation (8), the optimal θ_{j_0} satisfies $\theta_{j_0}^* \geq 1$. If $\theta_{j_0}^* = 1$, the possible station site $\theta_{j_0}^*$ is categorized in the worst-performer category. On the other hand, if $\theta_{j_0} > 1$, the possible station site θ_{j_0} rates higher than those in the worst-performer category. Each possible site is compared with the worst performer and is gaged by its efficiency "weakness" as the ratio of distances from the worst frontier in the same way as in ordinary DEA. Yamada, Matsui, and Sugiyama (1994) name this evaluation of the possible site with weakness as "Inverted DEA."

To make a straightforward comparison between the weakness score and the strength score, $\theta_{j_0}^*$ is inverted as

$$\tau_{j_0}^* = 1\Big/\theta_{j_0}^* \tag{11}$$

and called the weakness score. Table 7 shows the obtained weakness scores, along with the optimal weights under the assurance region constraints.

As shown in Table 6, the LG07 site has the highest strength score; however, Table 7 indicates that this site has the lowest weakness score. Moreover, it is interesting to observe that the LG04

Table 6
Strength of possible sites: optimal scores and weights.

		LG02	LG03	LG04	LG05	LG06	LG07	LG08
Score	$\theta^*_{j_0}$	0.8734905	0.9101653	1.000000	0.9601643	0.9842633	1.000000	0.9632154
Rank		**7**	**6**	**1**	**5**	**3**	**1**	**4**
Weight 1	u^*_1	0.014832	0.015704	0.015891	0.016296	0.016577	0.034010	0.053303
Weight 2	u^*_2	0.014158	0.010351	0.010402	0.015555	0.006743	0.022467	0.022155
Weight 3	u^*_3	0.033710	0.011661	0.011951	0.037035	0.016055	0.005404	0.006064
Weight 4	u^*_4	0.013393	0.023556	0.023316	0.014697	0.028097	0.015967	0.025025
Weight 5	u^*_5	0.003348	0.003545	0.003587	0.003678	0.003742	0.005118	0.004793
Weight 6	u^*_6	0.010123	0.004640	0.004663	0.011122	0.004821	0.024562	0.003329
Weight 7	u^*_7	0.033482	0.035692	0.035870	0.036741	0.023252	0.018012	0.006613
Weight 8	u^*_8	0.006000	0.006644	0.006576	0.006584	0.008757	0.003630	0.005701
Weight 9	u^*_9	0.017170	0.030201	0.029892	0.006584	0.031183	0.003228	0.003726

site has the highest strength score and the second lowest weakness score. These findings suggest that the LG07 site is the highest in the ranking amongst all possible sites.

The best site selection

We further evaluate the seven possible station sites using the DEA model with assurance region. First, both the lower bounds (L_{ij}) and upper bounds (U_{ij}) are estimated on the ratio of criteria i and j in (Eq. (1)) by

$$L_{ij} = \min_{k=1,\dots,5} \frac{W_{ki}}{W_{kj}}, \quad U_{ij} = \max_{k=1,\dots,5} \frac{W_{ki}}{W_{kj}}. \tag{12}$$

These bounds are used for the AR weight restriction method.

The result is illustrated in Fig. 3. As described in the previous section, we adopt the minimization and maximization approaches to obtain two indices for each study station site—one demonstrates its strengths and the other shows its weaknesses. We then plot the station sites on a two-dimensional plane in order to get a clearer picture when comparing them. Depending on the distribution of these plotted station sites, the region can be divided into four quadrants representing the strengths *versus* the weaknesses for each study site.

Previous studies (e.g., Thompson et al., 1986; Wey & Chang, 2009; Yoshiharu & Kaoru, 2003) suggest that the maximization and the minimization approaches may not always produce the same relative ranking (but we have the same relative ranking result in our study). If a study can obtain a desirable ranking result using the minimization approach, a maximization process is not required. Moreover, if the minimization process results in more than one variable having same rankings—for example, in our study, we have more than one study station sites having a score equal to 1.00 simultaneously in the DEA modeling result—the maximization calculation is needed to find another set of ranking. When the minimization and the maximization approaches are used together, they will produce essentially the same relative ranking. They will not produce different results. Accordingly, the maximization and the minimization approaches are the most promising techniques for researchers to make a better comparison when there are some variables with same scores.

Both the LG07 site (the strength score = 1 and the weakness score = 0.873491) and the LG04 site (the strength score = 1 and the weakness score = 0.898800) are shown in the upper left corner in Fig. 3. The other possible sites lag significantly behind the two sites. Moreover, although the LG07 site is located in areas beyond the CBD of Taipei, it has higher scores than that of the LG04 site which is located near the heart of downtown Taipei. These results indicate that the overall performance for each possible station site is influenced primarily by smart growth principles, which are used as evaluation criteria in this study.

Using the aforementioned traditional weighting method and the DEA/AR method, each possible site is first evaluated numerically with respect to a given set of criteria. Evaluations may be made objectively (quantitatively) or subjectively (using expert knowledge and experience). Thus, each expert assesses the relative importance of criteria based on his or her own judgment. To do so, evaluations can be performed by using either the FAHP method or the direct subjective judgment. When these conditions are satisfied, the proposed methodological approach reaches a group consensus in ranking a given set of possible station sites. In particular, the DEA/AR model result has several desirable effects. First, the model result is acceptable in the sense that the most preferable weights for the possible sites are assigned within the allowable bounds of the experts. The optimal weights vary from site to site in that the best set of weights is individually assigned to the possible station site. In a similar way, the relative weaknesses of each possible site can be evaluated. Both strength and weakness scores are then used to characterize the possible sites. Second, each expert can be assured that his/her judgment on the criteria is taken into account and that the ratios of every pair of weights fall within the allowable range. Despite the exclusion of several experts' ratios

Table 7
Weakness of possible sites: optimal scores and weights.

		LG02	LG03	LG04	LG05	LG06	LG07	LG08
Score	$\tau^*_{j_0}$	1.000000	0.983938	0.898800	0.922867	0.904099	0.873491	0.941091
Rank		**7**	**6**	**2**	**4**	**3**	**1**	**5**
Weight 1	u^*_1	0.061312	0.018653	0.018660	0.016739	0.015089	0.016981	0.018650
Weight 2	u^*_2	0.008491	0.017805	0.017811	0.029595	0.019619	0.016209	0.017802
Weight 3	u^*_3	0.006975	0.042392	0.042408	0.016358	0.034292	0.038592	0.042387
Weight 4	u^*_4	0.028785	0.016822	0.016829	0.020552	0.013624	0.015332	0.016840
Weight 5	u^*_5	0.005514	0.004206	0.004207	0.003779	0.003406	0.003833	0.004210
Weight 6	u^*_6	0.003829	0.012730	0.012735	0.004912	0.034060	0.011589	0.012729
Weight 7	u^*_7	0.009418	0.042056	0.042072	0.037786	0.034060	0.038331	0.042099
Weight 8	u^*_8	0.008119	0.007612	0.007540	0.009300	0.006104	0.006869	0.007545
Weight 9	u^*_9	0.036904	0.007537	0.007540	0.026349	0.006104	0.019657	0.007545

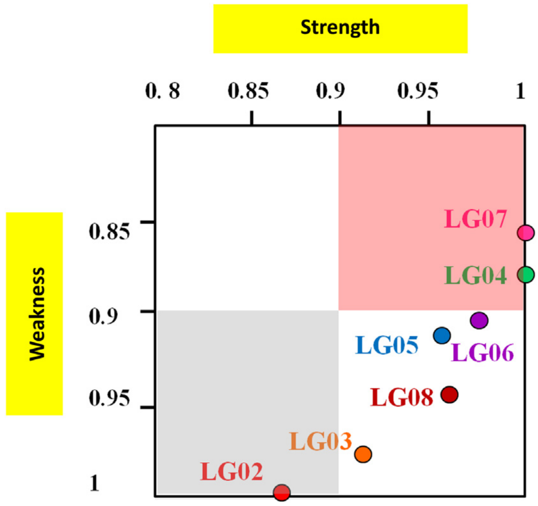

Fig. 3. Strengths and weaknesses of the seven possible station sites.

for the discrimination purpose, this approach is more reasonable and acceptable compared to the average weight approach. This is especially true in the case of a relatively high degree of scatter.

Conclusions

This paper proposes a combined methodological approach comprising the fuzzy analytic hierarchy process and the data envelopment analysis with probabilistic assurance region. The proposed approach is applied to a case study concerning the best site selection for building a new metro transit station in Taipei (Taiwan).

The Taipei City Council is responsible for selecting the most suitable site from the given seven sites. The site selection decision is based on a group of evaluators' rational thinking, and is open to the public. In the process of making the decision, not only the top-down expertise of planning and siting techniques are applied, but the bottom-up citizen participation procedure is carried out. In addition, based on the urgency and resource allocation efficiency reasons, the public sector (e.g., Taipei City Council) attempts to find the most suitable station site from the viewpoint of citizen needs and public benefits. Accordingly this paper proposes an approach, which integrates the Fuzzy Analytic Hierarchy Process (FAHP) into the Data Envelopment Analysis (DEA) model with assurance region, to solve a site selection problem.

The key characteristics of the proposed approach can be summarized as follows. Each possible station site is numerically evaluated with respect to a given set of criteria. There has, however, been a frustrating deficiency in the implementation of these methods within practical frameworks for decision-making and in forms that make them accessible to the lay policy analyst or regional planner.

The AHP method embedded with multiple criteria decision making approach shows simplicity and flexibility. These modeling shortages of AHP nonetheless can be greatly improved by combining it with other fuzzy and probabilistic methods that allow uncertainties be explicitly propagated. For example, Kouvelis and Yu (1997) represent the uncertainty using scenarios, each of which is a specification of all data. Their justification for these measures is that under uncertainty it is necessary to consider all possible consequences, including the worst ones, because we do not know which may one day be a reality. In this study, we incorporate a fuzzy matrix into the AHP method.

In addition to this traditional way of assigning weights, the AR weight restriction is used in this study. Through the ARs obtained by prior information, the DEA method can handle the cases in which weights are subjected to predetermined relationships. This paper develops a decision support tool using an integrated fuzzy AHP and DEA/AR approach. A two-phase modeling process is hence proposed to effectively deal with the site selection problem. The proposed approach extends previous studies by avoiding the main drawback of existing methods, and more importantly, by dealing with the site selection problem in a more convincing and persuasive way.

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